APPROVAL SHEET

Title of Thesis: SLEEP POSITION DETECTION USING WEARABLE ANKLE BANDS

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ABSTRACT

Title of thesis: **SLEEP POSITION DETECTION USING WEARABLE ANKLE BANDS**

Siddharth Utgikar, Master of Science, 2017

Thesis directed by: **Dr. Nilanjan Banerjee**
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Sleep plays a vital role in ones well-being. Sleep deficiency can result into or is a byproduct of sleep disorders. Prolonged sleep disorders can result into Heart Diseases, Diabetes and other severe problems [1]. The prevailing approach to study the sleep patterns and analyze the quality of sleep is by visiting sleep centers and performing a polysomnography [2]. In a Polysomnography, the patient is monitored during the sleep and data is recorded using EMG, EEG and videos. The study analyzes the breathing abnormalities, brain activity, limb movements, sleep positions etc to summarize the quality of sleep and diagnose a disorder. However, these studies are expensive and uncomfortable for patients due to the number of sensors being attached to them. We propose a in home, mobile and easy to use system, RestEaZe, that can predict the sleep quality based on wearable ankle bands. In this thesis, we have contributed to the system by analyzing the sensor data and predicting sleep positions.

Sleep position Detection Using Wearable Ankle bands

by

Siddharth Utgikar

Thesis submitted to the Faculty of the Graduate School of the University of Maryland, Baltimore County in partial fulfillment of the requirements for the degree of Master of Science 2017

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Dedicated to my mentors and friends at MPSS and Eclipse Lab.

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Chapter 1

INTRODUCTION

Sleep plays a vital role in ones well-being. Getting right amount of sleep at the right time along with good quality sleep is essential for maintaining the physical and mental health of a person as it helps the brain work properly and is also involved in the healing of heart and blood vessels [1]. Table 1.1 shows the amount of sleep a person of in an age group should have, to maintain a healthy lifestyle as recommended by the National Sleep Foundation [3].

1.1 Motivation

Sleep deficiency has different effects on individuals from different age groups, for example, in youngsters and children sleep deficiency may hamper their growth and development while prolonged sleep deficiency in adults may lead to chronic health problems over time.

As per the American Sleep Association,

- 50-70 million adults have a sleep disorder. 48% report snoring. 37.9% unintentionally falling asleep during the day.

Age	Recommended	May be appropriate	Not recommended
Newborns 0-3 months	14 to 17 hours	11 to 13 hours 18 to 19 hours	Less than 11 hours More than 19 hours
Infants 4-11 months	12 to 15 hours	10 to 11 hours 16 to 18 hours	Less than 10 hours More than 18 hours
Toddlers 1-2 years	11 to 14 hours	9 to 10 hours 15 to 16 hours	Less than 9 hours More than 16 hours
Preschoolers 3-5 years	10 to 13 hours	8 to 9 hours 14 hours	Less than 8 hours More than 14 hours
School-aged Children 6-13 years	9 to 11 hours	7 to 8 hours 12 hours	Less than 7 hours More than 12 hours
Teenagers 14-17 years	8 to 10 hours	7 hours 11 hours	Less than 7 hours More than 11 hours
Young Adults 18-25 years	7 to 9 hours	6 hours 10 to 11 hours	Less than 6 hours More than 11 hours
Adults 26-64 years	7 to 9 hours	6 hours 10 hours	Less than 6 hours More than 10 hours
Older Adults $\geq$ 65 years	7 to 8 hours	5 to 6 hours 9 hours	Less than 5 hours More than 9 hours

Table 1.1: Sleep recommendations by National Sleep Foundation

- Drowsy driving during the day is responsible for 1,550 fatalities and 40,000 non-fatal injuries annually in United States.
- Insomnia is a most common sleep disorder. 30% of which have short term problems while 10% have chronic insomnia.
- 25 million U.S. adults have obstructive sleep apnea
- 37% of age group 20 to 39 years and 40% of age group 40 to 59 years report short sleep duration.

The challenge is to diagnose the reason of sleep deficiency. Some of the causes of sleep deficiency are hectic schedules, work load, stress or one might be suffering from a sleep disorder like restless sleep syndrome, sleep apnea etc. Symptoms of sleep deficiency may differ for adults and children. Adults may feel drowsy, have problem concentrating, have slower reaction times etc while children might seem overly active, seem impulsive, have mood swings etc. The primary method doctors use to diagnose some sleep disorders is by asking questions to patients about the sleep schedules. In cases where this is insufficient, doctors might advise the patient to go under sleep studies in sleep centers. These studies are painless non-intrusive tests that measure various parameters of the patient during a full night sleep. Some of the parameters that are monitored during the night include the brain activity, breathing, limb movements etc. The recorded results are then studied by a sleep expert and a treatment plan is decided.

The currently prevailing approach for sleep studies is visiting the sleep centers. The technicians then visually score the videos which include characteristics like limb movements, body position, leg position, brain activity etc. These sleep centers are often very expensive and uncomfortable for the patients (as seen in Figure 1.1). We present a comfortable, affordable and easy to use approach using wearable ankle band system (RestEaZe™ described later), which records the position of the body through the night.

1.2 Overview and Contribution

Body position is one of the key parameters used to diagnose sleep quality of the patient. Metrics such as limb actions or breathing of patients, changes based on whether the person is sleeping on their back, on their stomach or one of the sides, define the position of the body [4] [5]. Results of research in neuroscience show that the position of the body during sleep affects the rate of clearance of waste

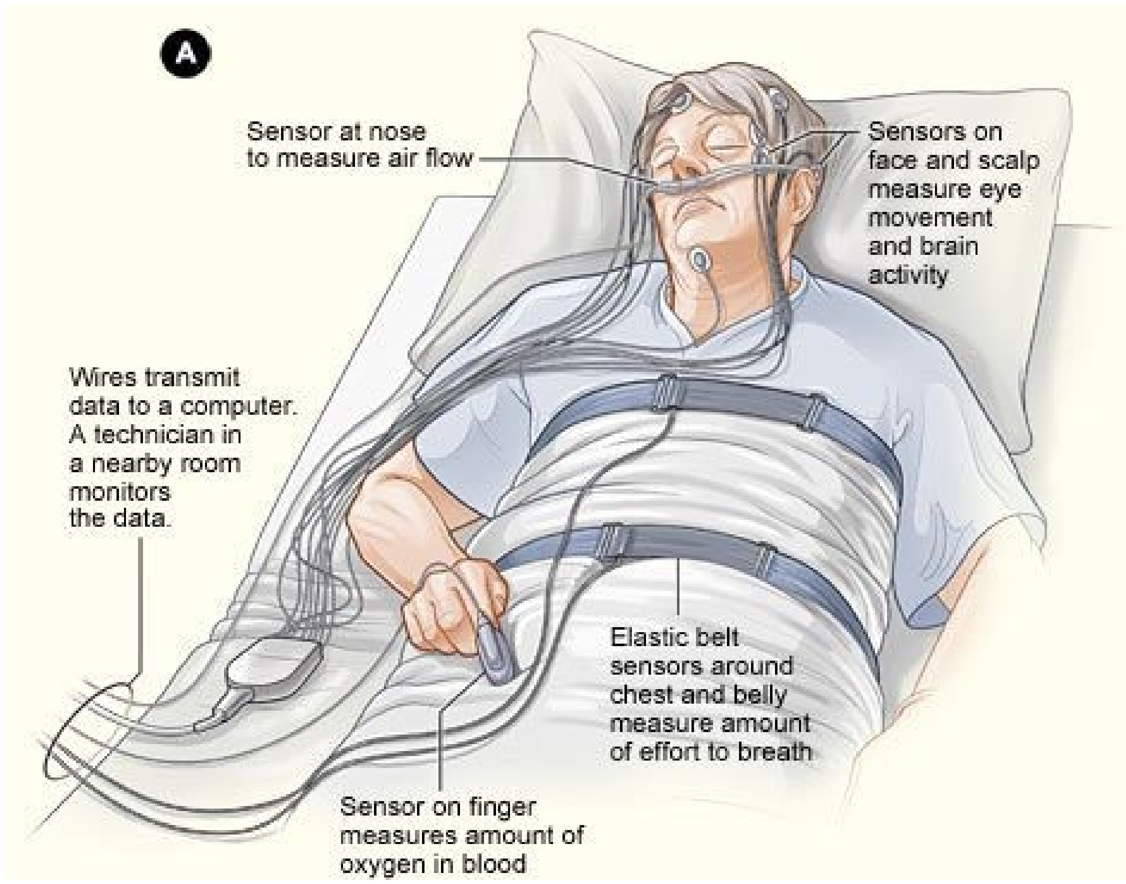

Figure 1.1: Polysomnography, an uncomfortable and expensive sleep study process.

from the brain through glymphatic pathway [6]. Obstructive sleep apnea (OSA) is a sleep disorder which has been gradually accepted as an important cause of increased morbidity and mortality. [7] OSA patients are divided into two types, positional and non-positional. Positional patients show most of their breathing abnormalities while sleeping in supine position. Simply, by changing this position to the lateral position helps to reduce the number of apneas significantly [8]. Positional patients constitute approximately 65% to 87% of the OSA patients. Non-positional patients are less affected by the body sleep position. Sleep Positions are broadly divided into three types,

1. Supine: Lying on the back with both shoulders touching the bed

2. Stomach: Lying on the stomach with neck turned towards one side

3. Lateral: Lying with one shoulder touching the ground

Figure 1.2: Ideal Sleep Position Classes

Figure 1.2 shows the sleep positions. These are the ideal positions. The challenge however is to quantify the variations in each of them. Sleep positions will vary based on age, gender, daily routine and personal choices. The magnitude of this challenge is realized by looking at Figure 1.3. In this thesis, we have analyzed the data collected over wearable ankle bands to predict body positions during sleep. The results of this analysis contribute to the calculation of sleep quality.

Figure 1.3: Variations in Sleep Positions

Chapter 2

Related Work

2.1 Wearable sensors

The field of wearable sensors has been growing recently. Wearable technology to monitor older adults or people with chronic conditions have been some of the rising applications [9]. The commercial market now has a variety of choices of smart watches and health bands which track a persons daily routine and provide them with a feedback [10]. This feedback includes the amount of time they spent sitting down, walking, running, bicycling and sleeping. This is achieved by the various sensors that are embedded in the wearable products. These sensors include accelerometers, gyroscopes, magnetometers etc. Some of higher end medicine grade devices also provide heart rate monitoring. These monitored values are aggregated to create a history of their activities. Sam Naghshineh, Golafsoun Ameri, Mazdak Zereshki present their idea [11] of tracking human motions in 3D using a tri-axial accelerometer. Their goal was to emulate upper body actions in 3Dimensions. They have presented dual axis and tri axis tracking based on the calculation of angles between two axes. One of their approaches was to measure the acceleration during movement and then find the displacement by taking the second integral of the measured acceleration. The approach is dependent on the users body specifics and tracks position based on displacement. Our application involves minimum displacement. However, we considered their approach of calculating angles between axes. In another research [10] the authors are tracking activity of the patient by wrist and ankle mounted accelerometers. Their model is like ours, where they use Bluetooth to transmit the data and collect it on a smart phone. They had participants perform activities in the lab under observation and used that annotated data to train a model, which detected the activities performed by the users. They have used the Single Magnitude Vector, SMV, given by SMV = $\sqrt{AccX^2 + AccY^2 + AccZ^2}$ to detect motion.

2.2 Sleep position detection

Sleep position detection has a lot of importance due to a lot of patients suffering from positional sleep apnea. Efforts in this field have been active and various techniques to derive the sleep positions and movements have emerged [12] [13] [14]. A mattress which uses Wireless Identification and Sensing Platform(WISPs) platform based RFID sensors, has been developed to track sleep positions and movement during sleep. The design of the authors is seen in Figure 2.1. They attached the WISP tags along all three axes. The design leverages the change in the deformation of the mattress when someone sits on it. When the mattress is empty, the tags would be aligned to gravity. The deformation when someone sits on it and when someone sleeps on it provides two separate signatures. Similarly, if a person sleeps

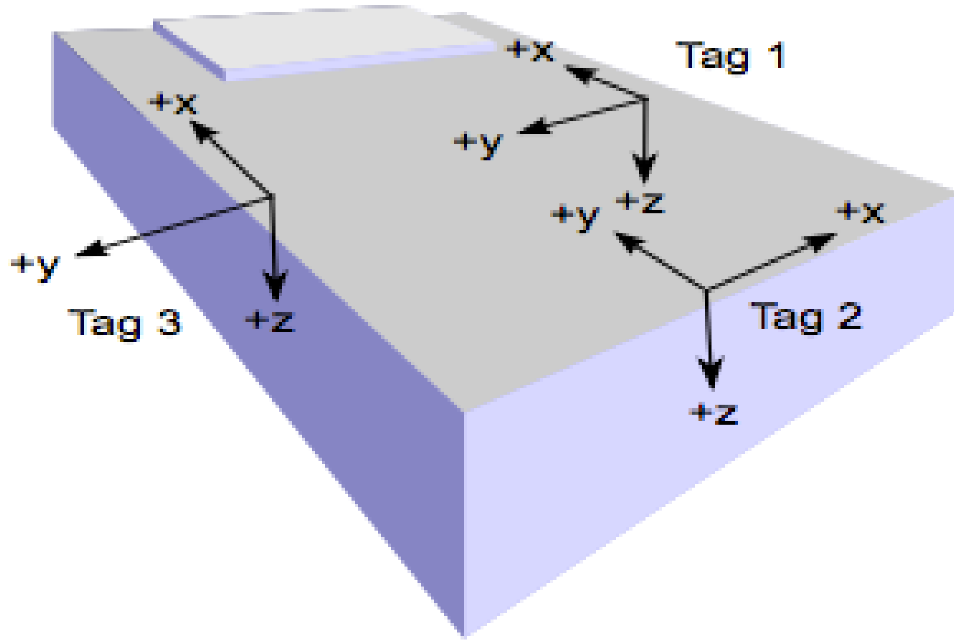

Figure 2.1: Mattress attached with WISP RFID tags

towards the left by lying on their shoulder laterally, Tag 1 shall show the maximum variation. The system is smartly developed but requires a professional setup. We have tried to provide an in-home solution to detect positions and movements during sleep.

BuzzPOD [12], a position monitoring and supine alarm device, is a small lightweight device that can be connected around the chest using a velcro strap as shown in Figure 2.2. It records sleep position at 1Hz and gives an alarm if a person is in the supine position for a long duration.

Figure 2.2: BuzzPOD attached to chest

Chapter 3

System design

Polysomnography, a standard practice to diagnose sleep disorders, is carried out by visiting sleep centers for a night or series of nights. As shown in Figure 1, in a sleep center the patient is connected to a machine which has sensors connected to his body to measure blood oxygen level, breathing and rapid eye movement. Along with these, an EMG is connected to measure the limb movements during sleep.

In our experiments, we have made use of

1. RestEaZe^{TM} System

2. Sleep Lab at Johns Hopkins

3.1 RestEaZe^{TM} system

RestEaZe^{TM} is a sleep monitoring system designed with the goal to overcome the cost and convenience issues faced in a sleep lab study. It is an affordable product and service that patients can take home and use in their natural sleep setting. The system tracks the leg movements made by the patient during the night and translates them to a sleep quality measure based on specific types of movements identified by sleep science laboratories.

RestEaZe™ is made of three pillars as seen in Figure 3.1.

1. Wearable Ankle Bands

2. Mobile Application

3. Back End System

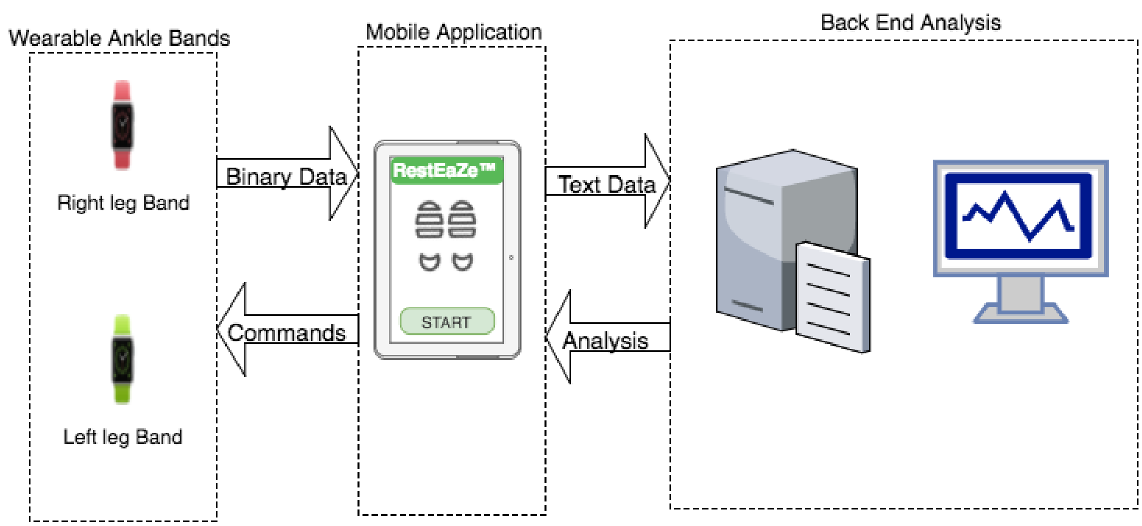

Figure 3.1: RestEaZe™ System

3.1.1 Wearable Ankle Bands

Every RestEaZe™ system has a set of two ankle bands that are equipped with a sensor array of three capacitive plates, a three-axis accelerometer and a gyroscope. Each band also has a Bluetooth module that is used to communicate with the mobile application on the smartphone and a flash chip for local storage. The capacitive sensors measure the change in capacitance, where the bands capacitor plays the role of one plate while the patients body surface, for example their foot, acts as the other capacitive plate. This change in capacitance has been used to measure foot flexions, especially Periodic Leg Movements (PLMs). Similarly, each sleeping position based on how the legs are oriented, creates a pattern in the capacitive plates which has been used to identify sleep positions. To ensure this data is received properly it is essential to put on the bands properly. The band seen in Figure 3.2(a) has three capacitor plates marked by the golden/colored border. To ensure we get the cleanest data, the band should be worn as shown in Figure 3.2(b) with the center capacitor facing forward. The accelerometer along with the gyroscope has been used to detect the orientation of the leg and the Complex Leg Movements (CLMs). The combination of data from the left and the right band enables us to identify sleep positions. The band collects data at 25Hz and works in two modes namely, Streaming Mode and Caching mode. In Streaming mode, the band transmits the data at 25Hz over Bluetooth to the smartphone application. In Caching mode, the band uses the onboard flash storage to store the data, which is later offloaded by the smartphone application. The band is in factory calibrated for the inertial sensors and undergoes a one click calibration for capacitive sensors before every study. In the factory calibration, the band is laid on a flat surface and the This ensures the sensors are outputting readings most accurate to the current environment of the study and patient. Figure 3.2 shows the bands design and the bands on a patient.

3.1.2 Mobile Application

RestEaZe$^{\mathrm{TM}}$ mobile application connects to two ankle bands simultaneously over Bluetooth. The application offers a basic user login which helps maintain user

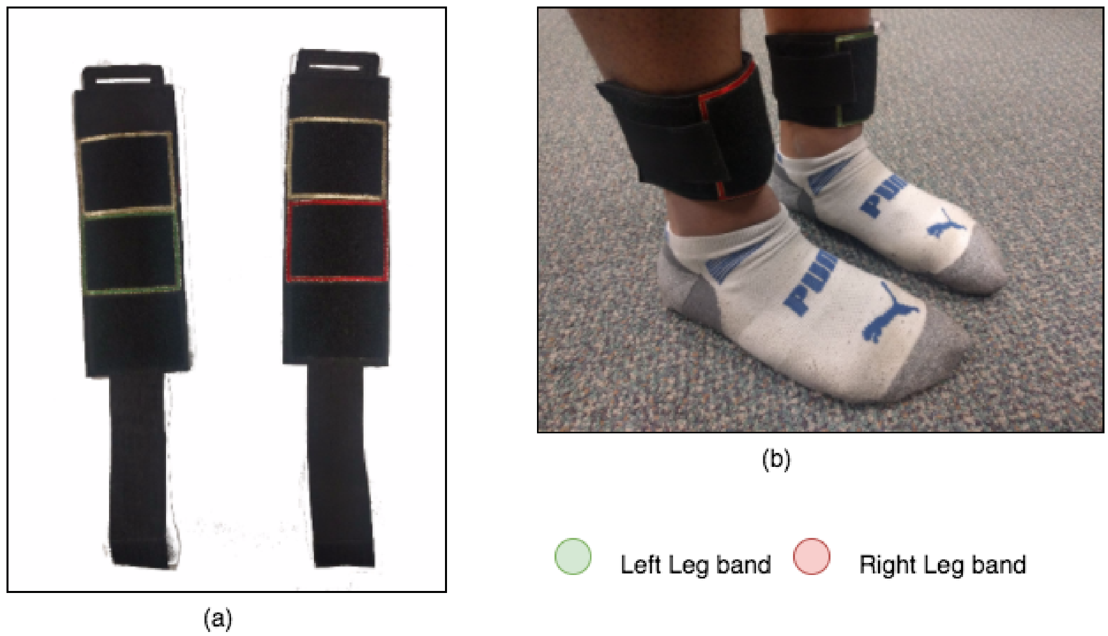

Figure 3.2: (a) Bands design (b) Bands put on a patient

profiles. It also offers one time configuration of the bands and then is responsible for automatically connecting to bands once started. The applications user interface has been designed targeting maximum population and minimum complication. The user can calibrate the bands, Start and Stop the data collection, configure the system to work in streaming mode or caching mode and configure whether the data received should be uploaded to the server or written to files locally by the settings provided in the app. The calibration offset values for all the sensors, the start time of data collection and the stop time of data collection is stored by the application in the form of sessions, to a metadata file. Each time a user hits Start, a new session is generated. That session is active until the user hits Stop. The data received over Bluetooth is saved to a database and gets either uploaded from the database to a server or written to files locally. Results of analysis of the sleep quality are displayed in the app to provide the user a quick feedback on the quality of sleep they are getting. Some of the screens of the app can be seen in Figure 3.3.

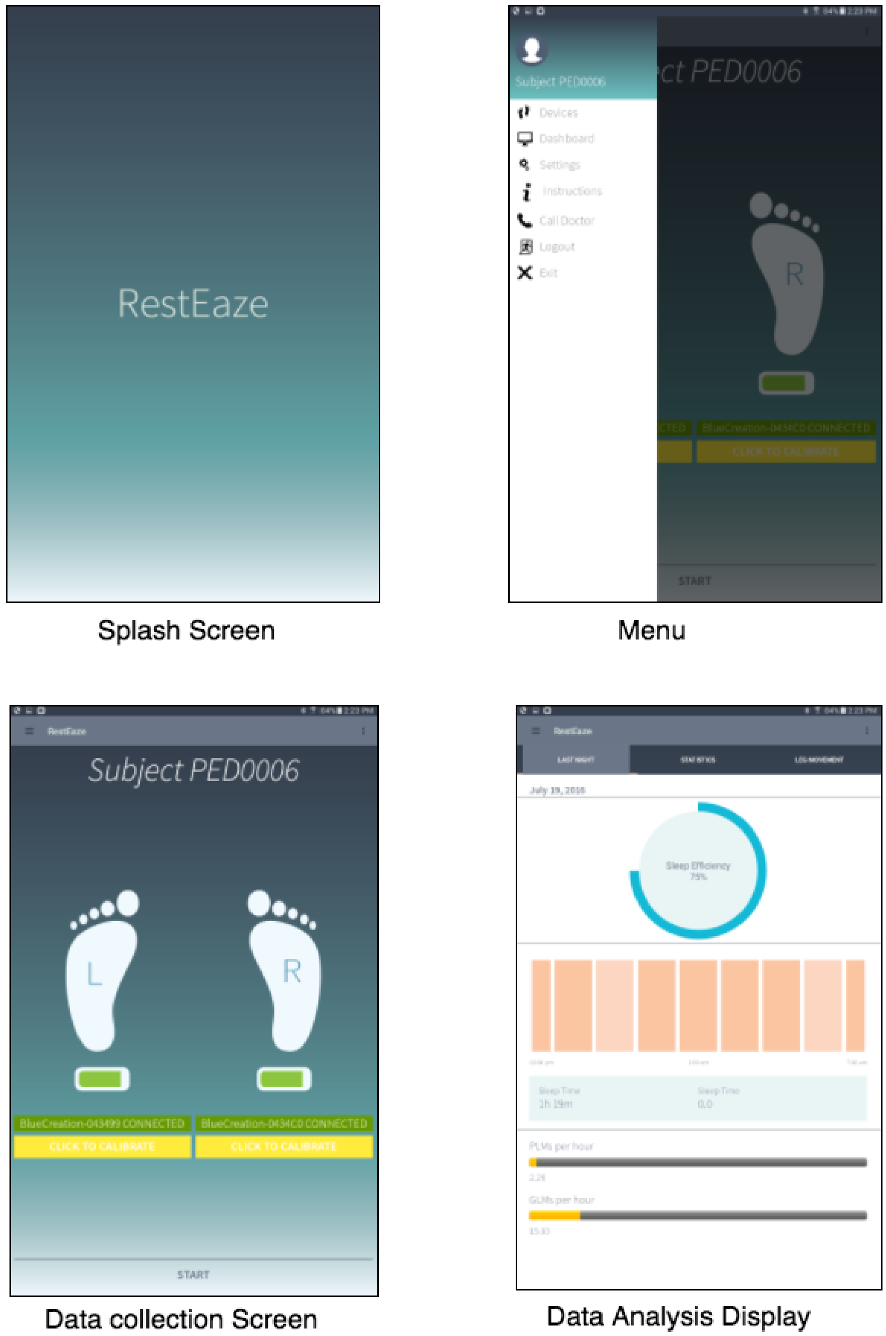

Figure 3.3: RestEaZe$^{\mathrm{TM}}$ Mobile Application Screenshots.

3.1.3 Back End Analysis

The data is uploaded from the smartphone app to the server in the form of text files. The files are organized in user folders. Each night of a study a file for each left and right leg is created. The metadata file gets updated with a session entry representing the nights study. These files are then processed to formulate sleep quality results. Figure 3.4 shows the steps in the analysis process.

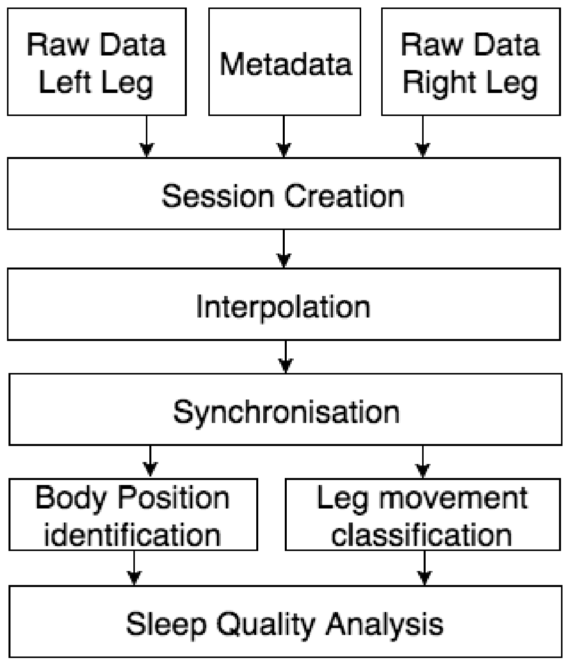

Figure 3.4: RestEaZe^{TM} Backend Analysis Steps.

3.1.3.1 Session Creation

A python script reads the raw data files of both legs and creates a separate .csv file for both left and right leg respectively. These files contain only the data for the session mentioned in the metadata file. This eases the further processing steps to get results for the specific night.

3.1.3.2 Interpolation

The data collected over the bands and transferred to the tablet is subject to losses due to dropping of packets over Bluetooth or packets are discarded by the System due to loss of integrity. Since these losses vary from left leg to right leg or one night to next, it is not possible to have a constant sampling rate of 25Hz from the bands. To make up for these losses the session files are linearly interpolated to achieve a constant sampling rate.

3.1.3.3 Synchronization

There is a minor timing delay between the left and the right leg data. Using this data as it is will introduce errors in the identification of patterns. To solve this problem the data from the left band is time aligned with the data from the right band. During this a relative timing is introduced for each sample. This timing (in seconds) starts from zero and is considered as reference for events. The sleep lap data is collected at 50Hz and the RestEaZe™ collects it at 25Hz. To use the visual scoring provided with the sleep lab data we use the sync signal, a pseudo random repeating sequence. This signal is recoded by both sleep lab and the RestEaZe™ system. We align the data points using this signal.

3.2 Sleep Lab Study

We have conducted 4 studies at the Johns Hopkins Sleep Lab. The motivation behind these studies is to get a reference point to verify the results of analysis achieved from the data collected using the RestEaZe™ . The Sleep Lab provided us with PSG data, EEG data and EMG data. They also provided us the video of the patients legs during the study and a visually scored file, marking events which include leg movements and sleep positions. During the sleep lab study, we collected data using RestEaZe™ along with the polysomnogram. The RestEaZe™ ankle bands were modified such that a repeating pseudo sequence signal could be provided from the bands to the polysomnogram machine. This signal was used for time synchronizing the data collected by the polysomnogram machine with the RestEaZe™ data.

3.2.1 Data Marker Tool

The visual scoring provided by the Sleep Lab was used to annotate the data from the RestEaZe™ Bands. We developed a tool which was used to visualize and annotate all the data from the RestEaZe™ ankle bands.

The sleep lab annotation for sleep positions include three sleep positions

1. Supine: Lying on the back with both shoulders touching the bed

2. Left: Sleeping lateral with left shoulder touching the ground

3. Right: Sleeping lateral with right shoulder touching the ground

We have used the same metric to train a classification model over the RestEaZe™ data to identify sleep positions. The annotations provided by the sleep lab mark sleep positions for every movement event during the night. A transition from one sleep position to another is marked accordingly. This is seen in Figure 3.5. The blue

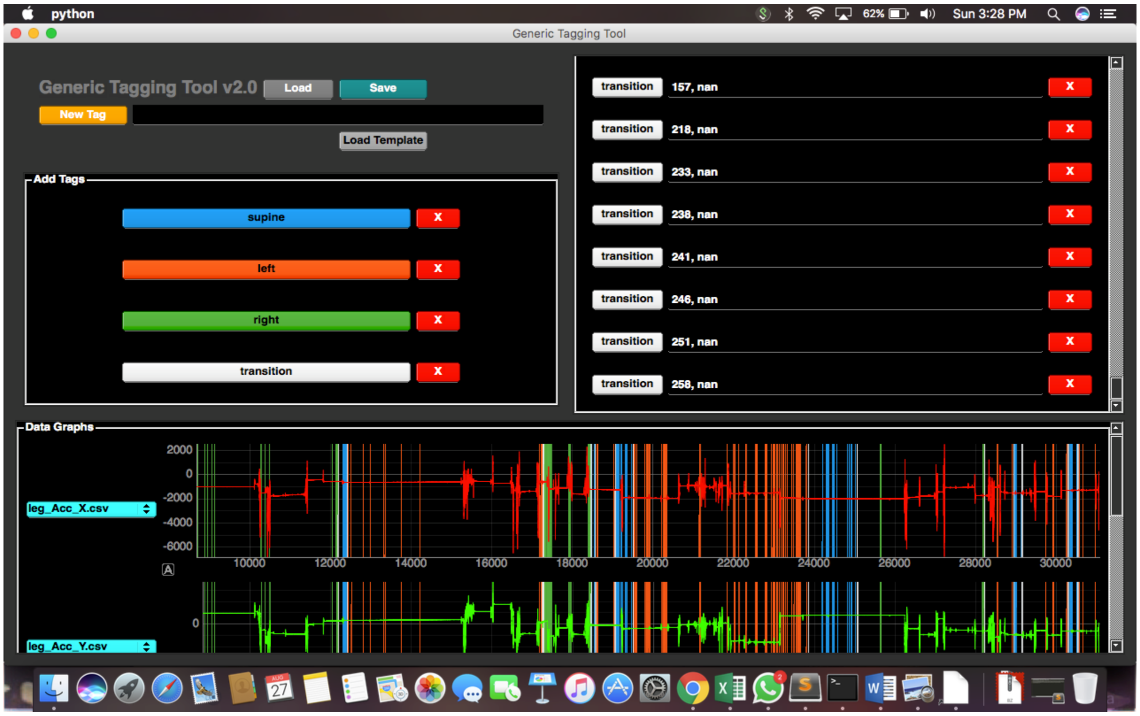

Figure 3.5: Marker tool with data files and Sleep Lab annotation

markings indicate the events in which the patient was in supine position, the orange markings indicate events during which the patient was in left position, the events in right position are indicated by green and the white markings are the transitions of the patient from one position to another.

Leveraging that unless an event mentions a transition of sleep position the patient will be in the same position, we used the marker tool to mark windows of sleep positions through the night. Figure 3.6 shows the windows marked. Every brown marking is a duration of the night in which the patient was in supine position, every grey marking is the duration of the night in which the patient was in left position and each red marking indicates the duration of the night in which the patient was in right position.

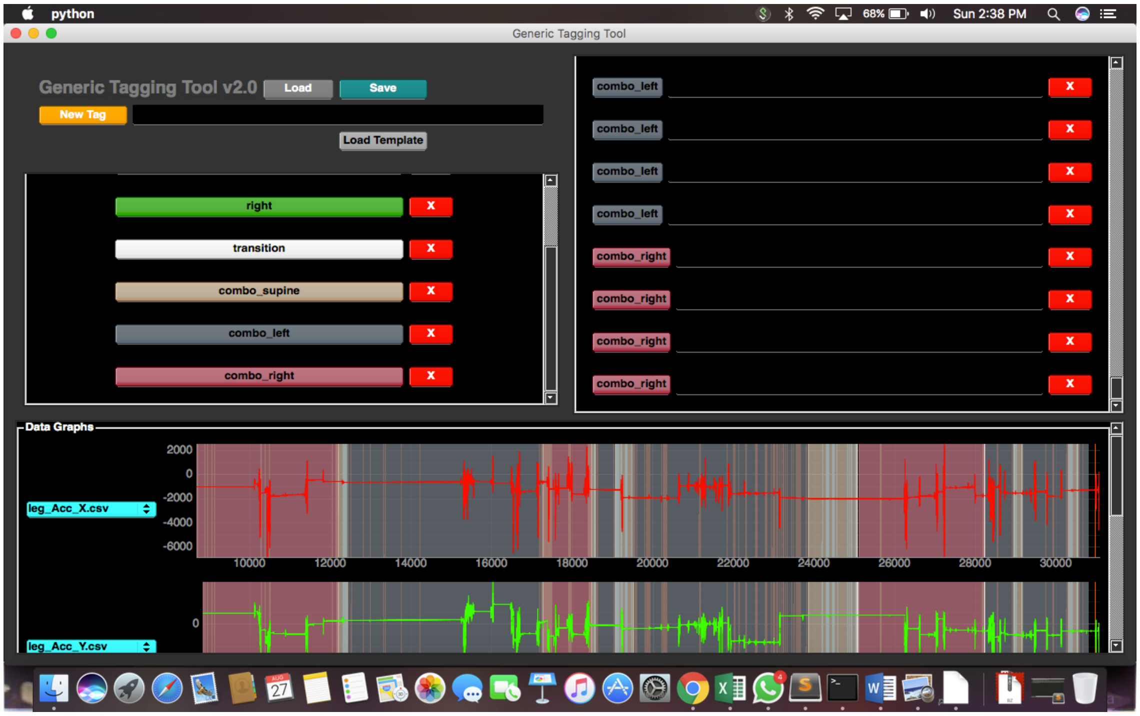

Figure 3.6: Marker tool with data files and Sleep Position Annotation by us.

3.3 Data Analysis

3.3.1 Annotation

The first step was to label all the data available for sleep positions. As mentioned in Section 3.2.1, we used the marker tool to visualize the annotation provided by the sleep lab and then manually annotated the sleep positions for the complete night.

3.3.2 Normalization

Following the labeling step, we normalized the data using the MinMaxScaler given by the formula below.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

This suppressed the variation in data between patients, and converted it in a common scale of 0 to 1.

3.3.3 Feature Extraction

As mentioned before, RestEaZe™ ankle band each, has data from the following sensors

1. Capacitor 1, Capacitor 2, Capacitor 3

2. Accelerometer X, Y, Z

3. Gyroscope X, Y, Z

We calculated features for each duration of a specific sleep position separately. Figure 3.7 displays the split of positions through the night. Table 3.1 explains how features were calculated. This covered the variations of a position by a patient through the night. For each of the above-mentioned sensors we calculated the first four statistical moments namely,

1. Mean

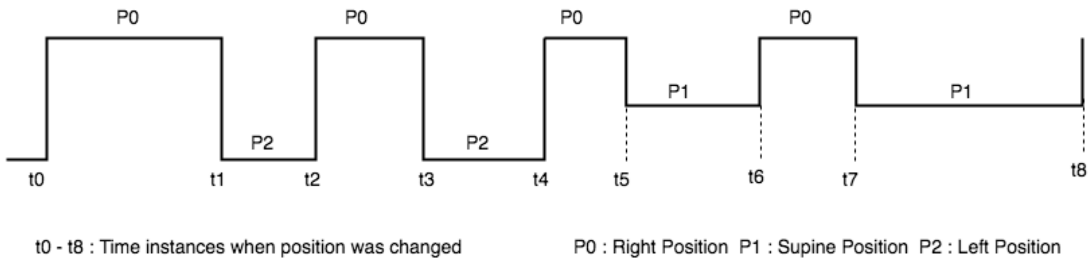

Figure 3.7: Position changes of patient through the night.

Label	Each time duration
P0	t1-t0
	t3-t2
	t5-t4
	t7-t6
P1	t6-t5
	t8-t7
P2	t2-t1
	t4-t3

Table 3.1: Feature Calculation on Segments of Data

2. Standard Deviation

3. Skewness

4. Kurtosis

We also calculated the Pitch, Yaw and Roll angles for the accelerometer. Table 3.2 shows all the features We used one band on each leg while data collection so we had twice as many features.

To calculate these features, we used the sliding window approach. The window size was decided by plotting a Cumulative Distribution Function (CDF) of the durations of all three sleep positions slept in by the four patients. Figure 3.8 shows the CDF plot. We used the median of the CDF to choose our window size. The median was 0.51 and hence the window size chosen was 1100 seconds. To verify we also

Sr. No.	Features
1	Capacitor 1 Mean
2	Capacitor 1 Standard Deviation
3	Capacitor 1 Skewness
4	Capacitor 1 Kurtosis
5	Capacitor 2 Mean
6	Capacitor 2 Standard Deviation
7	Capacitor 2 Skewness
8	Capacitor 2 Kurtosis
9	Capacitor 3 Mean
10	Capacitor 3 Standard Deviation
11	Capacitor 3 Skewness
12	Capacitor 3 Kurtosis
13	Accelerometer X Mean
14	Accelerometer X Standard Deviation
15	Accelerometer X Skewness
16	Accelerometer X Kurtosis
17	Accelerometer Y Mean
18	Accelerometer Y Standard Deviation
19	Accelerometer Y Skewness
20	Accelerometer Y Kurtosis
21	Accelerometer Z Mean
22	Accelerometer Z Standard Deviation
23	Accelerometer Z Skewness
24	Accelerometer Z Kurtosis
25	Gyroscope X Mean
26	Gyroscope X Standard Deviation
27	Gyroscope X Skewness
28	Gyroscope X Kurtosis
29	Gyroscope Y Mean
30	Gyroscope Y Standard Deviation
31	Gyroscope Y Skewness
32	Gyroscope Y Kurtosis
33	Gyroscope Z Mean
34	Gyroscope Z Standard Deviation
35	Gyroscope Z Skewness
36	Gyroscope Z Kurtosis
37	Accelerometer Pitch
38	Accelerometer Yaw
39	Accelerometer Roll

Table 3.2: Feature List Calculated for each leg.

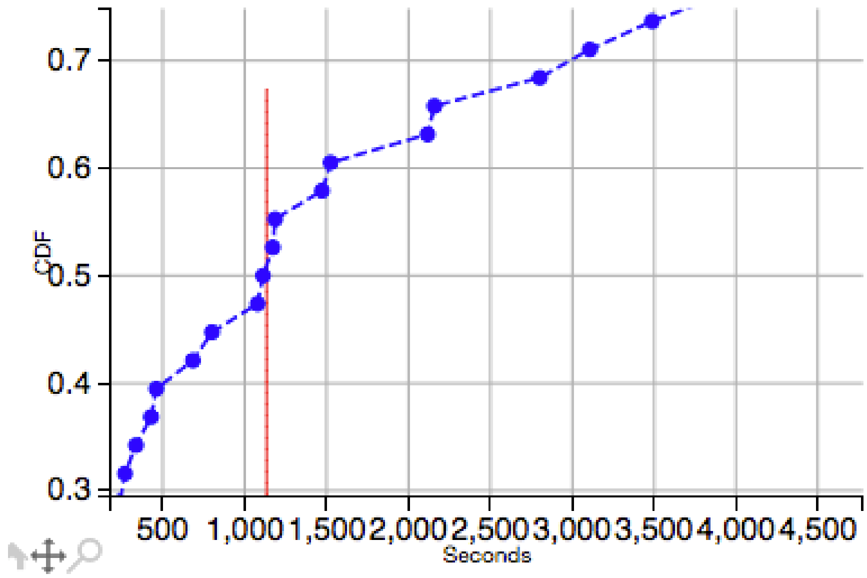

Figure 3.8: CDF of Durations in Sleep Positions

experimented with a window of 1000 seconds and 1200 seconds. The ankle bands collect the data at 25Hz. Hence the window size equals to about 27500 samples.

3.3.4 Classification

We classified using two models Support Vector Machines (SVM) and Logistic Regression (LR). To test the impact of each sensor we also used features of individual sensors and then all sensors combined. While calculating the features we also tried 50% overlapping windows to see the effect on the accuracy of prediction. To validate the result, we also performed 10-fold cross validation using each SVM and LR.

3.3.4.1 Support vector machine

Support Vector Machine is a classification algorithm that tries to find a hyperplane separating the classes while maximizing the distance from the closest point from each class. This method aims at maximizing the margin of support vectors from decision boundary. Predictor values near the boundary tend to have more influence on location of decision boundary and hence, have higher weight vectors. We have used a Linear-kernel [15] while creating the kernel SVM model.

Tuning of the hyper parameters is of importance in a kernel SVM. As σ^2 reduces, the hyperplane is increasingly dominated by data points near to the hyperplane as compared to distant ones. We have used the Python scikit.learn library to implement the SVM model with RBF kernel. The model is a multiclass classifier since we have three sleep positions to classify.

3.3.4.2 Logistic Regression

Logistic regression [16] is a statistical method for analyzing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable. It is based on the logit function. A simple logistic model with n independent variables has the form

$$Y = \frac{\mathrm{e}^{\alpha+\beta_1\mathbf{x}_1+\beta_2\mathbf{x}_2+\ldots+\beta_n\mathbf{x}_n}}{1+\mathrm{e}^{\alpha+\beta_1\mathbf{x}_1+\beta_2\mathbf{x}_2+\ldots+\beta_n\mathbf{x}_n}}$$

Chapter 4

Experiments and results

We have used annotated data from 4 sleep studies for the implementation of this thesis.

4.1 Patient details

The patients were chosen such that we cover maximum variation. **NOTE**: All

ID Number	Date of test	Age	Sex	Clinical Diagnosis
PED001	26-Jan-17	10	Male	ADHD
PED002	13-Mar-17	17	Female	ADHD
RZ0015	8-Jun-17	60	Female	Insomnia
RZ0016	29-Jun-17	71	Female	RLS

Table 4.1: Details of patients involved in sleep study

the patients were selected by the doctor at Johns Hopkins; these are regular patients who are being treated at the hospital. We cannot share additional information about the patients. We trained models to try and classify using individual sensors sets and all the sensors together.

4.2 Micro benching

We covered patients from separate age groups to provide a variety of data. Each patients requirement of sleep as per Table 1.1 and their actual sleep time that we recoded is seen in Table 4.2. We see that the patients are not getting recom-

Patient	Age	Recommended	Data Recording Start	Data Recording End	Approximate Sleep Duration
PED001	10	9 to 11 hours	20:58:15	6:05:32	< 7 hrs.6 mins
PED002	17	8 to 10 hours	0:04:41	6:40:49	< 6 hrs.36 mins
RZ0015	60	7 to 9 hours	22:42:33	6:05:54	< 7 hrs.23 mins
RZ0016*	71	7 to 8 hours	22:00:53	6:42:22	< 8 hrs.41 mins

Table 4.2: Recommended and actual time of sleep. *Patient could not sleep until 12

mended sleep hours but are not completely out of the expected range, making them good candidates for the study. Combining the data of all patients together we had a dataset accounting to approximately 26hrs of sleep time. After the preprocessing steps the annotated data gave us the time durations in which each patient was in for a sleep position. Table 4.3 displays these values in form of percentage. We

Patient	Supine	Left	Right
PED001	10%	52%	36%
PED002	31%	42%	26%
RZ0015	54%	21%	23%
RZ0016	52%	47%	0%

Table 4.3: Distribution of sleep positions for each patient.

had relatively equal distribution of dataset for each position. We calculated all the features mentioned in Section 3.2.3 and plotted them to visualize the separation of classes. Figure 4.1 displays features that provide good separation characteristics, Figure 4.2 shows features without good separation characteristics.

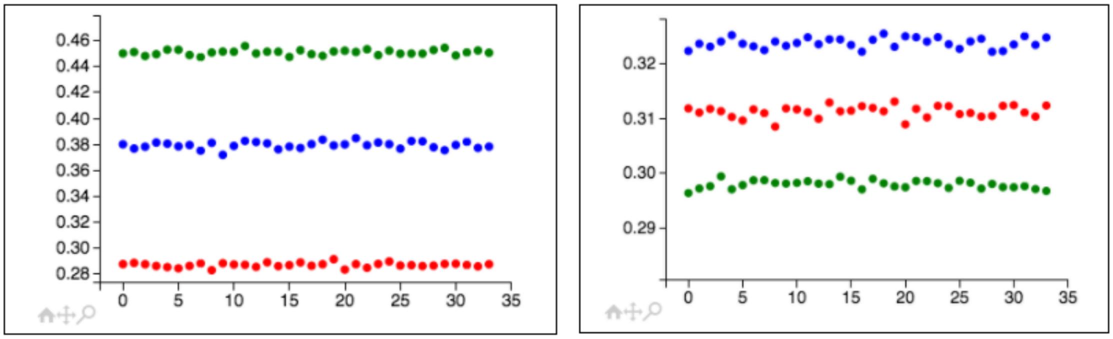

Figure 4.1: Features with good separation characteristics.

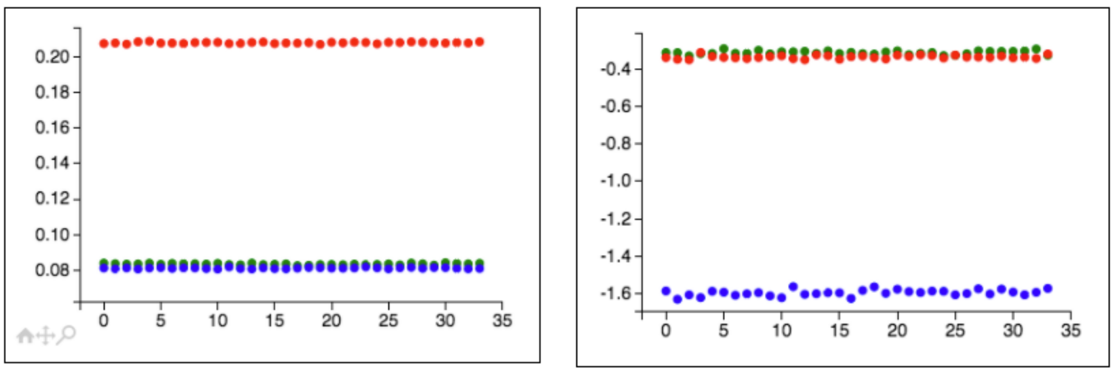

Figure 4.2: Features with poor separation characteristics.

4.3 Accuracy results

We have calculated the accuracy by varying several parameters. To start with, we trained a SVM model and a LR model with all 78 features calculated from using all sensors. The SVM model yielded an accuracy of 54% on 10-fold cross validation while the LR model after 10-fold cross validation demonstrated a 56% accuracy. The running time of the algorithm was close to 2 minutes. To reduce the running time, we decided to use only first two statistical moments, mean and standard deviation. We calculated the accuracy by training a model with individual sensors. We observed that each sensor contributed to the classification of sleep positions. For each model we trained, we used features calculated by two methods.

1. No Overlap Sliding window

2. 50% Overlap Sliding window

Results of 10-fold cross validation have been presented sensor wise. Features were calculated using a window size of approximately 8 minutes (12500 samples) and 18 minutes (27500 samples).

4.3.1 Accuracy using Capacitive Sensors

	0% overlap	**50% overlap**	**75% overlap**
SVM	66	69.54	68.72
LR	64.54	64.13	65.5

Table 4.4: Capacitor Sensors Window Size : 12500 samples

	0% overlap	**50% overlap**	**75% overlap**
SVM	66.00	66.66	69.74
LR	66.50	65.64	65.58

Table 4.5: Capacitor Sensors Window Size : 27500 samples

The capacitive sensors are affected by leg positions. For instance if a person is sleeping with legs crossed or with one leg on the top of the other the capacitor sensors will reach the maximum reading. Since this is a possibility in any of the positions including Left Right or Supine such low accuracy is observed. Figure 4.3 and Figure 4.3 show the miss predictions by the models trained using capacitor data.

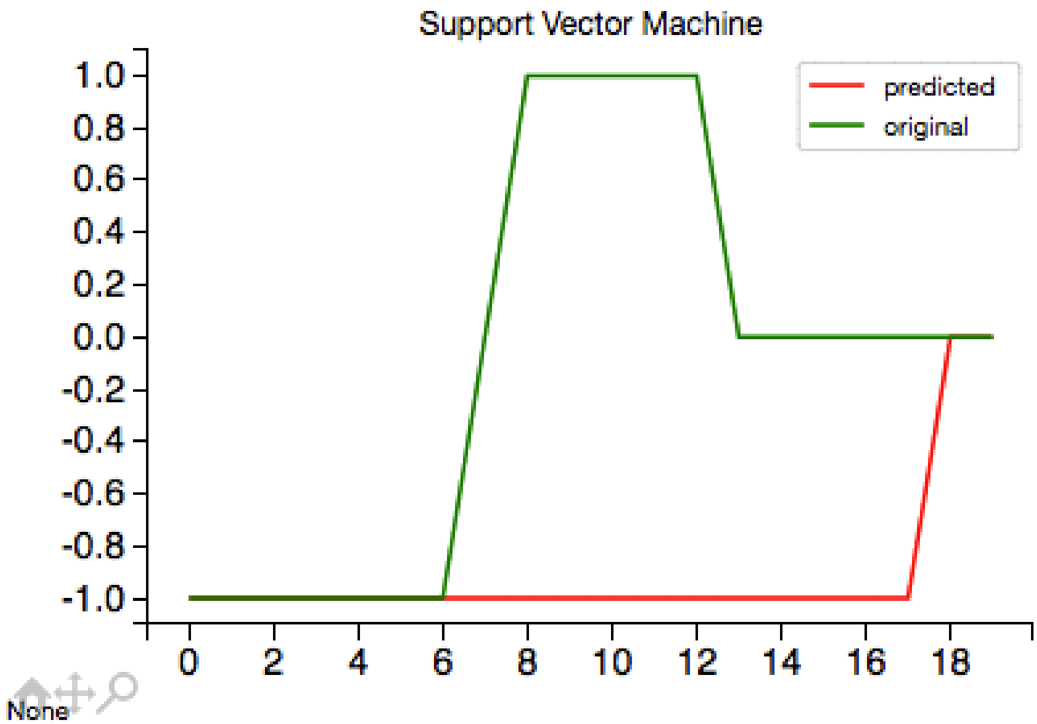

Figure 4.3: Capacitor Predicted and Actual Results by SVM -1:Left 0:Supine 1:Right

	0% overlap	50% overlap	75% overlap
SVM	69.09	60.00 8	60.63
LR	68.63	65.60	63.93

Table 4.6: Window Size : 12500 samples

	0% overlap	50% overlap	75% overlap
SVM	67.50	62.05	62.85
LR	68.50	68.46	65.58

Table 4.7: Window Size : 27500 samples

4.3.2 Accuracy using Accelerometer Sensors

The models trained by the accelerometer data perform better than the models trained using the capacitor data. As accelerometer measures the linear acceleration the gravity component helps the model provide better accuracy than capacitors.

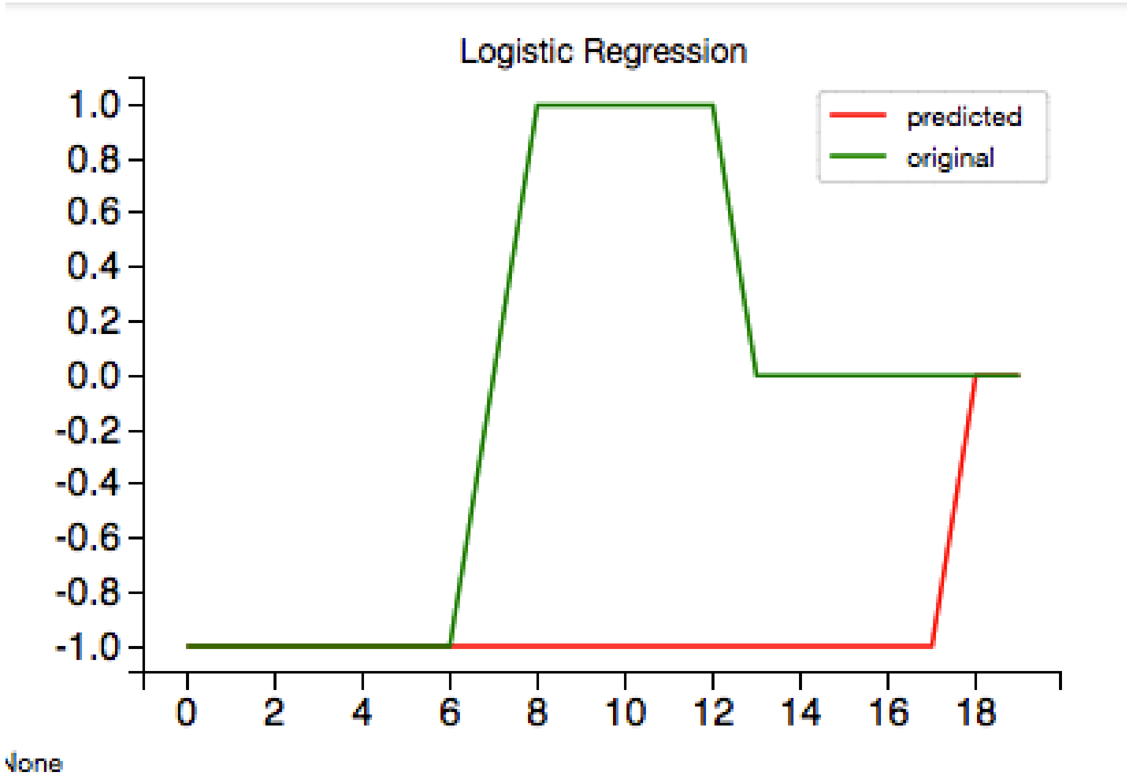

Figure 4.4: Capacitor Predicted and Actual Results by LR -1:Left 0:Supine 1:Right

However, in cases a person is sleeping supine with legs twisted to a side, the accelerometer fails to predict the correct position. Figure 4.5 and Figure 4.6 show the actual and predicted sleep positions using the SVM and LR model respectively/

4.3.3 Accuracy using All Sensors

	0% overlap	**50% overlap**	**75% overlap**
SVM	74.50	74.87	73.81
LR	66.50	68.20	69.47

Table 4.8: Window Size : 12500 samples

The combination of all the sensors contributes to the increase in accuracy. The capacitive sensors take care of the legs overlapping or separating, while the

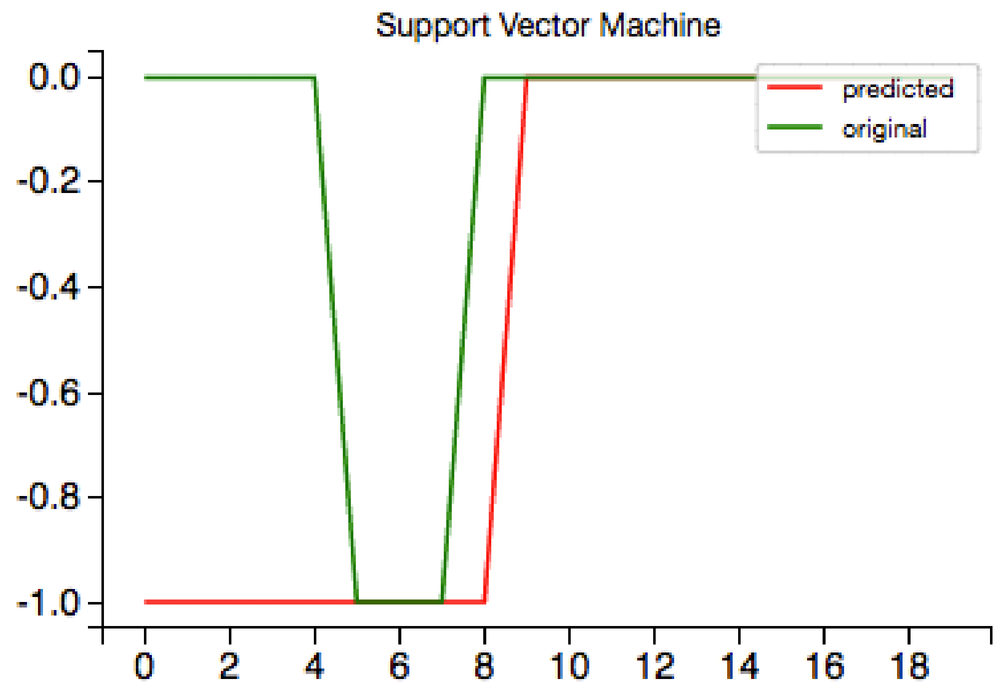

Figure 4.5: Accelerometer Predicted and Actual Results by SVM -1:Left 0:Supine 1:Right

	0% overlap	50% overlap	75% overlap
SVM	74.50	74.87	73.81
LR	66.50	68.20	69.47

Table 4.9: Window Size : 27500 samples

accelerometer and gyroscope take care of the orientation.

4.4 Temporal Analysis

The calculation of features in section 4.3 are statistical moments over windows of data. These moments lack the temporal features. Also, the time series data is subject to high frequency noise. To improve over these, we chose to calculate features using Discrete Cosine Transform (DCT). A DCT is a Fourier transform similar to a Discrete Fourier Transform, but only for the real numbers. It expresses

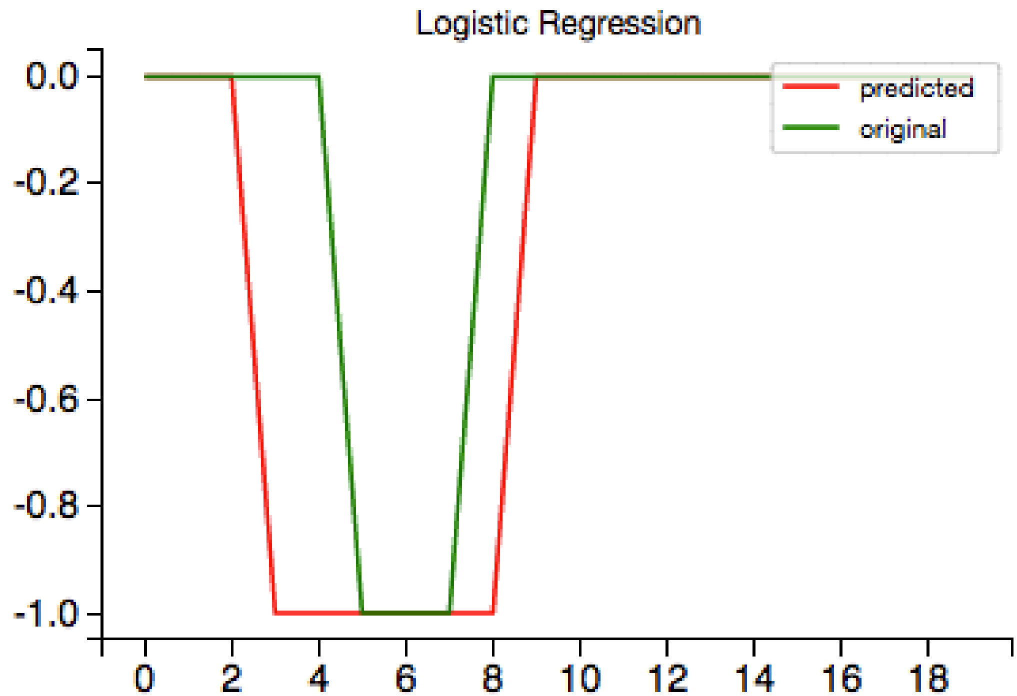

Figure 4.6: Accelerometer Predicted and Actual Results by LR -1:Left 0:Supine 1:Right

a finite sequence of data points in terms of cosine functions. This removes the high frequency noise. The mathematic representation of DCT is given as below.

$$y[k] = 2\sum_{n=1}^{N-1} x[n]\cos\left(k\pi(2n+1)/2N\right), 0 \leq k < N$$

We performed DCT with a non-overlapping time window of 10 seconds. This is the average time of a limb movement during sleep. 10 seconds with a sampling rate of 25Hz equals to 250 samples.

We trained separate SVM models using first component, the first five frequency components and the first ten frequency components of each window. The SVM trained using the first component gave cross validation accuracy of 50%. The

SVM trained using the first five frequency components of each sensor produced an accuracy of 80%. The scoring matrix is as seen in Table 4.10. The SVM model

Labels	precision	recall	f1-score	support
Left	0.72	0.82	0.77	715
Supine	0.90	0.87	0.88	1071
Right	0.75	0.67	0.71	409
avg/total	0.81	0.81	0.81	2209

Table 4.10: Precision Recall f1 Score Matrix for first 5 frequency components

trained using the first 10 components demonstrated an accuracy of 82%. scoring matrix can be seen in Table 4.11 The confusion matrix is seen in table 4.12.

Labels	precision	recall	f1-score	support
Left	0.76	0.84	0.80	708
Supine	0.91	0.87	0.89	1077
Right	0.79	0.72	0.75	417
avg/total	0.83	0.83	0.83	2209

Table 4.11: Precision Recall f1 Score Matrix for first 10 frequency components

Labels	Left	Supine	Right
Left	598	73	37
Supine	95	940	42
Right	97	20	300

Table 4.12: Confusion matrix for the SVM model trained with first 10 frequency components

Chapter 5

CONCLUSION

In our study we used data from four patients to analyze sleep positions using 3 models trained on capacitor data, accelerometer data and all sensor data respectively. We observed that the capacitor sensors gave the lowest accuracy. Our intuition to capacitors failing to predict the data is due to crossing of legs or extreme separation of them in which case they would be giving a similar signature irrespective of the sleep position. One leg laying over the other or crossing the other results in signatures which fail to determine sleep position. The model trained using the accelerometer data gave 3% better accuracy than the capacitor model. The combined result of the gravity vector in the accelerometer data along with the signature of capacitive sensors was able to provide 10% better accuracy than the others. The overlapping of windows did not contribute to much changes.

The statistical features don't account to the movements happening during the sleep. This is one of the reasons we believe the model failed with just the statistical features. The DCT features captured the change in sensor values over a small window and stitched them together to get movements dedicated to specific positions. This yielded 12% better accuracy than the statistical features. We believe that analyzing the movements in each position and characterizing them as features would improve the results.

Chapter 6

Future work

6.1 Algorithm Improvement

The current algorithm performs considerable yet has a significant room for improvement. The current features used are mean and standard deviation of each of the sensors. Features using data transformations might yield better results. Sleep positions are currently divided into broad categories Supine, Left and Right. These classes need to be divided into granular classes which describe the orientation of limbs while sleeping. This will help the sleep quality diagnosis. A stage of filtering can be introduced to remove high frequency components of the raw data.

6.2 Large Datasets

Our intuition for the models wrong predictions is the miniature size of data set and the lack of diversity in data. We believe that the models performance will improve if we get data from more patients. Also, data from a same patient for multiple nights would help introduce personalization to the model and increase accuracy.

6.3 Ankle Bands and RestEaZe$^{\text{TM}}$ Smartphone Application

The ankle bands are a state of art design but could be built for more durability. They are currently available in just two sizes. In case of a pediatric study, the patient might have tiny ankles, causing the band to loosely fit and rotate around the ankle. The change in orientation of band will disturb the readings of capacitors the most. The bands also be enhanced to support low power/ power saving mode enabling them to run for longer duration before charging. The smartphone application can be improved to make it more interactive by taking user feedback on performance or providing notifications on events. The application should be able to calibrate the capacitors, start and stop receiving data without human intervention. The application can show a detailed report of sleep quality.

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