Designing a Real-Time Seizure Detection Algorithm for cEEG monitoring of ICU patients with Epilepsy

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1.1. EXECUTIVE SUMMARY

Epilepsy is a disorder of the nervous system that is accompanied by uncontrollable seizures. Many cases of epilepsy are severe and require monitoring in a hospital to provide proper care and treatment before resulting in serious neuronal injuries. Seizure detection in epileptic patients in the intensive care unit (ICU) requires a commercially viable algorithm capable of detecting these seizures in real-time. The development of this algorithm could potentially reduce false positives and yield a high positive predictive value which would be an improvement of current non real-time algorithms. This will result in the ability to accurately alert hospital staff for the purpose of providing timely care for epileptic patients. The algorithm will detect seizures 10 seconds after its onset with an upper detection limit set to 20 seconds. The lower limit of 10 seconds has been defined in literature to be sufficient in filtering out false seizure activity and most absence seizures last up to 20 seconds. To stimulate a more accurate warning when comparing to current non real-time algorithms, the positive predictive value (PPV) must be higher than 13.2% and the sensitivity must be at least 93.3%. Several constraints have been determined which include limited human datasets, the algorithm’s performance in conjunction with the EEG, and a limited time of nine months to complete the deliverables. The design ultimately proposes to modify the parameters: mobility/activity and variance, fractal dimension, line length, wavelet entropy, power spectrum, autocorrelation, phase jumps and slope index. Seizures will be characterized using these parameters and support vector machine (SVM), detecting in real time. The algorithm will be tested by inputting human EEG data obtained from Hahnemann University Hospital in Philadelphia, PA into the program. The speed of the input will match that of a clinical setting. Seizures have been extracted from the EEG data and the
algorithm is in the process of training. Work on the design is not on schedule due to several problems/issues. In the current hospital setting, the main competitor is the widely established real time seizure detection monitors by XLTEK.
1.2. PROBLEM STATEMENT

Current widely accepted seizure detectors that are “real-time” have proven to be ineffective, primarily due to their high false positive rates. Additionally, currently accepted “real-time” seizure detection algorithms yield poor positive predictive values (PPV; the number of true positives over the sum of the number of true positives and false positives). Even detectors with high sensitivities (the number of true positives over the sum of the total number of true positives and false negatives) may not significantly reduce personnel requirements if the PPV continues to remain low. Moreover, faster nurse response times are more significant in determining life or death of critically ill patients in the ICU. Improving the PPV and sensitivity values will lead to a better seizure detection algorithm that can accurately alert the nursing staff and medical personnel and aid in patient care, quality of life and administration of timely treatments.
1.3. DESIGN CRITERIA

Real-Time Detection – Onset Time and Detection Latency

This project intends to develop an optimized algorithm that detects seizures in epileptic patients in the ICU, ten seconds after its onset as defined by a trained physician. Automated warnings to the appropriate caregivers can become a reality only if real-time seizure detection with 100% sensitivity and very low PPVs are made possible. Petit mal seizures, also known as absence seizures, are non-convulsive and last up to twenty seconds (Robinson et al., 2001). Using this information, the upper detection limit of the algorithm was set to twenty seconds since past this, several seizures will have completed, thus, make the “real-time” aspect of seizure detection futile. According to Gotman, Young, and their colleagues, a ten second lower limit has proven to be sufficient to filter out most artifacts disguised as seizure activity. Thus, “real-time” detection is defined as classification of a seizure not before ten seconds but within twenty seconds of the point of onset. This design intends to modify parameters such as mobility, activity, fractal dimension, line, length, power spectral analysis, autocorrelation, and wavelet entropy and integrate those with a support vector machine (SVM) that will help characterize seizures in “real-time”. In the future, automated warnings will help reduce nurse response times, decrease the risk of injury and increase the possibility of better healthcare for patients suffering from epileptic seizures in the ICU.

Sensitivity

The algorithm is supposed to perform with at least 93.3% sensitivity which is the current sensitivity of a similar non “real-time” detection algorithm. Hence, conversion from previous
algorithms to the proposed “real-time” algorithm must not result in decreased sensitivity. For the future, an algorithm with 100% sensitivity would be an ideal goal.

**Positive Predictive Value (PPV)**

A significant decrease in false positive values is a must in order to develop a viable, efficient “real-time” seizure detector. Thus, a PPV value higher than 13.2% (improvement over the current PPV value of the “real-time” seizure detection algorithm by XLTEK) is required for the success of this project.

These criteria will help in alerting intensive care unit personnel who can consequently intervene and deliver medical attention before the patient undergoes continuous or critical epileptic seizures. Thus, this design will greatly reduce the potential for patient injury and increase caregiver awareness to seizures. “Real-time” detection will reduce personnel for individual patient care and monitoring and in turn reduce the hospital costs.

1.4. **CONSTRAINTS**

One of the key constraints in this project is the limited amount of seizure data compared to non-seizure data. The EEG data obtained from patients with epilepsy, collected by the Drexel Neurology Department, from the Hahnemann University Hospital in Philadelphia, PA is rather limited. The shortage of data is further exacerbated by the atypical non-clarity of signals. Furthermore, since the algorithm is solely based on EEG readings (unlike video EEG data), the algorithm can only detect seizures as accurately as the EEG can measure brain electrical activity. This project requires the seizure to be detected by up to 20 seconds which might decrease
sensitivity due to the lack of additional data points. Limited funding and time (9 months) also serve as constraints in the completion and execution of this project.
1.5. PROPOSED SOLUTION

Background

The first step toward a working seizure detection algorithm is identifying the various parameters that could be used to help classify seizures effectively. In the past, most parameters and/or algorithms have been developed to identify a seizure after examining all seizure and non-seizure data. For example, the algorithm would screen through all collected data at the end of the day and then pick out any seizure that might have occurred. In contrast, the proposed solution will be at a disadvantage of having to identify the seizure with only a fragment of the seizure data and no access to the post-seizure data. Hence, most existing parameters will have to be modified to compensate for the inherent lack of collected data.

Several features have been examined and developed over the years to help characterize EEG data.

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<thead>
<tr>
<th>Author</th>
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Table 1: Various parameters developed in the past in seizure detection algorithms.
**Mobility and Variance/Activity**

Variance is the average of the squared differences of the mean or the squared of the standard deviation. Variance simply includes calculating the mean or average of a set of numbers or values, then calculating the difference of each value from the mean, squaring each difference, and then averaging that result.

The equation of variance is $V = \frac{((x-m)^2 + (y-m)^2 + (z-m)^2 + \ldots)}{n}$

Where $V$ is variance, $m$ is the mean, $n$ is the total number of the set, and $x,y,z\ldots$ are individual numbers within the set. Mobility was described as a parameter for EEG analysis by Bo Hjorth in the paper titled ‘EEG Analysis Based On Time Domain Properties’. Hjorth described the parameter as the “standard deviation of the slope” divided by the “standard deviation of the amplitude”. The squared standard deviation of the amplitude is also described in the paper as ‘Activity’ or ‘Variance’. An increase in ‘activity’ relates to an increase in amplitude. An increase in mobility will occur when an increase in frequency occurs.

**Line Length**

A better alternative to fractal dimension used by Pereda et al. and Freedman is line length developed by Esteller and colleagues. The logarithms will be eliminated from the numerator and denominator of the fractal dimension equation, and then the new equation includes $LL(n)$ which is the normalized line length at discrete time index, $K$ as the normalization constant, $N$ as the sliding window length, $L(n)$ is the running sum of the distances between points in the sliding window of $N$, and $x[k]$ is the data sequence value at the kth sample (Esteller et al., 2001) as shown below:
Seizure onset is detected when the running short term line length reaches or goes beyond the threshold, which includes the percent offset characterized from the desired patient plus the trend value. (Estellar et al., 2001)

**Fractal Dimension**

Fractal Dimension is a measure of complexity of a self-similar figure; it can be understood as how many points are present within a given line or a curve. In relation to EEG’s, calculating the fractal dimension involves the recursive length of the waveform (Paramanathan et al., 2007). The algorithm proposed by Paramanathan and Uthayakumar will estimate the dimension of the waveform. The procedure for calculating fractal dimension includes a time sequence \( x(1), x(2) \ldots x(N) \), choosing a range of \( k \) that is \( k_{\text{min}} \) and \( k_{\text{max}} \) using the equation below:

\[
k = \frac{1}{m} \sum_{i=1}^{m} |x_i - x_{i-1}|,
\]

\[
k_{\text{min}} = \frac{k}{2},
\]

\[
k_{\text{max}} = \frac{(N_k(C) - 1) \times k}{2}
\]

(Paramanathan et al., 2007).

The average length is also required, and then the sum of the average lengths needs to be computed as well; equations are provided by Paramanathan and Uthayakumar. Their run time of 0.43 seconds was equivalent to 4000 points, while their run time of 1.57 seconds was equivalent
to 8000 points (Paramanathan et al., 2007). The value of $\ln(k)$ versus $\ln(1/k)$ will be plotted, and the slope will be the fractional dimension of the waveform.

**Wavelet Transform, Wavelet Entropy**

Wavelet transforms localize frequency and time by using a mother wavelet which can be translated across signals. The mother wavelet function is represented as (Rosso et al, 2001):

$$\psi_{a,b}(t) = |a|^{-1/2} \psi \left( \frac{t - b}{a} \right)$$

Where $a$ is the scaling parameter and $b$ is the translation parameter. The value of the wavelet coefficient is higher when the mother wavelet is equivalent to the frequency of the oscillation across the signal in which it is translated.

Wavelet entropy is used to differentiate the extent of order and disorder related to a multi-frequency signal response. The Shannon entropy provides valuable measures for analyzing probability distribution (Rosso et al, 2001). It is given as:

$$S_{WT} = S_{WT}(p) = - \sum_{i < 0} |p_j| \cdot \ln[p_j]$$

Wavelet entropy will be a low value or very close to zero in an ordered signal represented by frequency signals exhibiting periodicity. In a disordered signal, the value of wavelet entropy will be higher (Rosso et al, 2001).

Seizures can be detected by observing the corresponding decrease in wave entropy as a dominant frequency repeats itself several times in the EEG data.
Power Spectral Analysis

The spectrum or the power spectral density function, $h(\omega)$, is the Fourier transform of the autocovariance (autocorrelation) function, $r(k)$. The autocorrelation function specifically characterizes EEG signals in the time domain while power spectrum characterizes signals in the frequency domain. The spectrum depicts the frequency content of an EEG signal, displaying the dependence of power to the wave’s frequency (Broersen, 2006).

$$h(\omega) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} r(k) e^{-j\omega k}, \quad -\pi \leq \omega \leq \pi$$

$$r(k) = \int_{-\pi}^{\pi} h(\omega) e^{j\omega k} d\omega, \quad k = 0, \pm 1, \pm 2, \cdots$$

The power spectral density can be estimated using the Fast Fourier Transform (FFT). According to a study done regarding human focal seizures, low spectral powers were found at high frequencies. Also, spectral power increases as amplitude increases across all frequencies in EEG data showing seizure activity (Jirsch et al, 2006).

Quiroga et al. have presented the power spectra of seizure EEG data collected from an epileptic patient measured with half overlapped windows of varying time (seconds) widths. The analysis demonstrated that short windows show poor resolution and larger windows show higher frequency resolution at the expense of a vague time scale. The study had chosen to use half overlapped windows of 5 second width to negotiate between frequency resolution and time (Quiroga et al, 1999).
Autocorrelation

Current autocorrelation seizure characteristics include an increased number of spikes with either slopes or amplitudes greater than the normal EEG recording, an increased average amplitude of the signal over the remainder of the record which is basically that the signal amplitude increase over time, an increased power of the signal, so the amplitude squared over time during the seizure, and a low-amplitude, high-frequency to higher amplitude lower-frequency signal progression during the seizure (White et al., 2005). Other characteristics included within the algorithm are decreased signal randomness and an increased autocorrelation in the amplitudes and slopes relative to the normal EEG record, a significant decline in the signal’s amplitude in the post ictal period or following the end of the seizure, a relatively unchanging spike frequency during a seizure, and a high chance of a previous high amplitude, wide sharp wave with a similar morphology to interictal spikes (White et al., 2005).

Autocorrelation will be implemented in order to determine the periodicity of the EEG signal, similarly to the function described in ‘Detection of Neonatal Seizures Through Computerized EEG Analysis’ by Liu et al. Autocorrelation as a mathematical function is used to compare a function to itself at a time lag. The result of the function can range from very high (Perfectly correlated) to a very large negative number (inversely correlated). In Liu’s paper EEG data was be examined in 30 second epochs, and broken up into five windows of approximately 6 seconds each. Liu described that windows of less that 6 seconds do not contain enough information to show that the data was periodic, and that windows larger than this contain too much background noise and changes in frequency. In each window autocorrelation was performed from a lag of zero to three seconds in order to obtain an autocorrelation function. This means that the first autocorrelation value will be high (perfect correlation) as the data is directly overlapped with
itself. The last value will be the correlation of the first 3 seconds with the final 3 seconds. The autocorrelation functions can then be analyzed using moment center analysis. The moment center of each peak is determined by finding the center of the area under the curve between zero-crossings. The time of the first moment center will be T1 the second T2 and so on. The ratio of the moment centers will be determined (T2/T1, T3/T1, T4/T1) and then scored based on their difference from the nearest integer. The closer the ratio is to an integer, the more periodic.

Phasejumps

Phasejumps are useful parameters for detection of low frequency (slow wave) seizure data. A phasejump is said to have occurred when the phase angle of rotation of the LFP data switches from \( \pi \times 180 \) to \( -\pi \times 180 \). Thus, a higher frequency, randomized signal would have a higher number of phase jumps than a epoch of slow wave seizure data.

This measure is calculated using the Hilbert transformation, given by,

\[
H[x(t)] = PV \left[ \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(t')}{t - t'} dt' \right]
\]

However, the Hilbert transform along with the analytic signal has been deemed useless without \( x(t) \) having a proper structure of rotation. In the equation, PV stands for the Cauchy principal value of the integral. This transformation converts the signal into a real and imaginary part. The phase angle can be thus, calculated using the equation,
Slope Index

This parameter is primarily used for low frequency seizure detection. Slope Index is a measure of how often the slope of a signal might change during a specific epoch. Similar to the phasejump measurement, the slope index measure increases during periods of slow waves and the occurrence of a dominant frequency. For example, given a set of data points, the slope index is calculated by exponentiating the number of consecutive data points that have either a positive or negative slope.

\[ \text{Slope Index} = \sum e^{\theta} \]

Unfortunately, increases in amplitude of LFP waves have been shown to reduce the ability of this parameter to accurately differentiate between seizure or non-seizure data. This is mainly due to the higher number of data points recorded for larger non-seizure waves which would show up as a higher slope index.

Support Vector Machines (SVM’s)

A SVM is a statistical tool mainly used for optimized classification of data. A SVM constructs a space in which every extracted feature is assigned its own dimension such that the number of features extracted equals the number of dimensions in the classification space. The SVM has the ability to learn to sort data into two different classes with the help of provided pre-classified data.
(training), thus, creating the best decision boundary (kernel) between the two classes and the most similar samples from each class. This can be used to classify extracted features from the EEG dataset for optimized seizure recognition.

**Preliminary Work**

EEG data of rats was recorded, in which seizures were induced using a pilocarpine model. Each recording consists of one seizure and surrounding non-seizure fragments. For each rat a MATLAB file was created which included the recordings for each of the 29 channels as well as the data-sampling frequency (2000 Hz). Channel 4 was chosen for analysis due to the clarity of the signal obtained; this channel will be used for all rats. The data from channel 4 was then plotted as voltage vs. time using MATLAB. This was achieved by creating a time scale based on the sampling frequency. Once plotted, the onset and offset times of the seizure were determined based on the rhythmicity and amplitude of the data through visual inspection. Non-seizure data has low rhythmicity and lower amplitude than seizure data. The onset/offset information was stored in individual scorefiles for each rat; these determinations will be reviewed by a trained expert to ensure correctness.

The same process will be repeated with data obtained from patients from the Hahnemann University Hospital suffering from epilepsy.
1.6. DESCRIPTION OF PROTOTYPE TO DATE

“Real-Time” Parameter Design

Due to the real-time criteria put forward for this project, the parameters outlined must be designed to analyze data differently from their original implementation. The design and the manner in which each parameter will be implemented is shown below.

*Mobility and Variance/Activity*

The Mobility and Variance parameters will be calculated for a 10-second epoch. The parameters will be recalculated once one second of new data is collected. For example a mobility value will be calculated for seconds 1 through 10. Once the entire 11th second of data is collected, the mobility will be re-calculated for seconds 2 through 11.

*Line Length/Fractal Dimension*

The procedure for calculating fractal dimension includes a time sequence x(1), x(2)...x(N) and choosing a range of k that is \( k_{\text{min}} \) and \( k_{\text{max}} \); which k is the time interval between points (Paramanathan et al., 2007). Based on Paramanathan and Uthayakumar’s method for calculating fractal dimension, we will choose \( k_{\text{min}} \) as 1. The average length and then the sum of the average lengths will be computed using equations provided by Paramanathan and Uthayakumar. The value of \( \ln(k) \) versus \( \ln(1/k) \) will be plotted, and the slope will be the fractional dimension of the waveform.
Wavelet Entropy

The EEG signal will be decomposed into frequency bands and the Shannon wavelet entropy will be calculated as 5 – 10 seconds worth of data will be stored in short-term RAM for overlap analysis. It will then be dropped to hard drive storage to keep the process computationally viable.

Power Spectral Analysis

Power spectral analysis will be implemented using Fourier transform function (FFT), adapting the time frame used in the experiment done by Quiroga and colleagues (half overlapped windows of 5 second width). Power spectrum will be estimated for 5 seconds of data and the window will shift every 2.5 seconds but maintain the 5 second window width. Essentially, the window of interest will begin at the midpoint of the preceding window, in which the power spectrum will be calculated. Data exhibiting an increase in spectral power parallel to an increase in amplitude at high frequency will identify a seizure.

Autocorrelation

The Autocorrelation parameter designed by Liu required 30 seconds of data for analysis. This amount of data is more than the upper notification time limit required in this project. Liu described that for the data analyzed that six seconds of data was required for each window, however neonatal data was being used and the frequency was around 1hz. After analyzing the data being used for this project, it was seen that the seizure wave frequencies were close to 6 or 7hz. Due to this frequency difference, the parameter must be reconsidered. In order to have enough data for autocorrelation analysis approximately 1 second of data will be needed (This will provide 6 or 7 full waves, and 3 or 4 autocorrelation waves). If more than one second of data
is going to be used there is a risk that frequency changes may occur, making it difficult to use autocorrelation. A ten second epoch consisting of ten one second windows will be implemented for the autocorrelation parameter in this project. Autocorrelation is performed in MATLAB using the ‘xcorr’ function and the function will be calculated to a lag of one half (1/2) second. The scoring system used by Liu et al. will be implemented.

*Phasejumps*

In the real-time design, the number of phasejumps for an epoch of one second will be calculated. The maximum phase jump (theoretically $2\pi$) in a noisy signal such as EEG or LFP has lower than theoretical values. In order to detect the phasejumps that occur in a phase angle plot, the discrete derivative of the wave is taken and the necessary equations are applied to calculate the threshold that determines whether a phasejump has occurred. Based on the best distinction between seizure and non seizure data, determined by the SVM algorithm, a seizure will have said to have occurred when the number of phasejumps in ten such epochs are all lower than the threshold value.

*Slope Index*

In the real-time design, an epoch of one second of incoming data will be chosen and divided into ten smaller non-overlapping windows. The average amplitude of each window will be measured and the slope of seven of the ten consecutive points will be calculated to determine whether the slope is positive or negative. After this determination, the number of incoming data points (average amplitude of one window) with a constantly increasing/decreasing slope will be added to the set, till the slope inverts (The derivative of slope will approach zero before the slope
changes from positive to negative or vice versa; this can be used to determine slope inversion). The total number of data points with a similar (positive or negative) slope will be exponentiated to measure slope index of the current epoch. A seizure will have said to be occurred if the slope index value rises above a threshold value determined by the SVM algorithm for ten such epochs.

**Training**

Specific algorithms will be designed in MATLAB to evaluate the effectiveness of each of the parameters separately. Each parameter will be run on seizure and non-seizure training data. For each file analyzed, a vector will be produced with a series of values, one for each defined time window. All files will be compiled into one file and this data will be analyzed through the SVM Function in MATLAB in order to determine the optimum boundary between the seizure and non-seizure data. Next the parameters will each be run on test data (not previously analyzed), and the SVM decision boundary will be applied to the data, thereby giving the decision for seizure and non-seizure data. For each parameter a PPV and sensitivity value will be calculated based on its performance within the established criteria. These parameters will then be strategically combined, based on the various features extracted, to obtain an algorithm with the highest possible sensitivity and best PPV. Decisions could be made using ‘if’ statements with boundaries set based on our own conclusions, however SVM performs this function for us on multiple parameters simultaneously, and in turn creates better boundaries and decreases incorrect choices.

It can thus, improve the performance of the seizure detection algorithm by creating the best decision boundary (kernel) to identify and separate any inputted data into the seizure or non-seizure class. All inputs will undergo an additional temporal constraint of ten seconds to filter any non-seizure artifacts.
Testing

To test the effectiveness of the new parameters and their combinations, EEG data will be fed into each of the designed algorithms at their original sampling frequency in order to mimic "real-time" data input. Alternatively, the data can be fed all at once; however, the data must be read by the algorithm such that only information prior to the current data point will be used. Based on the empirical results, and the properties of the parameters, the best combinations will be chosen for further testing and false positive reduction.

Based on our parameter design, the amount of data being used for calculations must not exceed 20 seconds, as this is our upper limit for seizure detection. Ideally the amount of data needed to confirm a seizure would be only 10 seconds as this is our lower limit for defining a seizure. All of our parameters aim to meet these specifications by using epochs no longer than 10 seconds.

Proportions of training data to be used

While it may be presumed that since both seizure and non seizure should be used in equal amounts for optimized representation of each data class, in reality, a little more seizure data is required in comparison to non seizure data. This was determined through a method for determining the overall performance of an algorithm was used which is called the area underneath the receiver operating characteristic curve (AUROC). When the AUROC is plotted as a function of the relative proportion of nonseizure and seizure data in the training set, the AUROC measure shows a bell shaped curve with a maximum occurring at 40% nonseizure data and 60% seizure data.

A possible cause for the slightly higher amount of seizure data required could be chalked up to the differences in variability in each data class. Introducing more data provides variability and a
wider range of values representing that class. Additionally, not all points in the training set are actually used by the SVM. Given that a class is represented by a cluster in the feature space, the SVM only uses those points which help define the optimal separation, or margin, of the decision boundary (Cortes et al., 1995).

Optimization of parameters used

This project has quoted eight different parameters to try and achieve maximum sensitivity. However, to reach maximum efficiency and sensitivity, all eight parameters would not be needed. Additionally, some of the parameters are better suited for only certain types of seizure detection (eg.: phasejumps are extremely good at determining low amplitude slow seizure waves but can be misleading when determining higher amplitude waves). Hence, to optimize the detection of seizures and avoid exhaustive yet redundant computational processes, this project intends to weigh out the optimal five parameters by means of an algorithm. The algorithm will identify a “possible” seizure type based on number of data points received (frequency) for a set time window (one second). Additionally, amplitude and time measurements will be taken into consideration. Based on the seizure type, the algorithm will trigger activate a particular set of five parameters which have been previously tested to be the most optimized in detection of the particular seizure type, thus hopefully achieving the highest accuracy and sensitivity. This will be determined experimentally through the training process. Additionally, thresholds to determine seizure types will be set by an SVM algorithm, which will optimize differentiation between seizure types.
1.7. PLAN OF ACTION FOR SPRING TERM

Parameters algorithms must first be finalized in MATLAB. Once this is performed, training of individual parameters may be completed, and testing of each will be performed. Final parameters will be determined and final training of the algorithm and final testing will be completed.

1.8. SOCIETAL AND ENVIRONMENTAL IMPACTS

There will be no environmental impacts caused due to our design since it involves designing an algorithm using MATLAB. The design does however come with some societal impact. There will be a positive impact to the patient, as they will be able to receive timely and accurate medical attention for their seizures. Additionally, hospital personnel and resources will not have to be as intensely dedicated to each patient when they are not in danger. Our design will help to require less doctor time to review EEG data, as well as less nurse time of continuously monitoring for seizures. This will allow the hospital to better allocate their resources and induce a cost saving, which can in part become a cost saving to the patient, who presumably already has high medical bills. The design however can have some negative impacts. As the system will be used to detect seizures, less dedicated attention will be needed for these patients. We must work to ensure patients are not completely ignored due to our design, as they are critically ill and do need medical attention aside from seizure monitoring. Our product will alert to seizures only and not make a prognosis of the general health of the patient. Ethically the use of our product should not have any issues however animal testing would likely be needed before implementing our
product and receiving FDA approval. This portion would cause an ethical issue as seizures are induced in healthy animals, and the animal may be eventually sacrificed for research.

### 1.9. SCHEDULE

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Boxes in green are completed; boxes in red have not yet been started or not yet complete; yellow boxes are in progress; and gray boxes are initially planned scheduled tasks that were not started during those months.
1.10. REFERENCES

1. Control for Disease Center and Prevention <http://www.cdc.gov/>
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