Night Owl: A Quantitative Sleep Journal

http://snooze.bananabrowning.com

Heart Rate Team:
Ashanti Hughes
Ngocngan Nguyen

Skin Resistance Team:
Tuan Le
Timothy Phan

Advisor:
Professor Pompili

Graduate Student Mentor:
Eun Kyung Lee

Project Code (see Appendix at end of this report):
http://github.com/sensorscapstone2012/Night-Owl

1 Introduction and Background

Sleep is one of the most widely used metric for monitoring the effectiveness of medical treatment by healthcare providers [1]. Furthermore, continuous monitoring of sleep-wake behavior at home allows for early detection of sleep disorders and allows for reducing healthcare costs [2]. The quality of sleep is most often assessed using subjective measures such as questionnaires, which may introduce systematic biases in reporting, depending on the health concerns of the patient. Ambulatory sleep analytics systems are especially attractive as an alternative to the costly polysomnography studies, which also place the patients in an unfamiliar sleep environment, reducing the naturalness of their sleep behavior. A popular method of assessing sleep behavior is through the use of accelerometers contained in a wrist-worn band, as this is both easy and cheap to use for long-term ambulatory studies. However, these devices indirectly determine a subject's sleep-wake state based on movement, which can be easily confused when a user is in a low activity task such as reading or watching television [3]. Validation studies have shown that although the uses of accelerometers result in high sensitivity to sleep classification, their specificity is often below 50%, meaning that sleep onset detection is inaccurate as low activity is misclassified as sleep [4].

The approach we chose is a more direct means of mapping sleep-wake behavior throughout the night by probing the nervous system. Studies in which skin conductance, the reciprocal of skin resistance, was measured during sleep showed that there are visible differences in skin conductance change when a user is awake and asleep [5]. This motivated us to use skin resistance to quantitatively discriminate between sleep-wake to offer an objective and quantitative measure of sleep. As the sweat glands is innervated by the sympathetic nervous system, skin resistance, which measures the activity in the sweat glands, allows us to measure sympathetic nervous system activity, which is active when a user is in a state of arousal. Furthermore, the eccrine sweat glands is very dense around the hands and feet, and although they serve a role in thermoregulation, sweating to allow for evaporative cooling, studies have shown that those located near the hands and feet are more responsive to emotional stimuli rather than thermal stimuli [6]. Consequently, despite sweating due to thermoregulation, measuring skin resistance near the hands and feet still allow for measurement of sympathetic nervous system activity.

The parasympathetic nervous system is another portion of the nervous system that we probe throughout the night to derive our sleep scores from the raw sensor data. This portion of the nervous system is most often called the "rest and digest" system, which helps calm the body during periods of rest. We chose to probe the parasympathetic nervous system by measuring the heart rate of the user throughout the night and extract a portion of heart rate variability known as respiratory sinus arrhythmia (RSA). This is the modulation of heart rate in tandem with respiratory frequencies. RSA is often used as a measure of parasympathetic tone, and consequently, impaired RSA has been implicated in stress-related disorders; evidence suggests that lower RSA is associated with sleep disruption [7]. Although RSA may be measured in various ways in either the time-domain or the frequency-domain, we chose a frequency-domain approach in quantifying RSA by measuring the power contained within a high frequency band of 0.15-0.4 Hz associated with parasympathetic activity and the power contained within a low frequency band of 0.05-0.15Hz associated more with sympathetic outflow. By taking the ratio of LF/HF power, we can assess the balance between the parasympathetic and sympathetic outflows. This is important to measure, as the balance of parasympathetic and sympathetic outflows have certain characteristics for certain diseases and emotional states, in particular, stress, hypertension, diabetes, and smoking. For instance, when a user is stressed, ideally, the parasympathetic system will be actively offsetting the sympathetic system to allow the user to better manage stress, and this will be evident in the LF/HF ratio with the denominator increasing more than the numerator. In the case of diabetics, when the patient is in an aroused state, a diminished increase in LF and diminished decrease in HF can be seen. For smokers, the LF values tend to be higher and the HF values tend to be lower [9].

2 Design

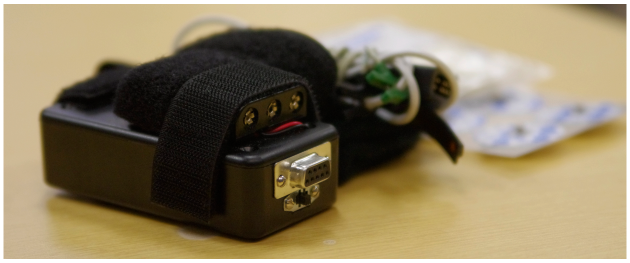


Figure 1. Prototype of the wearable sleep analytics device (front) with the galvanic skin response (GSR) electrode leads, pulse oximeter sensor, and disposable skin electrodes (back).

A small device prototype, shown in Figure 1, containing a Shimmer microcontroller along with a pulse oximeter board and a galvanic skin response sensor was designed to be strapped to the upper arm of the user throughout the night. As the user sleeps, the Shimmer microcontroller wirelessly transmits the raw sensor data via Bluetooth to a computer running the ShimmerConnect software, which continually appends the raw sensor data to a text file throughout the night. A switch located underneath the female DB9-serial header, for connection to the finger pulse oximeter sensor, controls the power to the pulse oximeter sensor. When the user wakes up and wishes to stop recording data, they would use the ShimmerConnect software to disconnect the Bluetooth pairing and execute our scripts to analyze the sleep data; during the prototype, this script execution was done using a Webmin interface running on the local computer, which included a page with a button to click to begin analyzing overnight sleep data, as shown in Figure 2. At the end of the analysis, the results are automatically published to the online sleep journal and organized by the date of analysis.

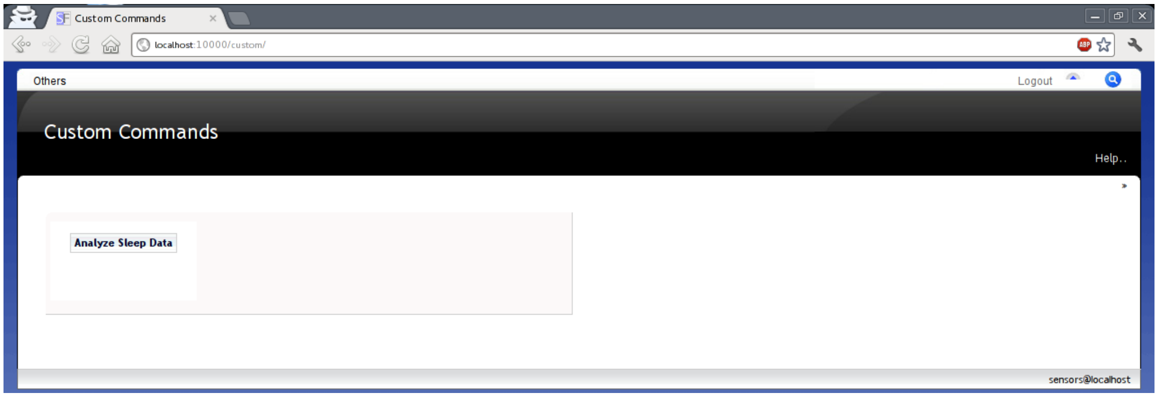


Figure 2. Webmin user interface for easily initiating the automated analysis and posting of sleep data via a single-click button in a simple web browser accessible interface.

2.1 Software

The software component of the project was divided into two separate tasks: one portion analyzed the overnight time-series skin conductance data, the second portion analyzed the overnight time-series pulse oximeter data. These two divisions converged at the end to generate a sleep journal entry containing the metrics derived from the raw sensor data.

2.1.1 Skin Resistance Analysis

When the user logs into the Webmin interface (see Fig. 2) and clicks on the *Analyze Sleep Data* button, the *analyzeSleep.sh* script is run. The script first runs the Python script, *convertToOhm.py*, to extract the raw ADC values for the skin conductance data from the appropriate column of the text file containing the raw sensor data. *conertToOhm.py* then applies the polynomial fit equation provided by Shimmer to convert the ADC values to resistance in ohm, and creates a new file in the *data/ohms* folder containing a list of skin resistance values.

The next script to automatically run is *extractFeatures.py*, which first performs a 500th order finite impulse response (FIR) high pass filter designed using the hamming window with a cutoff frequency of 0.04Hz; this allows us to only concern our analysis with the varying components of the skin resistance, as that was our choice of features to discriminate between sleep and wake states. Once the skin resistance was high pass filtered, the script then breaks the skin resistance files into blocks of 600 samples, which is the equivalent of 1 minute of sensor data with a sampling frequency of 10Hz, and begins to extract features from each block of 600 samples. The feature extraction begins by removing the trend from each block, windowing with a Hamming window to reduce spectral leakage, then performing a discrete Fourier transform (DFT) using the fast Fourier transform (FFT), then squaring the magnitude of the FFT to obtain the power spectrum of the 1 minute block of data. The trapezoidal rule was then used to compute the integral of power contained within the [0, 0.5Hz] band, termed the tonic power, and the integral of power contained within the (0.5Hz, 1Hz] band, termed the phasic power. As the tonic and phasic powers are extracted from each minute worth of sensor data, they are appended to a new file, which will only contain the features, tonic and phasic powers, for each minute, with each row representing each minute of sleep.

Once the feature extraction is completed, the next script to automatically run is *classify.py*. This script begins by using the Python *pickle* library to import a previously trained support vector machine (SVM) classifier with a radial basis function (RBF) kernel in order to classify each minute of sleep data; the classifier was previously trained with a single night of labeled sleep data, the sparseness of the training data was due to time constraints and hardware trouble that will be discussed later, and the object representing the trained classifier was saved using the *pickle* library. As each minute is classified as either asleep or awake, an array is updated to contain the sleep state of the user for each minute. The array is then processed to generate a sleep efficiency (SE) score, calculated by dividing the number of minutes classified as asleep by the total number of minutes the user spent in bed. The next score generated is the sleep onset latency (SOL) score, calculated by counting the number of minutes from the start of recording until when the user is classified as asleep. Graphical charts are then generated using the *CairoPlot* library and automatically uploaded to the online sleep journal, running a WordPress backend, with the entry labeled by date of sleep analysis (see Fig. 4 and Fig. 5).

In order to make the platform as user-friendly as possible and to remove the requirement of working in a terminal, we used Webmin to create a web-accessible page whereby the user simply pushes a button to initiate the sleep data analysis. This was done by using Webmin's Custom Command feature to create a button that is linked to the *analyzeSleep.sh* file described earlier to perform the data analysis.

2.1.2 Heart Rate Analysis

When analyzing the power spectral analysis for RSA, there are three major frequency bands to look for: very low frequency, low frequency and high frequency. Physicians are only interested in looking at the range from 0 to 0.4 Hz. In our project, we focus only on the low frequency and high frequency spectrum to detect RSA. The range for low frequency (LF) is from 0.04 to 0.15 Hz and this correlates to the body being under stress. The range for high frequency (HF) is from 0.15 to 0.4 Hz. Our objective is to get the ratio between the LF and HF (LF/HF). This ratio reflects the relative balance between the sympathetic-parasympathetic systems. It is a good indicator for assessment of alterations in the nervous system behavior and is usually about 1. The LF band is an indication of the behavior of the sympathetic nervous system, while the HF band relates to that of the parasympathetic system. The sympathetic and parasympathetic are branches of the autonomous nervous system (ANS). The sympathetic system stimulates functioning of the organs including the heart. The parasympathetic system inhibits functioning of the organs. Together they work together to balance the body externally and internally.

Of the two branches of the ANS RSA is related closely to the parasympathetic system. The parasympathetic system is the dominating system during a person's "resting" state which is the state in which your heart rate when you are not exerting yourself or fully recovered from activity. If the ratio LF/HF decreases it can be an indication of an increase in parasympathetic tone and/or a decrease in sympathetic tone.

In order to retrieve the necessary data for our project, we used various tools to retrieve specific information. The materials we used were the Nonin reusable PureLight Flex Sensors, Nonin OEM III Evaluation kit (Nonin 8000AA Adult Finger Clip pulse oximeter and OEM III Module Internal Pulse Oximetry) and the Shimmer anex expansion board.

Pulse oximetry is a noninvasive method that enables rapid measurement of the relative blood volume changes. It is a compact device and requires little maintenance. The pulse oximeter sensor consists of two high intensity pure light spectrum: red and infrared. The red LED measures deoxygenated hemoglobin and the infrared LED measures oxygenated hemoglobin. For our project, we chose the PureLight Flex Sensors and the Adult finger clip. These two external readers were picked out for different reasons. The Purelight Flex Sensor was ideal to use at night during our sleep study and the adult finger clip was used for quick trial runs. The Purelight Flex sensor was more comfortable to used for long term testing. The Purelight sensor is made with a durable silicone wrap and was secured to the finger by the flexiwrap adhesive, while the adult clip was clipped on between the fingers. As for our internal reader, we used the Nonin OEM III. The Nonin OEM III is a low power device that is easily integrated to a host device. This internal pulse oximetry was used to do translate the data from the external pulse oximeter through a evaluation board and to a computer program provided (data was transferred through a USB). The evaluation board was given within the kit.

The shimmer anex board is an expansion board that is used within our shimmer wireless unit. It allows easy third party prototyping and custom sensor to communicate with the shimmer platform. It is connected through a external connector pin and is place outside of the shimmer unit. We used this expansion board to help us translate the data from the pulse oximeter to the shimmer unit. This process was done by analyzing the breadboard lay out for each sensor and soldering each pin to its connective position.

Objective 1: Range of Frequency for RSA

There was a short latency period during the first few weeks where we did not have all the materials needed to start data collection, however we used other resources to ensure progress. The first thing we needed to do was verify the range of frequency for RSA. For two weeks we conducted our initial trial testing in a biomedical engineering lab operating a pulse photoplethymosgraph transducer sensor which acts our pulse oximeter (NONIN) would. The purpose of this trial was to familiarize ourselves with a pulse oximeter sensor and the process for detecting RSA. Using a lab manual as our guide (Assess the effect of respiratory activity on the activity of the autonomic nervous system in the context of heart rate variability). The lab conducted a series of experiments under three different conditions normal, controlled, and recovery. Using the Log-a-Rhythm software package we were able to graph the frequency spectrum of RSA. The objective was to verify the range that RSA occupies despite various activities on different test subjects. We were able to confirm that RSA was more pronounced in the high frequency range and lied between 0.1Hz to 0.4Hz.

Objective 2: Quantify RSA

One of the drawbacks to using the photoplethymosgraph sensor was it was integrated with software that was able to calculate the value for RSA (LF/HF) automatically. Our specific sensor would only provide the HR signal. From there we would have to perform spectral analysis on the signal and obtain RSA organically. However the advantage was we would be able to compare results with newer data.

In order to compare the results, it was important to replicate the activities conducted during data collection. Once we received the pulse oximeter (NONIN) we conducted tests similar to those we had done over the past few weeks (normal, controlled, and recovery). Ideally we would duplicate the same or fairly similar results to be able to compare them to our data we produced in the biomedical engineering lab. During our initial trials the "controlled" breathing portion was conducted using a breathing prompter. To simulate a similar response we kept the breathing rate set to 6 breaths per minute (5 seconds inhalation and exhalation), and used a stopwatch as an indicator. To reproduce the Speed/Accuracy Tradeoff (SAT) activity, the user would perform an activity, specifically a game on a smart phone/computer.

The data from the OEM is recorded in a format similar to that given by the pulse photoplethymosgraph transducer sensor. The difference with our particular sensor is that we are no longer able to use the BIOPAC acquisition unit, and therefore we are unable to automatically generate the frequency spectrum for RSA. We have to run the data that is produced from the OEM through a script in Matlab that will generate our desired results. This script will be automated so that any future data that is collected overnight can easily be quantified and accessible.

Objective 2b: Matlab Script

When the OEM runs the data is converted to serial data format (excel table). Each row is defined as a "frame" and each packet consists of 25 frames. Since three packets are transmitted every second the sample rate is 75 frames per second. Byte 3 (column 4) is the Plethysmographic (PPG) pulse amplitude we used this column to find the Peak-to-Peak interval variability (comparable to the RR interval variability of an ECG). However after the integration of all three sensors the signal is slightly increased by a factor. The sampling rate is also changed to 10. Iterating a for loop through the array of peak locations provided an array of intervals (RR intervals), with which we transformed to the frequency spectrum using FFT. Because our signal is not periodic, prior to using the FFT function there needed to be a windowing function (to prevent spectral leakage by getting rid of discontinuity). What we also learned is that the PPG signal consists of something called a quasi DC signal that corresponds to changes in the venous pressure. We need to remove this signal before analyzing it by performing a detrending function. Interpolation is also required to add additional points of interest. The final step was the power spectral density function and analysis for both low frequency (LF) and high frequency (HF). From there we were able to compute the ratio LF/HF.

2.2 Hardware

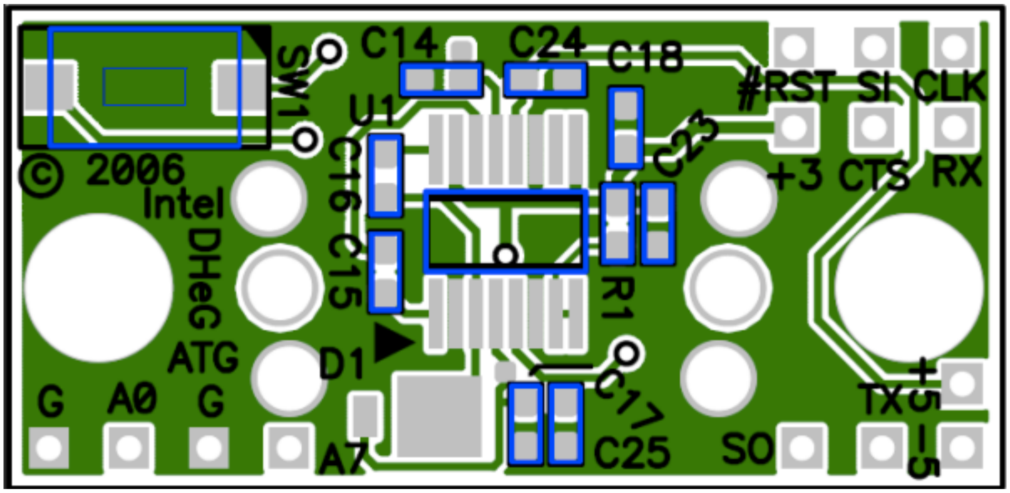


Figure 3. Layout of the Shimmer expansion board, with A7 as analog read-in port.

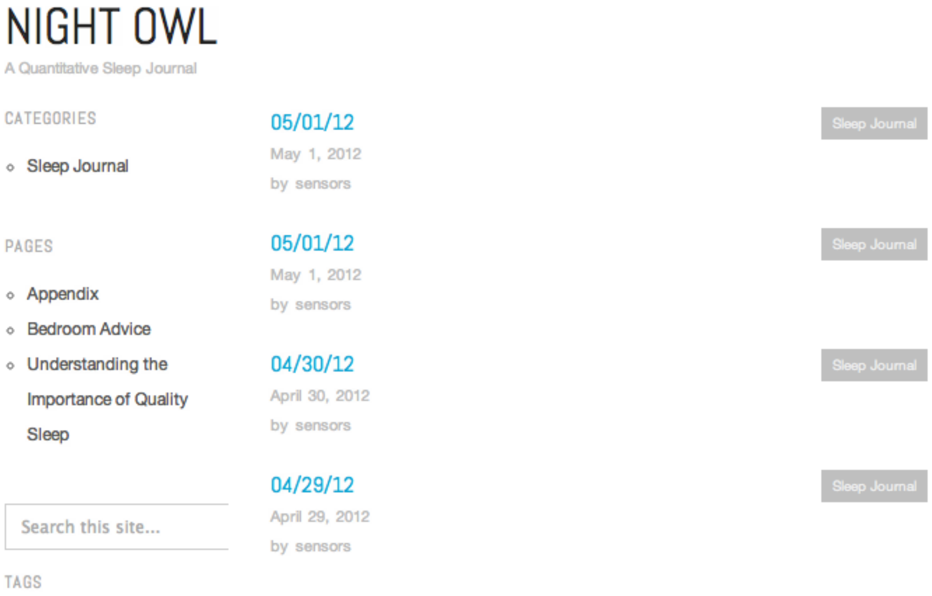
Beside the skin response analysis, the pulse oximeter analysis is used as further parameter for screening tool in sleep quality analysis. Therefore, addition data producing by the pulse oximeter is also collected and analyzed via the interface between the Shimmer expansion board and NONIN OEM III module. The promote advantage of this systems interface is the ability of collect multiple data parameters on a single subject in a single session.

The objective is to integrate the skin response sensor and pulse oximeter sensor into one single hardware unit for future use of multiple data parameters collection conveniently. The pulse oximeter sensor is operated by the NONIN OEM III module. Base on the specification provided by the manufacturer, the module operates with the input power supply in range of 3.2V to 3.5V or +5VDC ±0.25V, 50 mV maximum ripple. On the other hand, the Shimmer expansion board provides three regulated supply voltage of +3.0V, +5.0V, and -5V.

The immediate objective is to provide the power supply for the NONIN module. The immediate solution is to use the +5V regulated voltage to provide power for the NONIN module. The battery package of the Shimmer is rated at 450 mAh; however, base on the previous experience in working with Shimmer GSR module, the battery sometimes lasted less than 8 hours of data recording session with only the skin response sensor. Furthermore, to provide the correct power for the NONIN module, the 5V regulated voltage has to be shunted down to the operating range of the module; as the result of this immediate solution, the battery of the Shimmer would be drained more quickly. It is now desirable to look for the external power supply for the NONIN module.

The next solution is to use NiMH rechargeable batteries to provide the power for the NONIN module. NiMH batteries are rated at 1.2V; hence, the pack of three NiMH batteries will have the total power of the 3.6VDC. However, when the batteries are fully charged, the total voltage of the pack is up to 4.5V.To maintain the power supply for the NONIN module, the Zener diode with the constant drop of 3.3V is used to regulate the supply voltage of 3.3V for the module. The output of 3.3.V of NONIN module is fed into the analog reading port of Shimmer expansion board. However, the Shimmer is only capability to read data at 3V maximum; a regular diode is used to provide some voltage drop at the output of NONIN module before fed into analog reading port on Shimmer expansion board. The connection between the NONIN module and the external power supply can be determined by referring to manufacturer specification and technical information datasheet.

2.3 User Interface



NIGHT OWL

A Quantitative Sleep Journal

CATEGORIES

- Sleep Journal

PAGES

- Appendix
- Bedroom Advice
- Understanding the Importance of Quality Sleep

Search this site...

TAGS

05/01/12
May 1, 2012
by sensors
Sleep Journal

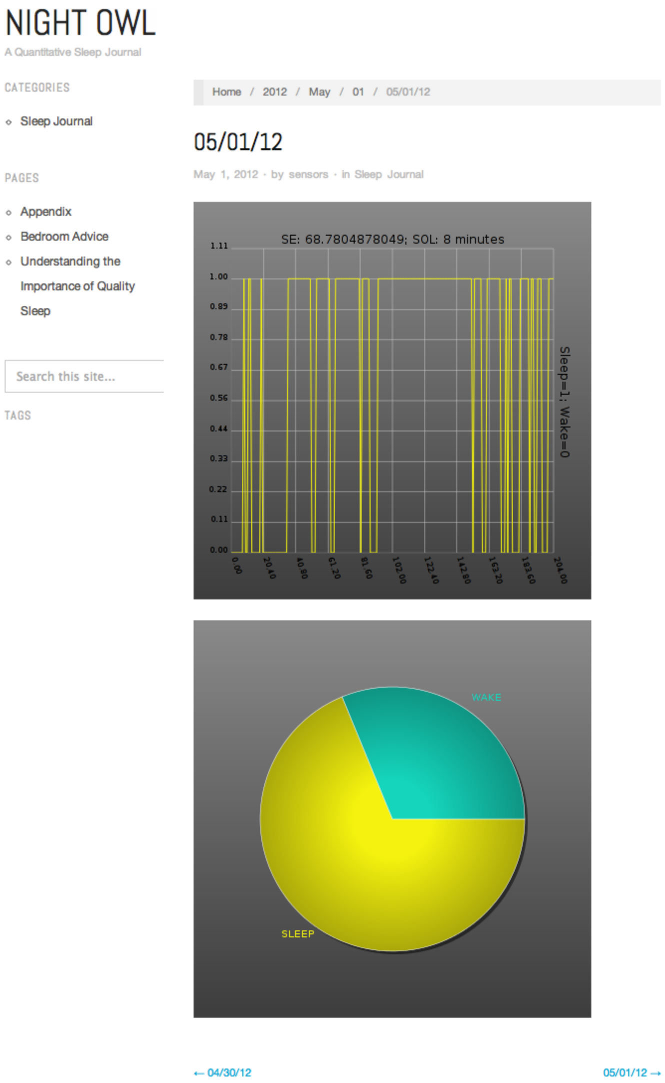
05/01/12
May 1, 2012
by sensors
Sleep Journal

04/30/12
April 30, 2012
by sensors
Sleep Journal

04/29/12
April 29, 2012
by sensors
Sleep Journal

Figure 4. Main page of the online sleep journal, with entries labeled by date of sleep analysis.

The user interface is a sleep journal with a WordPress backend. Each automatically generated sleep journal entry is dated and organized in a blog format for easy traversal of past data. This type of format allows for easy long-term monitoring of sleep, which can allow healthcare professionals to easily monitor patient progress as the blog is available on any device that can access the Internet. Another benefit of having a WordPress backend is that the code-base is very mature and secure, used by many large organizations such as The New York Times, CNN, Forbes, and UPS. This mature codebase allows the user to easily control the security of the blog, by either marking it as private or publically viewable, which can help in compliance with patient privacy concerns. Another useful feature of using WordPress is that each entry can easily be edited after-the-fact to include any information the user feels is relevant, such as adding comments that may explain unusual sleeping data. Additionally, the healthcare professional can also add comments to the blog post to provide any useful feedback to the patient. This platform allows for easy and secure communication between a healthcare provider and the patient, and easily follows the trend of electronic personal health records, improving dissemination of patient health history for improved and more personalized healthcare.



NIGHT OWL

A Quantitative Sleep Journal

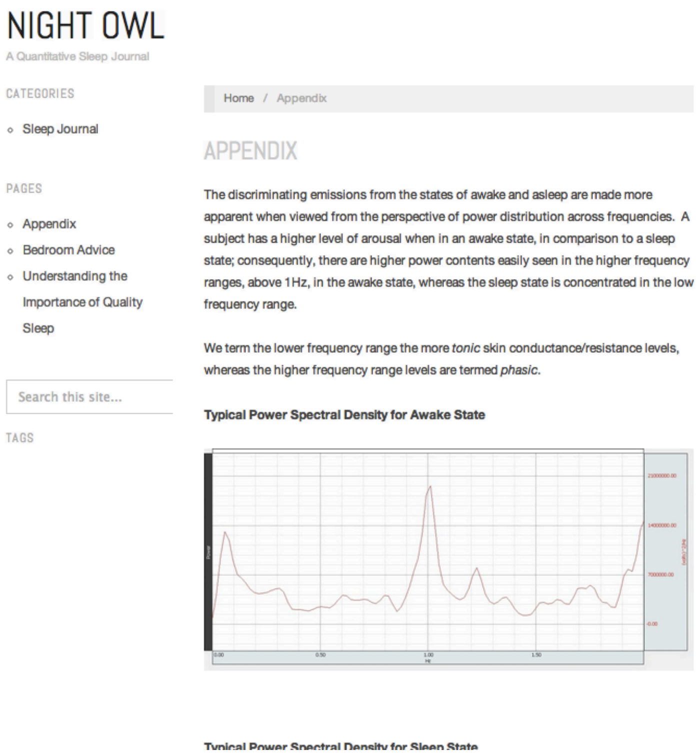
CATEGORIES
Sleep Journal
PAGES
Appendix
Bedroom Advice
Understanding the Importance of Quality Sleep
Search this site...
TAGS
Home / 2012 / May / 01 / 05/01/12

05/01/12

May 1, 2012 · by sensors · in Sleep Journal

Figure 5. Sample journal entry containing sleep scores derived from the raw sensor data. The first graph shows the sleep-wake states throughout the night, with the x-axis with units of minute. The second graph shows the distribution of wake and sleep states throughout the night.

In addition to the generated journal entries, the online sleep journal includes a few pages to help elaborate upon the information contained within the journal entries. Figure 6 shows a sample *Appendix* page that offers a brief explanation of how the classification of user state works. The user is also offered some sleep advice in the *Bedroom Advice* page, shown in Figure 7. In order to help the user interpret the journal entries, a page titled *Understanding the Importance of Sleep Quality* (Figure 8), offers some explanations of the results. Additional pages can easily be added to the platform to help the user understand the significance of their long-term monitoring of sleep data.



NIGHT OWL

A Quantitative Sleep Journal

CATEGORIES

- Sleep Journal

PAGES

- Appendix
- Bedroom Advice
- Understanding the Importance of Quality Sleep

Search this site...

TAGS

Home / Appendix

APPENDIX

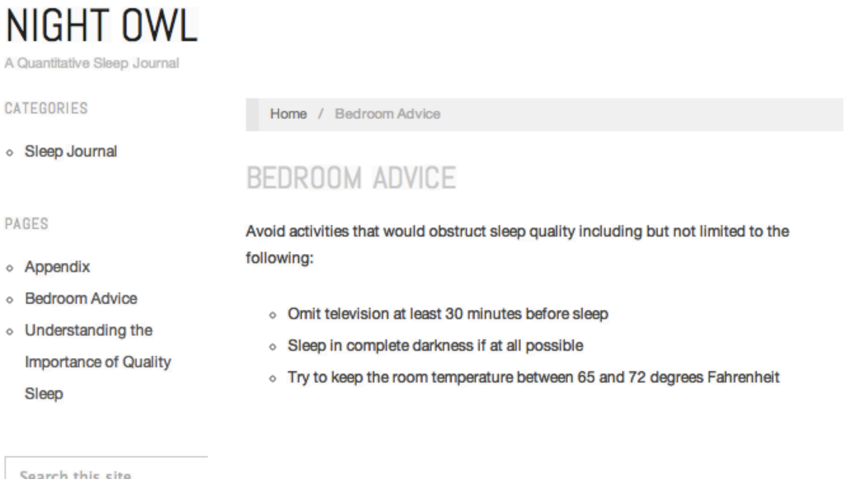
The discriminating emissions from the states of awake and asleep are made more apparent when viewed from the perspective of power distribution across frequencies. A subject has a higher level of arousal when in an awake state, in comparison to a sleep state; consequently, there are higher power contents easily seen in the higher frequency ranges, above 1Hz, in the awake state, whereas the sleep state is concentrated in the low frequency range.

We term the lower frequency range the more *tonic* skin conductance/resistance levels, whereas the higher frequency range levels are termed *phasic*.

Typical Power Spectral Density for Awake State

Typical Power Spectral Density for Sleep State

Figure 6. Appendix page offering a brief description of how we discriminate between wake and sleep states using the skin resistance data.



NIGHT OWL

A Quantitative Sleep Journal

CATEGORIES

- Sleep Journal

PAGES

- Appendix
- Bedroom Advice
- Understanding the Importance of Quality Sleep

Search this site

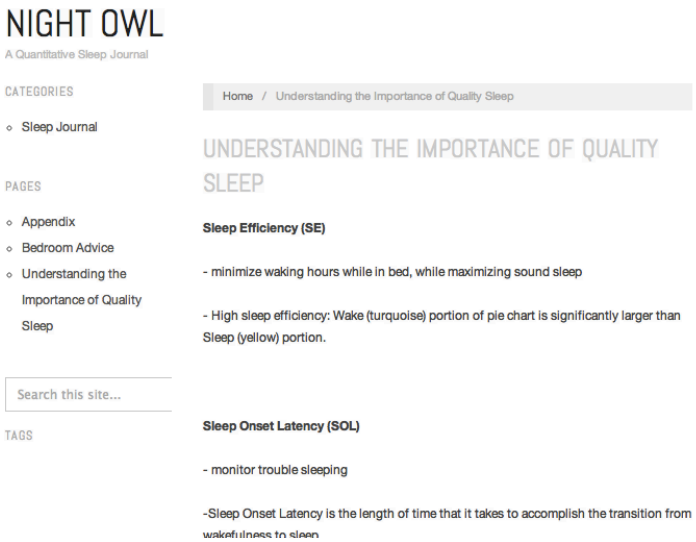
Home / Bedroom Advice

BEDROOM ADVICE

Avoid activities that would obstruct sleep quality including but not limited to the following:

- Omit television at least 30 minutes before sleep
- Sleep in complete darkness if at all possible
- Try to keep the room temperature between 65 and 72 degrees Fahrenheit

Figure 7. Sleeping advice page that can be edited to provide some general guidelines for improving sleep.



NIGHT OWL

A Quantitative Sleep Journal

CATEGORIES

- Sleep Journal

PAGES

- Appendix
- Bedroom Advice
- Understanding the Importance of Quality Sleep

Search this site...

TAGS

Home / Understanding the Importance of Quality Sleep

UNDERSTANDING THE IMPORTANCE OF QUALITY SLEEP

Sleep Efficiency (SE)

- minimize waking hours while in bed, while maximizing sound sleep

- High sleep efficiency: Wake (turquoise) portion of pie chart is significantly larger than Sleep (yellow) portion.

Sleep Onset Latency (SOL)

- monitor trouble sleeping

-Sleep Onset Latency is the length of time that it takes to accomplish the transition from wakefulness to sleep

Figure 8. Explanation of the contents of generated sleep journal entries.

3 Conclusion and Lessons Learned

We were successful in setting up an open-source based framework for ambulatory sleep analytics using a wearable sensor. With the framework set up, we can easily tune up various individual portions of the system to improve upon system features, such as improving the classifier performance. The low classifier accuracy of ~70% is attributable to training the SVM on such a small training set, namely only one night of labeled data. There are two main reasons for this sparse training set: early hardware issues and lack of a controlled method for validating labeled data.

The first major issue encountered in collecting reliable training data was hardware issues. For many days, our overnight skin resistance data was unreliable, showing a constant flat line value throughout the night. After contacting Shimmer, it was determined that our galvanic skin response (GSR) sensor was shipped without an insulating layer protecting the soldered leads on the GSR board. The result was that the GSR board was short-circuiting against a metal portion of the main Shimmer microcontroller board. Once we used electrical tape to insulate the GSR board from the main Shimmer board, we began to collect reliable sleep data.

The second major issue was a lack of a validation procedure to ensure the most noise-free labeling of sleep data. As we had no method for confirming when the user was awake or asleep throughout the night, we could only train with periods of time in which we were sure the user was awake or asleep. This resulted in a lack of labeled data for the very sensitive time when the user transitions from wake to asleep, and as a result, our classifier was not properly trained to perform well during the wake-sleep transition.

Writing the Matlab script for finding RSA was difficult. There were numerous resources regarding RSA but few details were provided about manual detection using a HR signal. Most processes were automatic and used unattainable software/equipment. We had to use various articles and piece together the correct process for determining the power spectrum using just our original signal. Once we produced the correct Matlab script we had to make alterations due to the soldering of the NONIN to the annex board.

The HRV TOOLKIT was momentarily a consideration for processing the HR signal from the pulse oximeter. The HRV Toolkit would help us analyze our record data from the pulse oximeter. The reason we were going to opt out of using a Matlab script was we had discovered that the array that housed our peak distances (RR intervals instrumental in conducting power spectral analysis) wass incorrect. The concern was finding the correct sampling rate in order to be able to perform the windowing, and FFT functions properly to get the desired output. Without the correct sampling rate, our script did not render the desired results. The frequency sprectrums did not resemble the behavior of normal RSA, nor did they resemble the frequency sprectrums of the trials we had done in the lab. Figure 9 displays the final output after the "controlled breathing" file is run through the script. We see that the result (Figure 10) from our trial using the BME equipment is not comparable to the output of the power graph from our current trial.

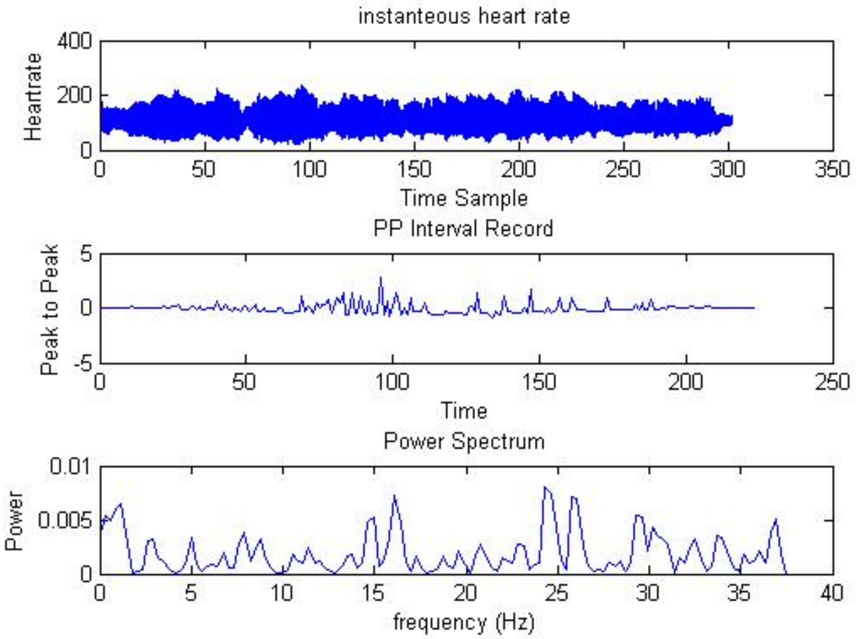
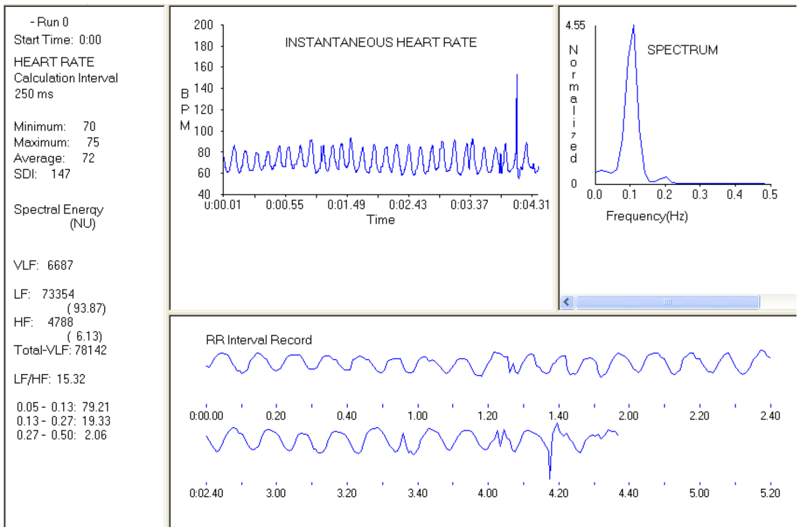


Figure 9. Heart Rate, Peak-to-peak, and Power graphs for controlled breathing.



- Run 0
Start Time: 0:00
HEART RATE
Calculation Interval
250 ms

Minimum: 70
Maximum: 75
Average: 72
SDI: 147

Spectral Energy
(NU)

VLF: 6687

LF: 73354
(93.87)
HF: 4788
(6.13)
Total-VLF: 78142

LF/HF: 15.32

0.05 - 0.13: 79.21
0.13 - 0.27: 19.33
0.27 - 0.50: 2.06

Figure 10. Trial using Log-a-rhythm to display prominent RSA in the frequency plot during controlled breathing

We elected to discontinue pursuing the Toolkit for two reasons. First, we could not determine how to input our data from the CSV file into the HRV Toolkit. Second implementing the Toolkit was also somewhat of a challenge as well. Before we could test the Toolkit, we first had to install it, which was somewhat of a challenge. First, we had to install the Cygwin to our windows computer; it is a terminal emulator like a Linux terminal. It uses the same commands, as you would type in a Linux terminal box, but includes a C complier to run all the different programs in the HRV toolkit. After install the Cygwin terminal box, we had to install different software packages in order to use the HRV Toolkit. The two software packages that we installed were the WFDB and PLT. The WFDB package helps use view, analyze and create recordings of any physiological signals. The PLT package helps us view graphs/plots of our data. The third package we installed was the HRV Toolkit. This last package consisted of different scripts and C code to use the HRV Toolkit. All the files were untarred in the Cygwin terminal and installed through there. If the results were verified we would have only used Matlab to find the PP intervals. The Toolkit would have then been able to take those intervals, filter them, calculate the time domain, and calculate the power from the power spectrum.

Another challenge we faced, which was a final task, was converting our Matlab script into Python for purposes of automated syncopation to the online journal. During the final week we had begun the process of converting our code into C. The difficulty we found was subsidizing vital Matlab functions that we would be unable to use in C code.

As the framework was successfully set up in this project, it is a matter of training the classifier with more reliable and validated sleep data to improve classification performance. At the conclusion of this project, we feel that we have successfully covered a lot of ground in the culmination of our undergraduate electrical engineering studies in this senior capstone project. We have used material learned in digital logic design, computer architecture, and electronic devices in determining how to interface sensors with the microcontroller and using electronic components to properly scale down voltages for successful sensor-microcontroller interfaces. Additionally, material we learned in digital signal processing, namely filtering design techniques and Fourier analysis, allowed us to properly process the raw sensor data to aid in extract meaningful parameters amongst a noisy environment. Lastly, we applied the software skills we learned in programming methodology and machine learning coursework to come up with the software for classification and user interface for the online sleep journal. The added diverse background of our team also brought in experience with Linux, server administration, webserver setup, web technologies including WordPress and Webmin, GitHub, and the ability to pick up new technical paradigms to complete our project.

4 Future Work

One issue that may be present with our system is that if the user wears our device for a long period preceding actual laying-in-bed time, our sleep efficiency score will not be accurate as it is currently based on the entire time that the device is recorded, which will account for the period that the user is not laying in bed but is wearing the sensor. One approach toward this issue is taking advantage of the power switch we installed for the pulse oximeter. If the user is instructed to only turn on the pulse oximeter when they are in bed, the analysis script can easily be modified to only account for the data when the pulse oximeter is on; when the pulse oximeter is off, there should be no real information other than noise inputted to the analog input of the Shimmer. Consequently, the script can be set to start analyzing the data starting from when pulse data is actually detected as coming from the pulse oximeter, which will correspond to the time when the user switches on the power switch and is in bed.

Additional future work may be put in polishing the blog interface and packaging the entire sleep analytics system into an easily deployable single executable package for easy installation. Furthermore, other classifiers may be investigated, such as one based off of Hidden Markov Models (HMM). A reason for interest in HMMs is that they also contain transition probabilities, which may be useful as the probability of a user being asleep, given the emissions of the extracted power spectrum features, if they were asleep the previous minute is more likely than being awake. If a combination of emissions and transition probabilities are used, classification accuracy may be improved, as sleep data is a sequential time-series. Additionally, we may incorporate spectral analysis of heart rate variability as another feature for sleep-wake detection. Studies have shown that there are significant increases in inter-heartbeat intervals during sleep onset, and very low frequency power in heart rate variability decreases significantly before sleep onset [10].

The Shimmer turned out to be more powerful than we needed of a microcontroller and much larger than desired. Consequently, it can be replaced with something smaller, such as the Arduino Lilypad, which will make the wearable device much smaller and easier to wear during sleep. Furthermore, the cost of an Arduino Lilypad is much cheaper than a Shimmer unit, which will make the system more attractive as an ambulatory sleep analytics device.

5 References

[1] Johns, M. W., B. A. Cornell, and J. P. Masteron. "Use of Skin Resistance in Monitoring Sleep and Wakefulness." *Digest of 9th International Congress on Biological and MEdical Engineering.*

[2] Colten, H., Altevogt, B., *Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem*. H.R. Colten and B. M. Altevogt, Eds. Washington, DC: National Academies Press, 2006.

[3] Karlen, Walter, and Dario Floreano. "Adaptive Sleep–Wake Discrimination for Wearable Devices." *IEEE Transactions on Biomedical Engineering* 58.4 (2011): 920-26.

[4] DeSouza, Luciane, Ana Amelia Benedito-Silva, Maria Laura N. Pires, Dava Poyares, Sergio Tufik, and Helena M. Calil. "Further Validation of Actigraphy for Sleep Studies." *Sleep* (2003).

[5] Shiihara, Yasufumi, Akio Umezawa, Yasujiro Sakai, Norikazu Kamitamari, and Masahisa Kodama. "Continuous Recordings of Skin Conductance Change during Sleep." *Psychiatry and Clinical Neurosciences* 54.3 (2000): 268-69.

[6] Dawson, Michael E., Anne M. Schell, and Diane L. Filion. "The Electrodermal System."

[7] Furman, G. D., A. Baharav, C. Cahan, and S. Akselrod. "Early Detection of Falling Asleep at the Wheel: A Heart Rate Variability Approach." *Computers in Cardiology* 35 (2008): 1109-112.

[8] Palesh, Oxana, Jamie Zeitzer, Ansgar Conrad, Janine Giese-Davis, Karen M. Mustian, Varinia Popek, Karen Nga, and David Spiegel. "Vagal Regulation, Cortisol, and Sleep Disruption in Women with Metastatic Breast Cancer." *Journal of Clinical Sleep Medicine* 4.5 (2008): 441-49.

[9] http://users.isr.ist.utl.pt/~jmrs/research/research/ANS/HRV/HRVNL.pdf

[10] Shinar, Z., S. Akselrod, Y. Dagan, and A. Baharav. "Autonomic Changes during Wake–sleep Transition: A Heart Rate Variability Based Approach." *Autonomic Neuroscience* 130.1-2 (2006): 17-27.

[11] Nilsson, Markus, and Peter Funk. "A Case-Based Classification of Respiratory Sinus Arrhythmia." *MÄLARDALEN REAL-TIME RESEARCH CENTRE.* Web. <http://www.mrtc.mdh.se/publications/0719.pdf>.

Appendix

This project was developed using the Git revision control system. The repository for our code, which contains the most up-to-date commits, can be viewed at http://github.com/sensorscapstone2012/Night-Owl. Comments within the code may help elaborate on our methods.

Alternatively, you can clone our entire repository onto your local machine using git:

git clone git://github.com/sensorscapstone2012/Night-Owl.git

Heart Rate Analysis Code for RSA [MATLAB]

```
clc

clear all

cbreathing = csvread('ShimmerData_GSR_PULSE_4_28_12.csv');

hri = cbreathing(1:8000,5);


numSam = floor(length(hri)/75);



[pks, loc] = findpeaks(hri, 'MINPEAKHEIGHT', 2500);



k = loc;

width = [];

for i=1:length(k)-1;

        width1(i) = k(i+1) - k(i);

        %disp (width1);

end


width = (width1/10);

N = length(width);

x = 0:1:N-1;

xi= 0:1/4:N-1;

y = width;

inter = spline(x,y,xi);
```

```
Fs = 10;


%calculate FFT
nfft = 2^(nextpow2(length(inter)));
%remove trend
trend = detrend(inter);
%remove DC offset
offset = trend - mean(trend);

%windowing function
hanningWin = hanning(length(offset));
offset = hanningWin(:).* offset(:);
fftx = fft (offset, nfft);
uniquePts = ceil ((nfft+1)/2);
fftx = fftx(1:uniquePts);
mx = abs(fftx)/length(offset);
mx = mx.^2;
if (rem(nfft, 2));
    mx(2:end) = mx(2:end)*2;
else
    mx(2:end-1) = mx(2:end-1)*2;
end


f = (0:uniquePts-1)*Fs/nfft;


%calculate the power between .04-0.15Hz and 0.15-.4Hz
pw1 = 0.04:Fs/nfft:0.15;
pw2 = 0.15:Fs/nfft:0.4-(Fs/nfft);
```

```
Lpw1= length(pw1);

Lpw2= length(pw2)+length(pw1);

power1 = trapz(pw1, mx(1:Lpw1))

power2 = trapz(pw2, mx((Lpw1+1):Lpw2))


LFoverHF = power1/power2


subplot(2,1,1), plot(hri), xlim([75,200])

xlabel ('Samples')

ylabel ('ADC')

title(' RAW SHIMMER DATA (Figure 1)')

subplot(2,1,2), plot(f,mx), xlim([0,.5]), ylim([0,70*10^-4])
Title ('POWER DENSITY SPECTRUM (Figure 2)')
xlabel ('Frequency (Hertz)')
ylabel ('PSD (s^2/Hz)'
```