Final Project for Exploring Neural Data
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The Next “Quantified Self” Metric?
Frequency Domain Analysis of A Good or Bad Night’s Sleep

<u>Sleep Data Analysis</u>

My final project used the data from the laboratory of Dr. Mary Carskadon, specifically the *Sleep EEG Data Projec*t. I looked at 2 subjects under two test conditions: *baseline* night of rested sleep and *recovery* night following sleep deprivation.

<u>The Question: Can Short-term Sleep Deprivation be detected using EEG data?</u>

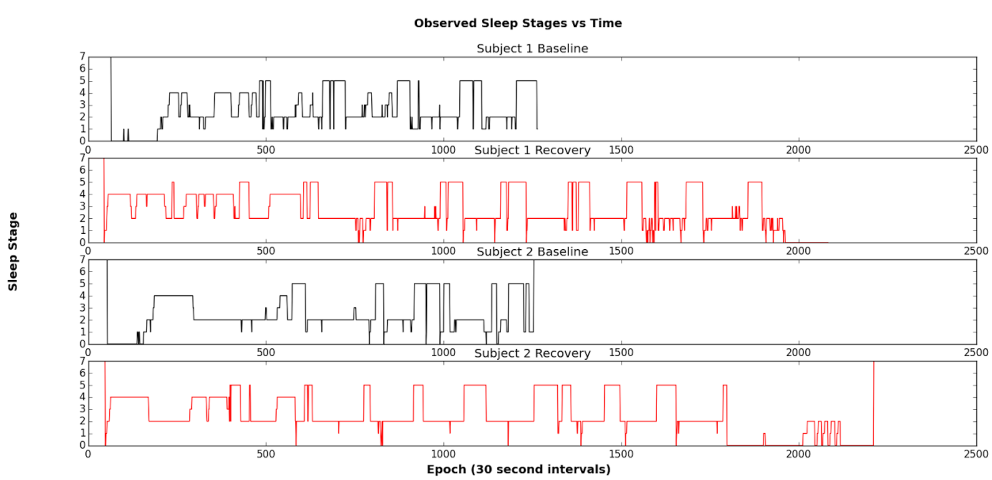
I am interested in the usage of personal biometric data. Can sleep data be used as a “Quantified Self” daily metric of wellness? If so, what measurements are most predictive?

<u>The Path of Investigation</u>

I started investigating the raw data for the time series measurements from 9-channels of sensors: EEG neural activity, EOG eye movement and EMG facial muscles movement. As I expected, the data is not easily interpretable in this form.

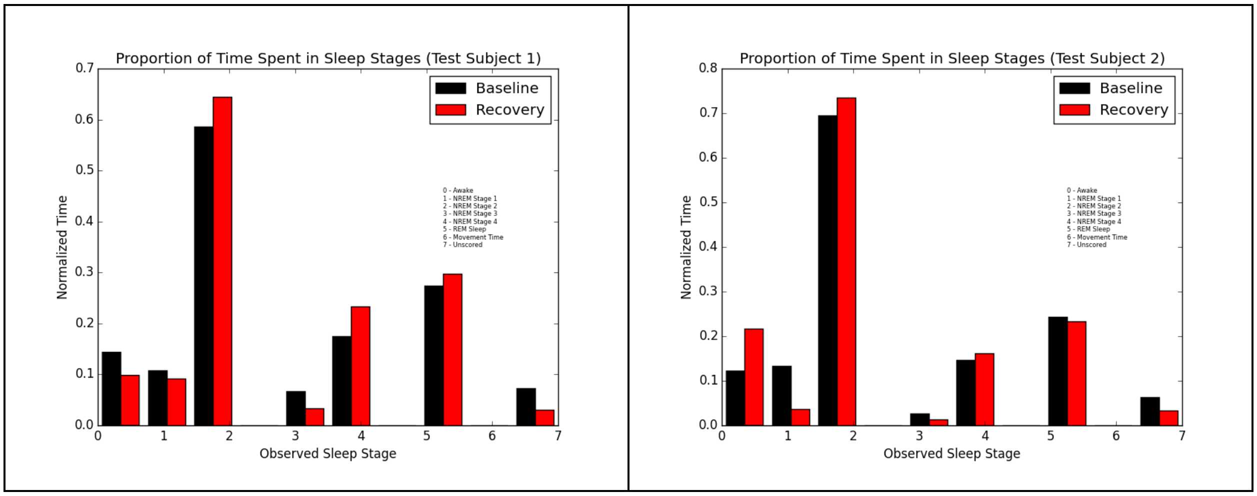
Also included in the dataset are the researcher’s manual observations of the subject’s sleep stages (shown in Figure 1). Note the length and sleep stage patterns differ significantly between the rested baseline condition and the post-deprivation recovery condition.

Figure 1. Two Subjects Sleep Stages (Baseline vs Recovery)



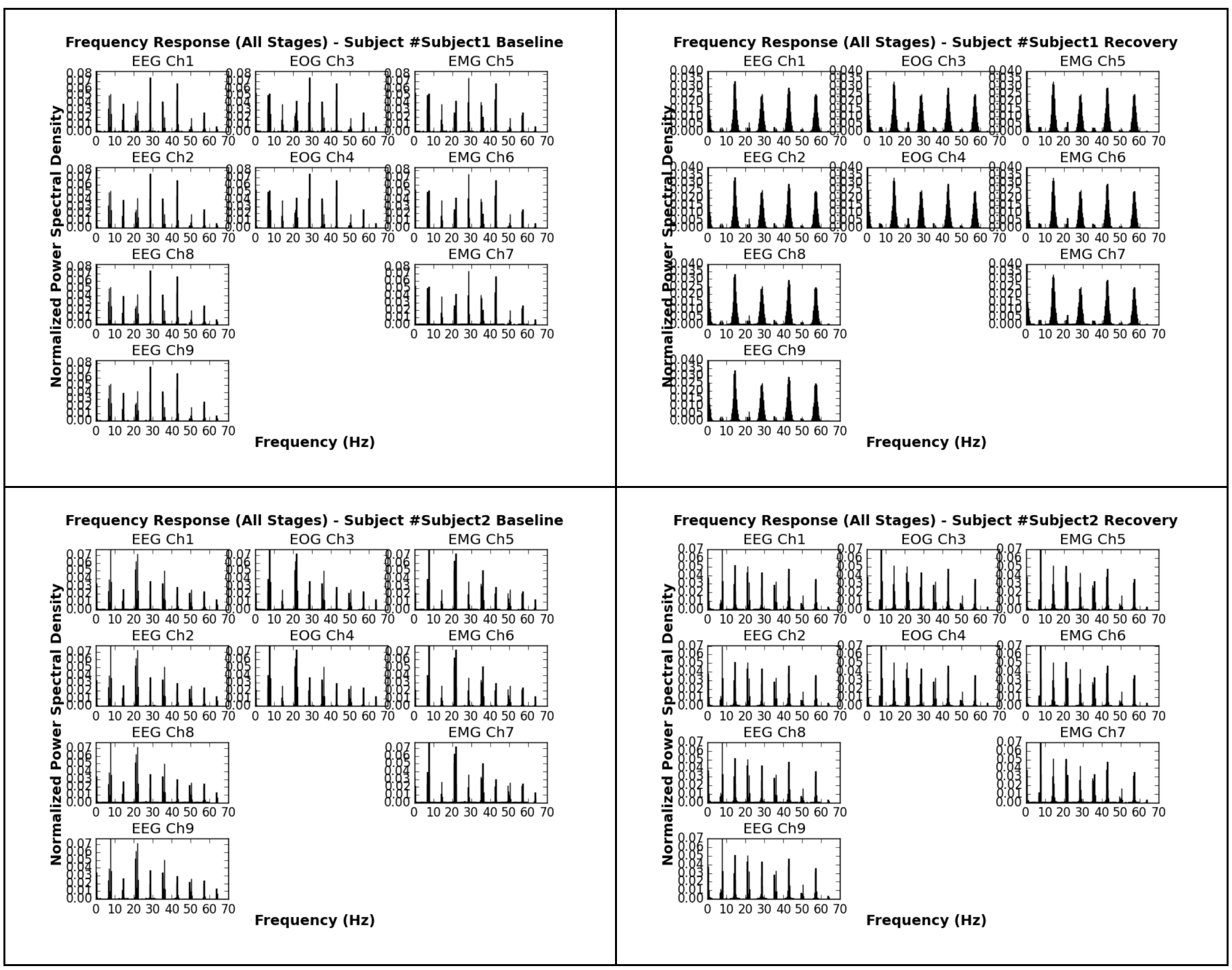
Shown in Figure 2, the histograms of this data reveals the relative lengths of the sleep stages and the pattern changes observed in this sleep deprivation experiment. Looking at these patterns illuminated the data classification tasks and helped me understand some sleep physiology. Initially, I did not assume I needed for sleep stage classification information.

Figure 2. Histograms of Observed Sleep Stages for 2 Subjects



Next, using the power spectrum density function (Figure 3), I analyzed the frequency domain characteristics for the entire time series measurements for each electronic sensor.

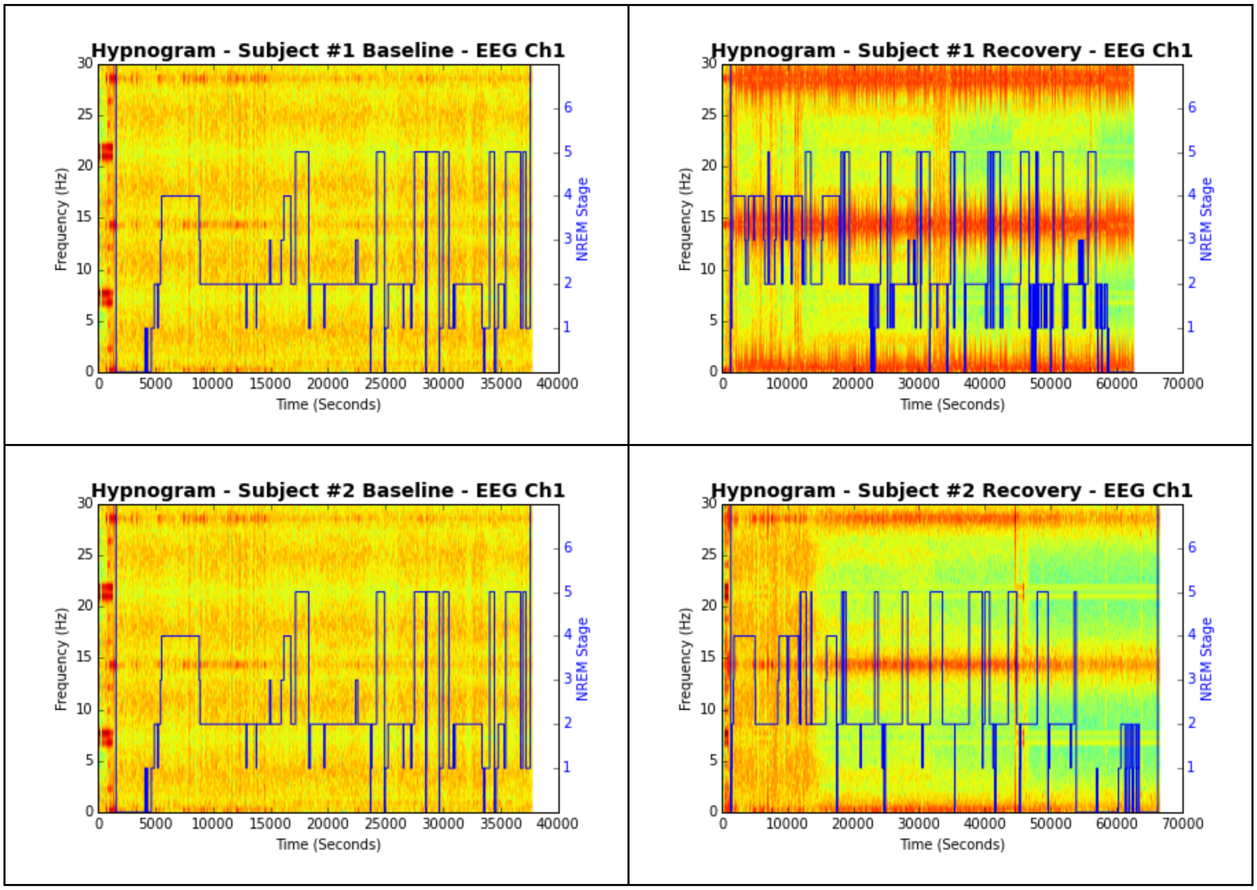
Figure 3. Histograms of Observed Sleep Stages for 2 Subjects



For Subject #1, there is a very large increase in the width of the frequency response peaks. This occurred on all 9 channels. Unfortunately, the classification problem is not so simple since this pattern is not seen in the other subject's data. Perhaps a measurement artifact?

Therefore, I proceeded to other analysis methods. Figure 4 displays the hypnograms that consisting of the spectral power response over time overlaid with the stage observations.

Figure 4. EEG Channel 1 Hypnograms



In both subjects, these hypnograms suggest a marked response of short-term sleep deprivation that is observable in the time domain. It was unclear to me how to translate this into an algorithm.

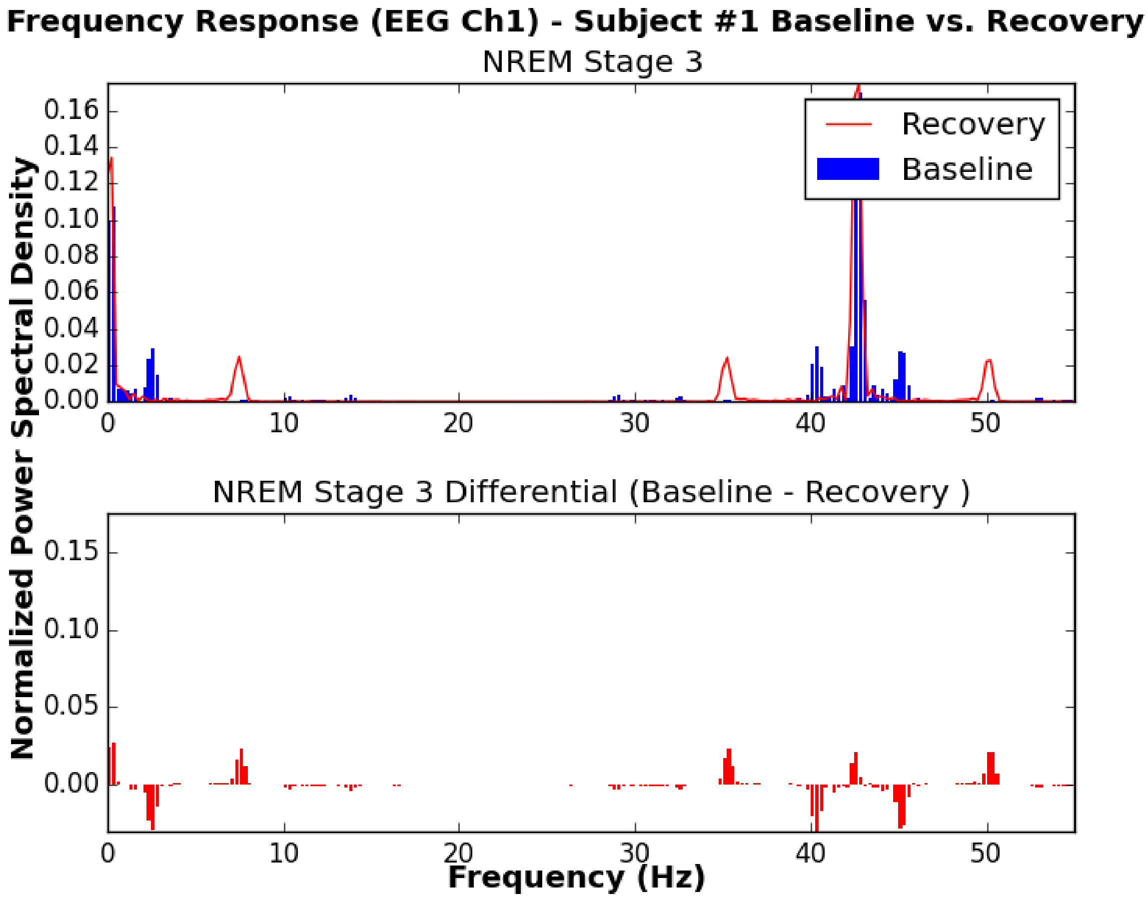
In search of a classifier, I further subdivided all of the time series measurements by the observed sleep stage. Ultimately, I created a data structure with multiple levels of indexing:

data[subject][condition][channel][stage][combined time series data]

For my analysis of 2 subjects, 2 conditions, 9 channels and 7 stages this meant 216 time series datasets. Each dataset was converted to the frequency domain using the psd() function, low-pass filtered to remove the 60 Hz noise and then normalized.

Next, I compared the power density spectrums for the baseline and recovery conditions for each channel and sleep stage combination (108 in total). In Figure 5, you see the baseline and recovery spectral responses are overlaid in the top subplot. The bottom subplot is the difference between the two conditions.

Figure 5. Differential Analysis of Baseline vs Recovery Spectrums



For each of these datasets, I attempted to rank the most significant changes between the baseline and recovery conditions. My simple algorithm was to take the absolute value of the differentials between the power spectral densities and then sum these into a single score.

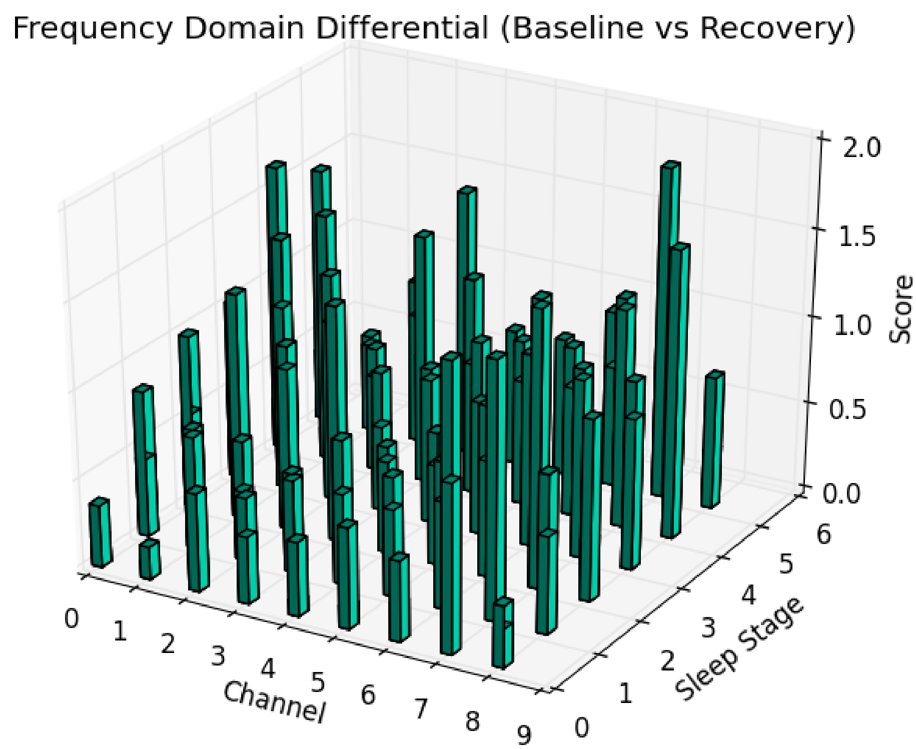
This analysis resulted in a ranked table of 108 comparisons showing the most significant spectral differences between the baseline and recovery conditions. The top of the rankings is shown in Table 1.

Table 1. Largest Differences in Power Spectral Densities (Baseline vs Recovery)

locatorID	subject	condition	channel	stage	score
47	Subject1	bsl vs rec	EMG Ch6	REM Sleep	1.889193
106	Subject2	bsl vs rec	EMG Ch7	NREM Stage 4	1.651067
42	Subject1	bsl vs rec	EMG Ch6	Awake	1.640619
98	Subject2	bsl vs rec	EMG Ch6	NREM Stage 2	1.639155
58	Subject2	bsl vs rec	EEG Ch1	NREM Stage 4	1.637138
44	Subject1	bsl vs rec	EMG Ch6	NREM Stage 2	1.589343
77	Subject2	bsl vs rec	EEG Ch9	REM Sleep	1.515945
43	Subject1	bsl vs rec	EMG Ch6	NREM Stage 1	1.478864

I found it useful to visualize the results in a rotatable 3D plot. A snapshot of this plot is shown in Figure 6.

Figure 6. Results of 108 Pairwise Frequency Domain Comparisons



Preliminary Results

Initial results indicate there are likely to be detectable changes that characterize a good night's sleep. At least from this limited set of data, we do see that sleep deprivation can induce noticeable effects on electronic measurements.

Using this simple differential spectral analysis method, I found that the top score belonged to an EMG sensor monitoring REM sleep. In fact, 6 of my top 10 scores came from EMG readings. I speculate that perhaps a single, well-placed electrode can be predictive. Much more experimental data and programming refinements are needed.

Programming Tricks

Here are a few very simple tricks that I learned:

- Modules As my program got longer and longer, I needed to organize my code into separate files. I discovered it was easy as "import myModule as s"
- Commenting out comment blocks   Use # """ to disable the comment blocks of code, then use find/replace to revert back. Processing 2GB of raw data in this project required doing this trick often.

- Pandas dataframe slicing techniques
```
df2 = df.ix[df.stage==5]              # slice df by row (sleep stage= 5)
df3 = df2['edata']                    # slice df by column (just the edata)
df4 = df.ix[df.stage==5]['edata']     # slice by row and column
```
- Multi-dimensional lists As the many permutations expanded, I needed to design a data organization scheme. Using this method made it much easier to find and manipulate the data. I used this schema:

  data[subject][condition][channel][stage][time series measurements]

Problems

I declined to use datasets for 3rd and 4th subjects in my analysis. Comments posted on the forum and my own verification detected inconsistencies in the datasets that could be problematic for this time sensitive project. Using these other datasets would clearly provide more samples for better algorithm development and verification.

As I moved through the final project, I realized what a data organization task! I am wishing that I had a better grasp of data structure theory.

Next Steps

This research project requires much more work to answer the question it seeks. Can sleep data be used as a “Quantified Self” daily metric of wellness? Much of the effort to date has been directed at learning Python skills.

In general, I would like to verify the initial findings that frequency spectrum changes can detect sleep abnormalities and EMG maybe another useful measurement in addition to EEG for this question.

There are many aspects to moving forward. Here’s my list of future tasks:

- Integrate my sleep stage classifier from the previous assignment
- Acquire and run many more datasets to test and refine algorithms
- Acquire monitoring EEG equipment and start my own N=1 data collection
- Also correlate with other metrics like heart rate variability, blood pressure, blood glucose, body weight/fat, food log, exercise log, temperature, pulseOx