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Mathematical Evaluation of Ulnar Nerve Somatosensory Evoked Potentials (SSEPS)

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MATHEMATICAL EVALUATION OF THE ULNAR NERVE SOMATOSENSORY EVOKED POTENTIALS (SSEPS)

A Thesis

by

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ABSTRACT

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As the number of individuals suffering with low back and neck pain rises, we find people undergoing spinal procedures more often. In means, of safeguarding the patient and their neurological structures during the procedure intraoperative neuro-physiological monitoring (I.O.M) has been more widely used amongst surgeons orthopedic and neuro alike. During these procedures, a modality widely used for both low back and neck surgery is somatosensory evoked potentials (SSEPs). The aim of neuro-technicians is to obtain a baseline waveform that can be considered present and reliable. When obtaining SSEPs the technician can encounter obstacles with 'noisy' wave-forms due to signal interference which may be from physiological sources, as well as environmental (technical) sources. The primary purpose of this paper is to provide a mathematical SSEP model through observation of the cable equation, and an algorithm for recovering a noisy SSEP signal through fast fourier transform (FFT), modal thresholding, and the application of bandpass filters (BPFs) to obtain a baseline. This baseline is crucial to present a reliable waveform.

DEDICATION

It is with great pleasure that I dedicate this to each member in my immediate and extended family that believed in me to pursue an education beyond high school. To my mother who showed me discipline and respect for myself and my education. To my brother who without him saying, "you always have to talk to people and get out in the world" in order to experience life and do something; for without these words I do not believe I would have taken to a life in the operating room. To Eric Ramos who has stood and sat by me even when it wasn't easy and making me all the coffee to help me stay up. To the friends I never knew I would have Ferdi Garcia, Nirali Mithal,Brandon Silvester and Tristan Barboza who encouraged me when I didn't even believe in myself to be capable or felt like stopping.

Above all this dedication goes to my Ma, who now lays at rest but she showed me to never give up no matter the hurt and pain–we push to see ourselves succeed.

ACKNOWLEDGMENTS

My sincerest gratitude goes to Dr. Josef Sifuentes for taking the time to help me along this journey and accepting to be the Committee Chair. Dr. Sifuentes not only helped along the way with this paper but restored my faith and reminded me of the reason why I decided to pursue a graduate degree in mathematics. To those in the committee, Dr. Cristina Villalobos, Dr. Brandt Kronholm and Dr. Sergey Grigorian for being willing to be a part of my committee, and see not only my dreams but my work come to light.

I can also not give enough thanks to my managers, with special note to my fitness manager Genaro Mercado who took the opportunity to hire me and allow me to continue my education. In addition, to standing and sitting by me while I worked on this in between clients and meetings. To all my clients who worked with my schedule, who listened sometimes one too many sessions about my ideas and helped me understand how to better explain myself. A very special thank you also goes out to Kolade Adjibi who I was lucky to have met throughout this journey.

Above all the greatest thanks goes to our creator who allowed me the time, grace and patience to pave my pathway of experiences that lead me to the book Mathematics for Neuroscientist and further expanding my ideas, understanding of evoked potentials.

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CHAPTER I

INTRODUCTION

Back pain ranging from the neck, upper back around/near the shoulders and low back pain radiating down to the lower extremities has been increasing amongst individuals. While some back pain can be treated, many individuals are not improving through incorporating movement into their day to day. The majority end up seeking alternative methods in the forms of prescription medicine, injections or even surgical alternatives. During these procedures neurological structures are put at risk and can be compromised. Orthopedic and neurosurgeons thus try to safeguard patients by calling in clinical neuro-physiologists to monitor evoked potentials(EPs), electromyography (EMG) and electroencephalography (EEG). One of the modalities most commonly and first used during spinal procedures are Somatosensory Evoked Potenitals (SSEPs).

In preparing to study for a certification as a Clincical Neuro-physiologist or Certified Intraoperative Neuro-monitor (CNIM), it can be seen that SSEPs have a very familiar pattern to those with a mathematical eye-they take the form of trigonometric waveforms.

The primary purpose of this paper is to provide a mathematical model of obtaining an SSEP measurement by application of the passive cable equation and fast fourier transform to reduce the time in obtaining a baselines, and being able to get a present and reliable waveform. The overall aim is to produce a mathematical model of a simulated ulnar nerve (UN) and producing an SSEP using an algorithm coded in Matlab by applying numerical solutions of the cable equation, fast fourier transform and ACNS guidelines. Intraoperative monitoring guidelines, obligatory peaks will be used as a sample to compare the mathematically generated waves. In the application of this method we hope to be able to extend this to other evoked potentials used to monitor the peripheral and central nervous system to create a full simulator that can later be manipulated by adding different

variables which can cause increased noise or create a change in the signal. Where noise will be any other peak or trough in the signal that is not the most discernible peak around the given range for each obligatory peak. Then further help in narrowing the parameter windows provided by the guidelines to help determine the difference between increased noise or a potential change due to patient alertness, technical artifact or actual injury as well as obtain the frequency for an SSEP waveform that will generate an obligate peak, leading to a more efficient use of time. [5]

$$\tau\frac{\Delta_v}{\Delta_t}(x,t)+v(x,t)-\lambda^2\frac{\Delta_x}{\Delta_t}(x,t)=0 \qquad ,0<x<\ell \qquad ,0<t \tag{1.1}$$

[11]

CHAPTER II

IOM

2.1 Introduction to Intraoperative Neuromonitoring

The use of intraoperative neuromonitoring (I.O.M) came about to help surgeons safeguard neural structures during spinal corrections. Evidence shows that the use of I.O.M dates back to the 1970s. Other studies state it dates even further back to the 1930s where the idea of neural stimulation involved placing microelectrodes to record neural activity, thus leading to the development of electroencephalography (EEG) and electrocorticography (ECoG).

It's primary use and motive was to understand epilepsy in more detail. From the endeavor, EEG gave us insight to what is today known as brain waves. Further resesarch and experimentation showed that neural stimulation produces neural activity, bringing to life the field of intraoperative neuromonitoring.

I.O.M. was also used to omit the stagnara wake-up test during scoliosis and other corrective spinal procedures. The first known surgeon to do this was Tamaki [8]. SSEPs were used in lieu of such a test to bypass the patient not being properly unanesthesized.

2.2 Modalities

Based on the procedure a neurotechnician can help inform the surgeon of what modalities may benefit the patient to ensure a reduction in post operative defecits. The following are the most widely used modalities during a spinal procedure setup: monitoring of evoked potentials: (SSEPs) somatosensory evoked potentials (sensory cortex/peripheral nerves) and (TcMEPs) transcranial motor evoked potentials (motor cortex/muscle), compound motor action potential(CMAP), such as (EMG) Electromyography (muscles), often times accompanied with a train of four. The train of four

is used to help the tech inform of the reliability of the EMG channels or help the anesthesiologist know if the level of muscle relaxation has changed via stimulation of the peripheral nerve. In order to determine these modalities the neurotechnician must be aware of the level of surgery, as well as the location. In obtaining this information the clinical neurophysiological team can determine which neural structures are at risk and which modalities can be most beneficial. Communication takes place between the reading neurologist and surgeon by means of the CNIM for overall determination of what will be monitored during the procedure.

2.3 Data Acquisition

The technician can communicate to the anesthesiologist the modalities both surgeon and reading neurologist have agreed to use throughout the procedure to ensure the patient receives the adequate amount of care. The communication between anesthesiologist and neuro-technician must also be relayed to the reading neurologist. The level of anesthetic as well as the type plays a pivotal role in data acquisition.

The anesthesia team informs the room and technician when the patient is sedated, and the technician can then proceed to placing the required electrodes. Electrode placement is dependent on the modalities being used throughout the procedure. A typical setup involves subdermal needle electrodes which are placed on muscles relevant to the surgery, in addition to a control. These electrodes are often used to evaluate nerve stimulation or elicit a motor evoked potential. Surface electrodes or subdermal needle electrodes near peripheral nerves are used for stimulation and head electrodes (electrode type can vary, commonly subdermal needle electrodes) are used to record evoked potentials.

Once all electrodes are placed and the patient has been positioned, the electrodes will be connected to a system, commonly CADWELL Cascade and data can be collected. Each system has a subset of pre-prepared templates that are created by the technician or provided by the technician's company. The templates ensure preset settings for the channels being observed, as well as, the bandpass filter settings. Each modality has a range for the hi and lo cut. The filter setting can typically range per company protocol as well. The bandpass filter ensures that data being obtained

is within the range of the signal being observed and no outside sources can be rendered.

ACNS guidelines ensure parameters are within range to ensure patient safety in a clinical and intraoperative setting. Evaluation and observance of them is one of the components that will be used in modeling the intraoperative signal. For example, ACNS guidelines gives the range of 30-3000Hz for bandpass filters when pertaining to SSEPs. [6]

ACNS guidelines also recommend voltage parameters for stimulation. The technician adheres to these guidelines while communicating with the reading neurologist. In the event the voltage set does not give a robust signal, adjustment is made via manipulation of stimulus settings, as well as increase in voltage all amidst patient safety. However, it should be noted that in increasing the voltage of the stimulus the possibility of the signals becoming contaminated exists. Contamination of the waveform can be with gaussian noise which the technologist refers to as "noisy". Gabianni and Cox refer to a signal having noise as a dirty signal.[11] Once all signals are ran all members of the operative team are informed, baseline waveforms are stored and used as a comparison prior to any surgical manipulation. [4]

2.4 Troubleshooting

The morphology of the SSEP can vary based on type of stimulation, injury, noise, as well as placement of electrodes. These waveforms are monitored once the patient undergoes anesthesia to completion of the surgery. It is the technologist's job to obtain data during the procedure per company protocol, surgeon's request, or as requested by the online reading neurologist. In the event that wave-forms cannot be obtained, the technologist must troubleshoot from computer to patient and patient to computer.

Often times troubleshooting is not needed at the start of the procedure; other times it is needed during initial data acquisition. Troubleshooting techniques consist of the following, but are not limited to, issues that can be technical, physiological, or anesthetic. The technician must observe the anesthetics being used. Once there is an understanding of the anesthetics being used, it is important to check the stimulation parameters. Stimulus parameters are done per guidelines and to ensure patient safety. However, at times the possibility of the stimulus producing a nociceptive

response exists. In an event such as this, the technician can observe a change in frequency of the waveforms in the EEG window, often defined as 'increased noise'. Determining the obligate peaks of the waveform is done through analysis of the waveform but also communication with the reading neurologist. The most common modalities looked at in this situation are EEG and SSEPs. Careful evaluation can result in understanding the frequency of the signals in EEG data.

Some of the techniques and areas observed when troubleshooting are the following: ensuring filters did not somehow change or changing the Hi and Lo filters (adjusting band-pass – however is not preferable during the surgery) or the addition of a notch filter, if applicable and when ringing artifact cannot be created or is possible. Typically notch filters are not advised for SSEPs, as this is when ringing artifact can most be encountered. The range of the lo-filter is not changed as there is a risk to cutting off potential data. Troubleshooting areas still within the computer system can also include checking the impedance which will ensure that the electrodes are still making appropriate contact and are not faulty. In the event the impedance does not read below 5kOhms, per company protocol and ACNS guidelines – the technologist can proceed by changing the electrodes or ensuring proper contact between skin and electrode. Other computer techniques involve changing the rep rate and evaluating signal frequencies. At the level of the patient, troubleshooting consists in ensuring proper patient positioning both patient, patient's extremities and equipment near the patient and cables. Troubleshooting can be faster and more efficient when there is a basic understanding of the physiological complexity of the waveform and observance of the changes of wave-forms.

2.5 Analysis of the Wave-forms

Throughout the procedure signals are ran intermittently. The number of times the signals are stored can vary by company, as well as per surgeon. Certain modalities are run continuously throughout the procedure but stored during critical stages (manipulation of neural structures, placement of hardware...). Other modalities are run about every 5-10min unless other sources of electrical (60Hz Gaussian) noise is present and can saturate the amplifiers. These subsequent signals are compared to the initial baseline waveform.

In obtaining baselines the technicians must ensure that the signals meet criteria to be

considered present. Communication with the reading neurologist is crucial at this stage as the reading neurologist can guarantee that the signal morphology is present and can be considered reliable or if adjustment in parameters is needed to obtain a more robust signal.

The SSEP morphology is typically trigonometric in appearance. At first glance to those with a mathematical background can state the morphology looks like sine or cosine waves. ACNS guideline 11B states that the SSEP is a monophasic rectangular pulse ranging 100-300($\mu s, microseconds$). Understanding waveform morphology will not only help in obtaining a robust and repeatable signal but it can also ensure fast troubleshooting. Often times one can get a square wave recording and this can be indicative of being in an improper channel—thus having a technical issue[12].

After baseline acquisition ACNS has what is known as alarm criteria. [4] From SSEPs the waveform must retain its morphology. If there is a decrease in amplitude 50% or greater or a change in latency that is 10% or greater, the technologist must inform the surgical team. At this point in time the technologist will communicate with the surgeon to determine if there was any change to neurological structures to help with troubleshooting the change in waveform morphology and get a return that is like baseline or no longer within alarm criteria. If the waveform does not return the technologist must continue to advise the surgical team and continue to troubleshoot throughout the procedure. If a technologist ever encounters a signficant amount of interference, "excess noise" the possibility of running more trials (averaging) exists. [4]

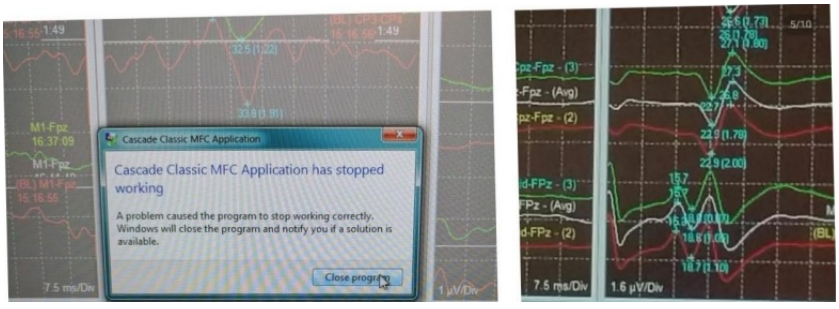

Figure 2.1: OR SSEP Acquisition, with troubleshooting example

CHAPTER III

SOMATOSENSORY EVOKED POTENTIALS

3.1 Somatosensory Evoked Potentials (SSEPs)

Median Nerve (MN) and Ulnar Nerve (UN) SSEPs are used to monitor and gauge the peripheral and central nervous system during procedures in which the dorsal column are at risk. They are mostly monitored during spinal procedures, carpal and cubital tunnel procedures. However, UN monitoring also occurs if there is a concern in the positioning of the upper extremity that can compromise the integrity of the brachial plexus or other concerns of a deficit to the upper extremity.

We will primarily be doing an evaluation on UN SSEPs. UN SSEPs are evaluated by applying a stimulus to the upper extremities. The relayed stimulus passes through an amplifier and a resulting signal that has a sine/cosine wave appearance. Prior to the procedure, the technologist obtains a set of baseline wave-forms and continuously monitors this signal throughout the procedure. If at any point during the procedure the signal hits alarm criteria or is lost, troubleshooting takes place to ensure that the loss or change of waveform, decreased amplitude, and increased latency are not due to technical issues.

3.1.1 Clinical Guidelines

Intraoperative monitoring technologist are required to pass a certification exam after completing a program and participating in data acquisition during procedures. Standards and protocols are set by the American Clinical Neurophysiology Society known as the, ACNS [6]. ACNS has a set of guidelines that anyone in the field of intraoperative monitoring must know and understand. These guidelines help safeguard the patient while also setting a standard for data acquisition.

ACNS guidelines for SSEPs are both for clinical and intraoperative standards and are listed

under an overall guideline for evoked potentials. SSEPs also have their own guidelines listed under sections 9 and 11. These guidelines provide what is known as the obligate peaks. Obligate peaks for upper extremity SSEPs are a peripheral point known as Erbs point (N9), cervical points (N13) subcortical points (P14 and N18) and cortical point (N20). N and P is used to differentiate between the peak (maxima) and trough (minima) of the waveform and are used to discern repeatability and reliability of the waveform. ACNS guidelines also provide what is known as the montage, the location sites of where the electrodes are placed and recording from. Stimulus parameters are also provided as a range for the technologist to have a baseline to compare. Manipulation or deviating from these parameters is done if needed after there is communication with the reading neurologist and the surgeon in the event waveforms cannot be obtained. Stimulus parameters given range from the intensity (voltage) of the stimulus, band-pass filter settings (Hz), duration of the stimulus (pulse width/duration, μs) as well as the rate at which the stimulus is being delivered (rep rate/s) [7]

3.1.2 Data Acquisition

When arriving at the operating room the technologist typically has a preset template for the type of procedure that is being done. For simplicity and for this paper we will only cover the section for SSEPs.

The template setup is to have three to four channel settings for upper (UE) and lower extremities. This section will begin with evaluating and discussing the template settings for the UE, the ulnar nerve (UN). The channel settings are Erbs Point (EP) which has a typical montage of EPi-EPc meaning the ipsilateral and contralateral point (left and right). Placement of this electrode is at the level of the clavicle. ACNS gives the specific location for placement of each. For future instances in this paper EP will be denoted as N9 and is present in our window with a peak at about 9ms. The next channel is the cervical point N13 (Cs) and has the montage Cs-Ep, Fpz is the location of the electrode at the frontal cortex per EEG guidelines. The trough of this point is typically at about 14ms and will be denoted P14. The subcortical potential is a subthalamic point which will be denoted as N18, Cpz-Fpz. Finally, the channel most often observed, but also most affected by anesthetics is our cortical point (Cp3 or Cp4), denoted as N20. These obligate peaks are what is

monitored throughout the procedure. Included in the template is the preset settings for the lo and hi cut filters, typically the lo filter is set to 30Hz and 250Hz is set for P14/N18 and N20 waveforms, while 30-1500Hz is used for N9. Understanding and changing the passband filters is important as they can affect the overall morphology and latency of the signals, not to mention their size which per guidelines, range 20-500μV. [7]

Baseline acquisition consists of setting a stimulus intensity, typically per ACNS guidelines 30-40mA. The intensity will only be increased further if the waveforms are not presenting. The rep rate for intraoperative settings is set between 2-8/s [7] and ensuring it is not a multiple of 60Hz gaussian noise—the only time it is set higher, (up to 20/s) is if obtaining the waveform is needed in a faster amount of time. On average a total of 100 – 200 trials are done. This can vary per company protocol and guidelines up to 1000 trials can sometimes be run. The trials are run to allow for averaging, presenting in a waveform that has less noise such as done in Algorithm 3, Ch 5. Pulse duration is typically between 100-300μs, this is another value can vary per company guidelines—a typical parameter is about 250μs.

Once all parameters are set, the stimulus is turned on and the signal is run continuously throughout the procedure unless there is anything that can saturate the signal. This however, can also vary and some studies have shown that it may be best to not run the signals continuously as to prevent fatigue. It is of utmost importance that a baseline be taken and the signal be run prior to a stage of change and immediately after a change in the operating site has occurred.

3.1.3 Ulnar Nerve

The ulnar nerve is typically used as the primary monitoring site when the surgical site is at C8 or below or in the event that the brachial plexus being stretched out is at risk. For purposes of this paper we will mainly be evaluating the ulnar nerve SSEP. The electrodes placed at the wrist are typically surface electrodes, while the recording electrodes at the level of the clavicle (N9) and head (N13, P14, N18 and N20) are subdermal electrodes, as listed with generator sites in table 3.1. [5] However, subdermal electrodes can also be used at the wrist, this is however dependent on technologist and patient need.

The ulnar nerve SSEP obligate peak latencies are often times determined by the length of the extremity and temperature. The length of the ulnar nerve is important because it is what will connect us to our area of concern, the UN and applying the passive cable equation. The UN runs along the lateral aspect of the upper extremity passing the elbow (cubital area) up the arm through the clavicle and branches off from the brachial plexus. The brachial plexus branches off from the cervical roots and that subsequently continues through the brainstem, subthalamic and cortical level.

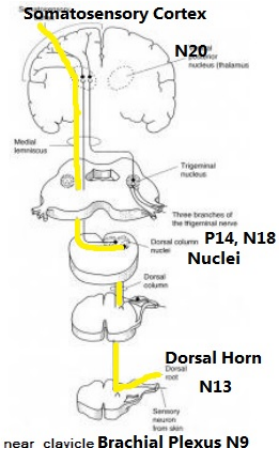

Figure 3.1: SSEP Pathway
[1]

Table 3.1: Somatosensory Evoked Potenitals and their generators

Somatosensory EPs		
SSEPS	Obligate Peak	Generator (ms)
Erbs	N9	Brachial Plexus
Cervical	P14	Cervical gen
Cortical	N20	Cortical gen
Cortical 2	P24	Cortcal 2 gen

CHAPTER IV

ULNAR NERVE AND THE PASSIVE CABLE EQUATION

4.1 The Ulnar Nerve

Gabbiani and Cox [11] apply the passive cable equation to a neuronal model. A neuron is the cell that constitutes our vast nervous system. The means by which our nervous system communicates is still thoroughly being investigated. We know however, that a collection of neurons is known as a neural network by which neurons communicate with each other. The anatomical structure of a neuron is made up of separate parts which we will consider as compartments for purposes of this paper, figure 4.1 all of which are taking the limit as the compartment size goes to 0. Given that we are evaluating the nerve with a set of compartments, and there is a start and finish to our SSEP we will consider the investigate via a discrete laplacian as Gabbiani and Cox, which proves the existence of the passive cable equation. Overall, a neuron has a structure that is like that of a cable and communicates via an electrical impulse. A nerve is an enclosed bundle of axons and nerve fibers found in the peripheral nervous system (PNS) as denoted in the figure 4.2 below.

When looking at the anatomical structure of a nerve fiber we find that they too are cable-like. The electrical impulse, known as an action potential is the means by which nerves communicate and is known as cable theory [13] We will expand the theory of the cable equation to an entire nerve and applying similarly Gabbiani and Cox who limit themselves to a cable that is uniform and unbranched. [11]

The ulnar nerve is a peripheral nerve that branches off the brachial plexus containing both motor and sensory outputs. For SSEPs we are mainly observing the sensory output of the ulnar

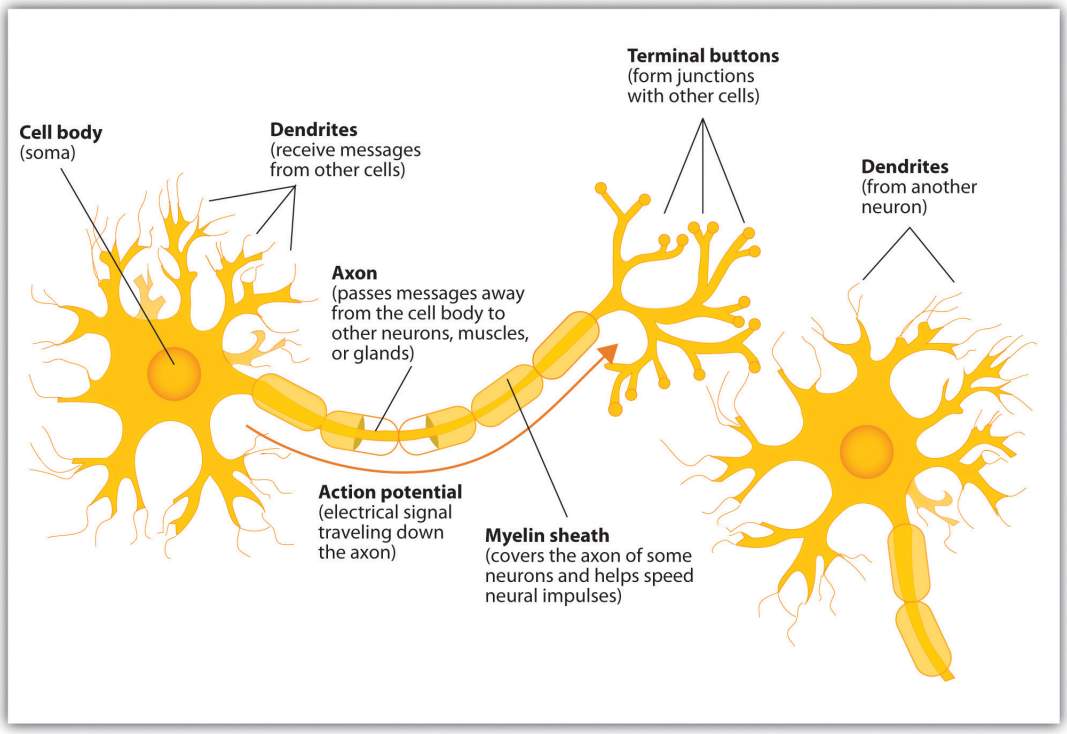

Figure 4.1: Neuron anatomy
[2]

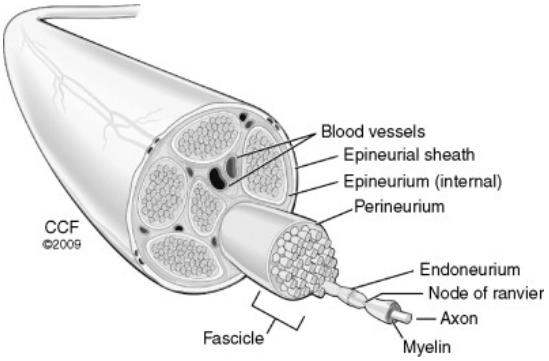

Figure 4.2: Cross sectional area of a Peripheral Nerve
[3]

nerve. We will consider the ulnar nerve as a cable of length l and having a radius r which we have found using the ranges for cross sectional areas given by [9], which are between 5.9 - 6.7 mm. The radius of the ulnar nerve was mathematically computed under the assumption that the ulnar nerve primarily takes a cylindrical shape and cross-sectional area A given by

$$A = \pi r^2 \tag{4.1}$$

As per Cartwright et. al, [9] the ulnar nerve is a circle mid-level of the humerus. Further, studies can be done using the fact that the ulnar nerve takes an elliptical shape. For this paper, we will maintain the assumption that the ulnar nerve is circular throughout.

4.2 The Ulnar Nerve and Ohm's Law

As discussed in the SSEP chapter, a current is sent via an electrode to obtain a stimulus response while a patient is under anesthesia throughout surgery. The electrical signal and change of voltage can then be evaluated via Ohm's law which studies the relationship between current I, voltage V and resistance R. Ohm's law is given by $I = \frac{V}{R}$ Given that the voltage transcends the nerve we can state there is a change of voltage that can be evaluated, ΔV. For SSEPs and passive cable theory we know that there is a current being injected, that will be denoted as I_{stim} giving a resulting signal with an amplitude in microvolts μV. The potentials that move through the nerve are known as, transmembrane potential V_m. Therefore,

$$I_{stim}(x,t) = \frac{\Delta V_m}{R}(x,t) \tag{4.2}$$

The voltage can be calculated at any point x along the ulnar nerve and is time dependent. The SSEP, is a function of set points in space, x at time, t. By ACNS guidelines, there exist a set of obligate peaks given at a set frequency, given by a rectangular pulse. The obligate peaks can be recorded at a point in space, x when a current is injected I_{stim}

4.3 Passive Cable Equation

Our passive cable equation is given by [11]

$$\lambda^2 \frac{\partial^2 V_m}{\partial x^2}(x,t) - \tau_m \frac{\partial V_m}{\partial t}(x,t) - V_m(x,t) = 0 \tag{4.3}$$

$V_m(x,t)$ is the potential that travels through the UN after a delivered stimulus is provided

across time, t. λ which is our space constant. The space constant, λ is given by

$$\lambda = \sqrt{\frac{r}{2R_i g_{cl}}} \tag{4.4}$$

R_i is the intracellular resistivity in Ωcm. g_{cl} is the conductance. Gabbiani and Cox take R_i as resistivity of the cytoplasm. For purposes of this paper we will assume R_i remains the same for a nerve as though it were a neuron since we know membrane potentials vary in time, but not in space. τ_m is the time constant given by

$$\tau_m = C_m R_m \tag{4.5}$$

Since we know that our potentials vary in time, we know τ_m can take varying forms depending on the cell being observed. We also know that C_m is proportional to the surface area of the cell being evaluated. R_m is the specific membrane resistance. C_m however will be set and assumed to be $1\mu F/cm^2$ since the exact membrane capacitance for a dorsal horn has not yet been found. Per Gabbiani and Cox, solutions to the passive cable equation, when dealing with sealed-ends is an example of a Fourier Cosine Series. The eigenfunctions themselves are also cosine functions. [11]. Given that the solutions are cosine, and we assume our sensory pathway is a sealed-end we then assume, that our model will also use a cosine function, as opposed to a sine function. We therefore, use *cos* when creating the algorithm for our equation, and applied stimulus. We find our ulnar nerve to be of a given length, ℓ and a radius, r. We assume the ulnar nerve to be divided into compartments, N each of length $dx = \ell/N$ as done by [11]. Based on the morphology of a neuron each individual component (axon, soma or dendrite) is considered a compartment within the neuron. A nerve is composed of multiple neurons therefore we can extend the idea of compartmentalization to the UN. Each point at which an evoked potential can be recorded will be considered a compartment. We take the cross sectional area using Cartwrights findings on normal ulnar nerves [9] and assume the cross sectional area to be given by the equation as discussed above. Gabbiani and Cox, give a model of a simple cable that is compartmentalized. Below is a figure that was constructed by guidance of said model. Each compartment has a capacitor, membrane capacitance, as well as a resistor, G in

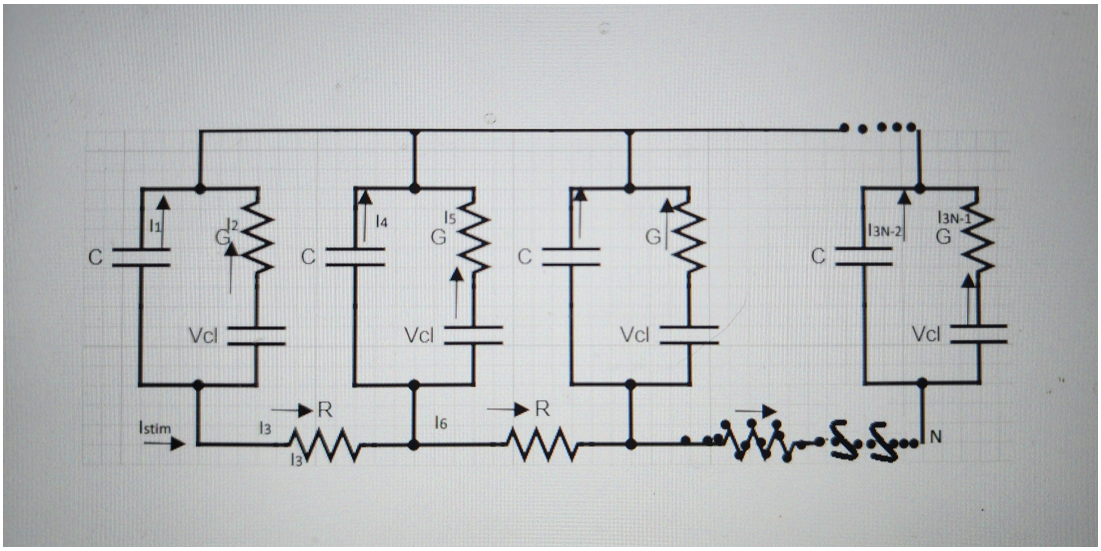

Figure 4.3: Simple Cable

figure 4.3 which is the conductance.

When comparing our simple cable above to our cable of interest, the ulnar nerve we can compare how our SSEP is generated. Extending the idea of compartmentalization a little further, the compartments like our levels, our obligate peaks are each points in space at which the signal is being recorded during the procedure. The electrical potential that travels via an ulnar nerve can be recorded when there's an applied stimulus which provides our recorded SSEP.

For an SSEP to be an obtained we apply a stimulus at the level of the wrist, our first node To obtain a signal Gabbiani and Cox take each collective compartment and derive the passive cable equation. V is the electrical potential difference and I is the current in terms of conductance, $I = gV$ and our equation then takes the form [11]

$$I_{stim}(t) = I_1 + I_2 + +I_{3N-3} \tag{4.6}$$

Each compartment that we evaluate has a capacitor and resistor. As a stimulus, I_{stim} enters the compartment it travels through the compartment and our transmembrane potential takes the

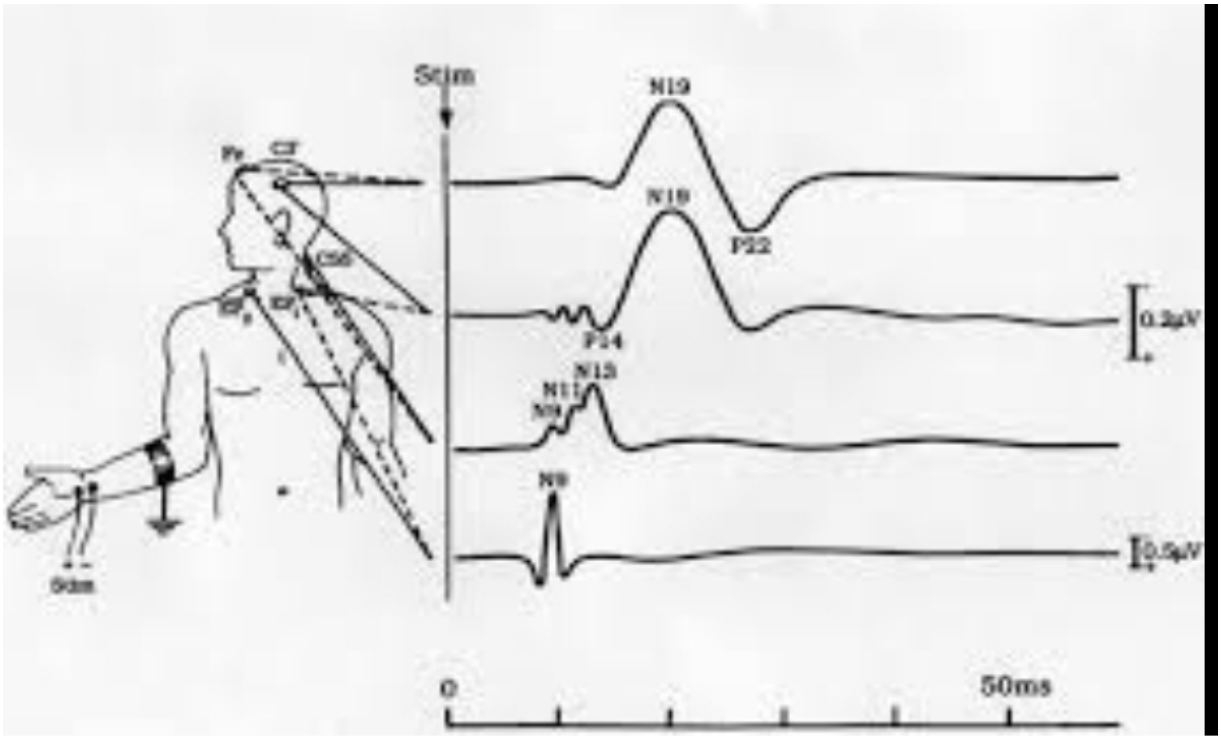

Figure 4.4: UN SSEP Obligate Peaks

form, $V = \theta_n - \theta_0 - V_{Cl}$, so our stimulus as it transcends compartment, and the ulnar nerve becomes

$$I_{stim}(t) = \frac{C(\theta_1 - \theta_0) + G((\theta_1 - V_{Cl}) - \theta_0)' + (\theta_1 - \theta_2)}{R} \tag{4.7}$$

It has been found that spinal cord ventral horn capacitance is $2.4\mu F/cm^2$ [15] but neural capacitance's can range from 0.75 – 2.4 $\mu F/cm^2$. Since we are evaluating the UN for an SSEP we will be evaluating the UN using the derivation of the cable equation that Gabbiani and Cox use for current injected into a compartment [11]. This then allows us to investigate the space step Δ_x which allows us to understand the means by which current is injected. Our equation will then take the following form:

$$I_{stim}(t) = \frac{C_m(2\pi r\Delta_x)\frac{dv}{dt}(\frac{\Delta_x}{2},t) + g_{cl}(2\pi r\Delta_x)v(\frac{\Delta_x}{2},t) - v(\frac{3}{2}\Delta_x,t) - v(\frac{\Delta_x}{2},t)}{\Delta_x} \tag{4.8}$$

The injected current will be a constant current or voltage per SSEP guidelines at the level of the wrist as compartment starting point. When the stimulus is turned on by the neurotechnologist we

will assume the current is injected and the cable equation becomes

$$\frac{\Delta_v}{\Delta_x}(0,t) = \frac{R_i}{\pi r^2} I_{stim}(t), 0 < t \tag{4.9}$$

The above equation will then be evaluated at the first node – level of the wrist in relation to the SSEP. By the means of an action potential, as the neuron depolarizes or repolarizes the membrane potential gets closer to 0 which is given by the equation above as d_x approaches 0. As the length of the nerve continues to become the nerve at the level of the cervical cord and transcends all the path through the level of the cortex where the head electrode is located by the cable's far end [11]

$$\frac{\Delta_v}{\Delta_x}(\ell,t) = 0, 0 < t \tag{4.10}$$

The obligate peaks are than recorded at different levels of the tract (i.e., cable) by comparison on a cable it would be all interior points. The equation for all interior points of the cable (peripheral, cervical and sub-cortical obligate peaks) thus each interior obligate peak is given by the equation above then as Δ_x approaches 0

$$\tau \frac{\Delta_v}{\Delta_t}(x,t) + v(x,t) - \lambda^2 \frac{\Delta_x}{\Delta_t}(x,t) = 0 \qquad ,0 < x < \ell \qquad ,0 < t \tag{4.11}$$

which is our passive cable equation. Lastly, once the injected current is turned off and the tract is at rest then our SSEP would be displayed by

$$v(x,0) = 0 \qquad 0 < x < \ell \tag{4.12}$$

Gabbiani and Cox then evaluate the steady state solution with the applied stimulus. They suppose a constant current stimulus by guideline 11B [7] and as discussed in Ch.SSEPs, we know a constant current stimulator is recommended by guideline 9B which defines an SSEP, shows us that the pulse/stimulus delivered is done with a constant voltage or constant current stimulator. It is most

beneficial to use a constant current stimulator as with SSEPs we're dealing with an impedance that is constantly changing. Gabianni and Cox construct the exact eigenvector expansion solution to current being injected into the cable. Evaluation and analysis is done using the two dimensional Laplacian matrix, denoted as a second difference matrix. The solution of the passive cable equation, results in a series of eigen functions, the eigenvalues are then taken for the ulnar nerve of interest. This shows that when considering a cable of length ł and calling on the function evecS(ell, n) where 'ell' is our cable length ℓ and N is our set number of compartments. The length of an upper extremity is determined by Tyler Edmond et. al [10] the equation for the length of the arm and forearm are given as the following:

$$\ell_{arm} = 0.14(h) + 0.28(A) + 0.41(S) \tag{4.13}$$

$$\ell_{forearm} = 0.12(h) + 0.01(w) + 0.27(S) \tag{4.14}$$

taking the sum of these two equations, we then use this as the length for our UN since the area used to determine the length of the upper extremity is the area of which the UN transcends. If the sex is male than 0, if not than sex input is 1. The h, is for height in cm, A is for the age in years, and w is for the weight, in kg. However, it must be noted that this is specific for children. We will assume for the instances of this paper the l, is 1. All other parameters remain the same. Eigenvectors of the two dimensional laplacian under a set of neumann boundary conditions and the finite difference method. Our solution and the equation we use for our algorithm is then:

$$V_m(x,t) = \sum_{n=0}^{\infty} \frac{q_n(0)q_x}{2\pi r C_m} \int_0^t I_{stim}(s) exp((t-s)\zeta_n) ds \tag{4.15}$$

where ζ_n is

$$\zeta_n = (\lambda^2\theta - 1)/\tau \tag{4.16}$$

where θ is a constant value which is equal too $\frac{-n^2\pi^2}{l}$ determined by Gabbiani and Cox. The above equation can be further evaluated at both a steady and dynamic response, I_{stim}. The steady and dynamic response will take on a constant stimulus at which is denoted, I_o. The steady response

will have $I_o = 1mA$ and the dynamic response will be evaluated at $I_o = 40mA$ per SSEP guidelines. For steady.m the following parameters are defined: $r, l, I_o, C_m, G_\ell, R_2$. Both the steady and dynamic response is taken by evaluating our stimulus response by the weighted product of our eigenvalues and eigenvectors.

CHAPTER V

MATHEMATICAL EVALUATION OF THE SSEP

As discussed in Ch.4 Gabbiani and Cox identify the resulting eigenvectors as cosine functions for a passive cable equation. The exact solution is a Fourier Cosine Series when evaluating a sealed-end condition. An SSEP is a signal evaluated along the UN, starting at the level of the wrist and ending at the head (somatosensory cortex), as per Ch.3. We thus assume our UN is cable-like, with an N9 obligate peak which begins at the wrist and ends at the brachial plexus, since it is a sealed-end we can apply Fourier Cosine Series. So the sensory pathway is too a sealed-end, beginning at the point of stimulation and ending at the somatosensory cortex, and can apply Fourier Cosine Series.

The applied stimulus by ACNS guidelines is a monophasic-rectangular pulse, as discussed in Ch.2 with a set of bounding parameters, known as I_{stim} in our passive cable equation (4.20). A neural response will sum together in space and time by summation of synaptic potentials [14]. By adhering to the guidelines, sealed-end conditions of passive cable equation, properties of synaptic potentials and EEG we then assume I_{stim} to take on a Cosine function with a set pulse width, rep rate and current. Using Matlab we create a function for I_{stim} with these parameters and substitute the function for I_{stim} in our equation (4.20). The I_{stim} function invokes `rectpuls` to reflect the type of pulse our stimulus has, as well as `pulstran(t,d,func)` to apply all bounding parameters. Figure 5.1 demonstrates the rectangular pulse with a unit-height from 0 to 1 (on or off), Cosine function, designated rep rate, evaluated along 40ms time window. This is then evaluated with the passive cable equation, resulting in our *original* signal, figure 5.2.

The rectangular pulse generated a unit-height response with a set sample rate at random between 2-5Hz, as well as a randomly generated rep rate at 1.77Hz from prior experiences in the OR

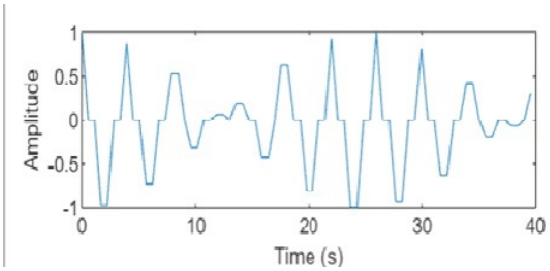

Figure 5.1: I_{stim}

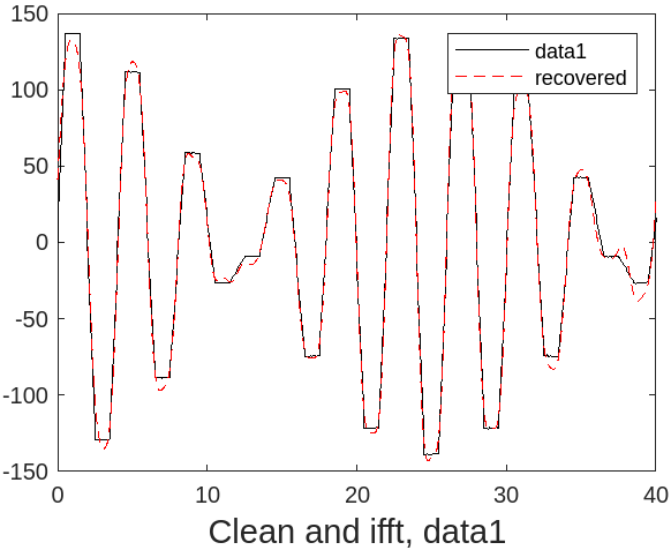

Figure 5.2: original passive cable equation evaluated with I_{stim} and iFFT of noisy passive cable equation

per a reading neurologist in attempt to troubleshoot a signal. In addition to a pulse width between 100-300 (μs), microseconds, per Ch.2. Figure 5.1 demonstrates the rectangular pulse applied, is on for a set current and continues throughout the tract. As described in chapter 3, the electrodes placed along the nerve $V(x,t)$, produce a resulting potential at time t ms. This is observed for $V(20)$, $V(5)$, and $V(80)$ which were selected at random and using I_{stim} function with a rep rate of 1.77. The resulting waveform is then evaluated by running an `fft` to find which frequencies are present

within the signal. The Discrete Fourier Transform by definition is:

$$y(t) = \sum_{n=-\infty}^{\infty} C_n \frac{e^{int}}{\sqrt{2\pi}},\ t \in [0, 2\pi]$$

$$where, C_n = < y, \frac{e^{int}}{\sqrt{2\pi}} >$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{2\pi} y(t) e^{-int}\, dt$$

$$\approx \frac{1}{\sqrt{2\pi}} \sum_{j=0}^{N-1} \frac{y_j}{N} e^{\frac{-inj}{N} 2\pi}$$

with a DFT array $(\frac{1}{N}[y_0, y_2, ..., y_{N-1}])$ The FFT is an algorithm to calculate the DFT functions in $O(N \log N)$ steps. Our `FFT` shows peaks between 0 - 1000 Hz, as seen in the figure (5.3). FFT of the original signal is taken to help in determination of the frequency domain. It takes our signals and outputs all present frequencies to allow an easier comparison to our dirty signal $u_{dirty} hat$.

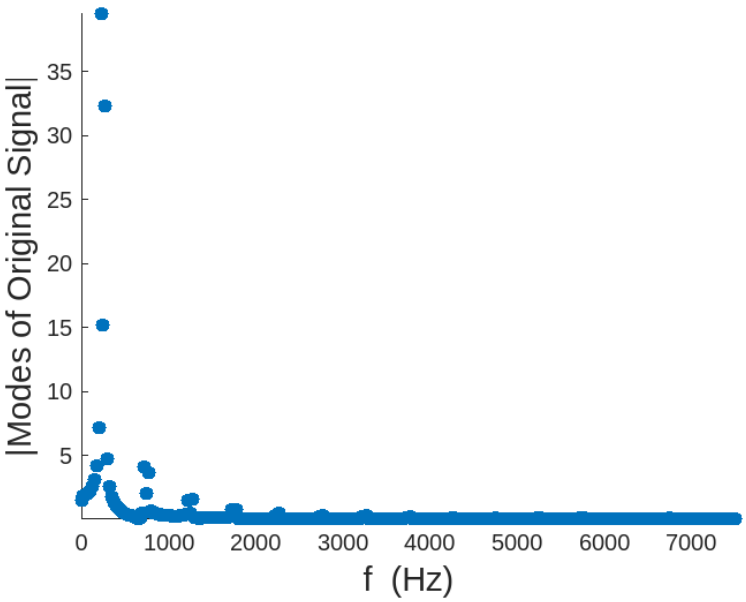

Figure 5.3: FFT of original signal

By *theorem*: Let $u(t)$ be the periodic, SSEP signal over the interval $[0, T]$ and $\eta_j(t)$ for $j = 1, \ldots, M$ be independent, random variable with mean 0 and variance σ^2. Then if

$$\widetilde{u}(t) := \sum_{k=1}^{M} u(t + (k-1)T) + \eta_k(t), \qquad \text{for } t \in [0, T]$$

then the Variation of the noisy, average signal is given by:

$$Variation(\widetilde{u}) = \frac{\sigma^2}{M}.$$

and *Corollary*: If the Signal-to-Noise ratio (SNR) of the noisy SSEP is defined as the ratio of signal power to noise power:

$$SNR = \frac{\text{signal power}}{\text{noise power}}$$

where

$$\begin{aligned} \text{signal power} &:= E(u^2)m, \qquad \text{and} \\ \text{noise power} &:= E(\eta^2) = \sigma^2 \end{aligned}$$

then the SNR of the average noisy SSEP signal $\widetilde{u}$ is given by

$$SNR_{avg} = \frac{M E(u^2)}{\sigma^2} = M \cdot \text{SNR}_{single}.$$

The original signal is repeated and periodic and it is then made dirty, 'noisy' by adding noise over a set of a ten, one hundred and one thousand signals independently to mimic OR conditions, figures 5.4 to 5.6.

We assume Gaussian, independent and mean 0 noise. Thus if we take N snapshots corresponding to a period or multiple of a period, and then take the averaged of the snapshots, then we expect a denoised signal. The average of these signals is then taken to be used as our *dirty* signal. Noise was added to the original signal at 25 %, 50 %, and 90 %, figures 5.7 to 5.8.

Averaging is 25 %, done to mimic the OR conditions but also to help with reducing the amount of noise that is present within the signal. [12] Hassan and Anwar state the theory of signal averaging as follows:

$$v(k) = v_s(k) + v_{noise}(k) \tag{5.1}$$

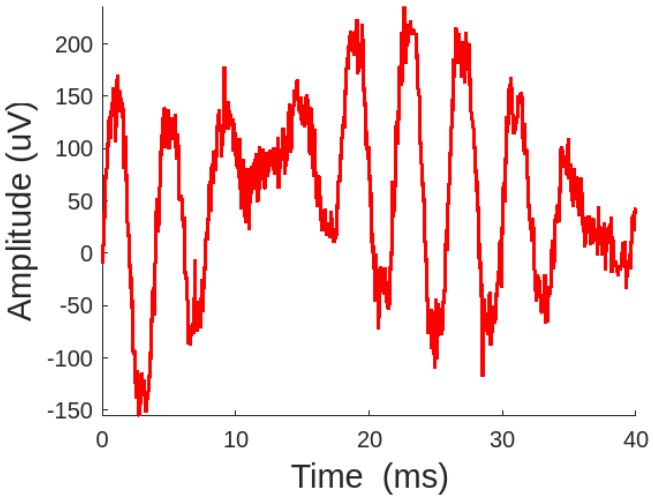

Figure 5.4: Noisy signal averaged 10 times

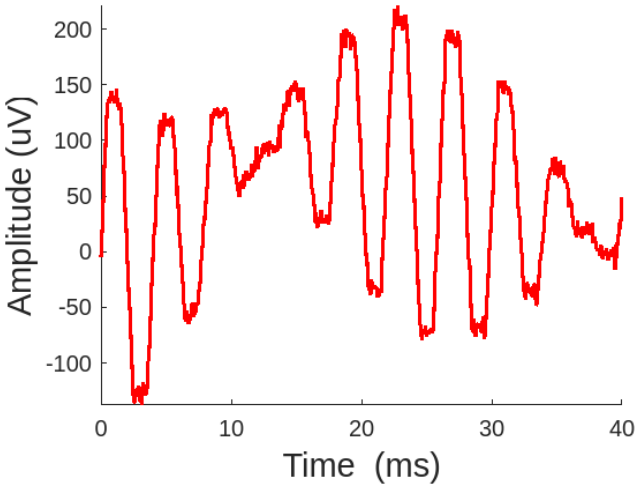

Figure 5.5: Noisy signal averaged 100 times

Where $v(k)$, is the signal, $originalhat$ or $u_{dirty}hat$ that will be evaluated and have the addition of noise $v_{noise}(k)$, as noted in the theorem and corollary above. The signal that we are evaluating is on an assumed periodic signal that is repeating around an expected mean of 0 for noise, as noted by Hassan and Anwar, signal averaging is then expressed [12]

$$y(k) = \frac{\sum_{i=1}^{N} Z_i(k)}{N} \tag{5.2}$$

The resulting signals were then evaluated with an `FFT`, figure 5.4. This was done to evaluate our signal frequencies and determine if there was a consistent peak that continued to present within

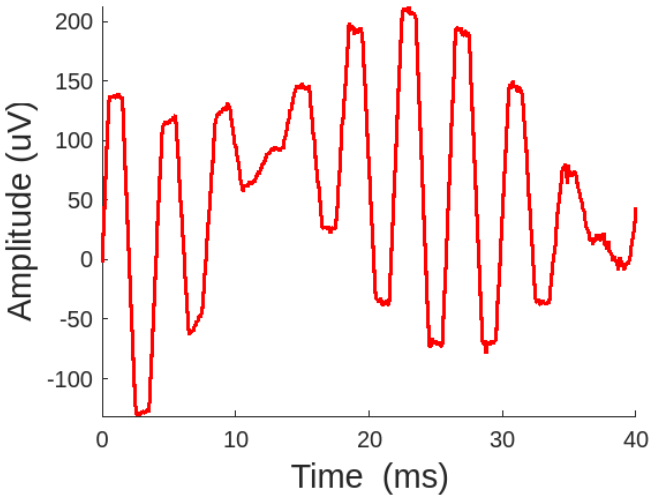

Figure 5.6: Noisy signal averaged 1000 times

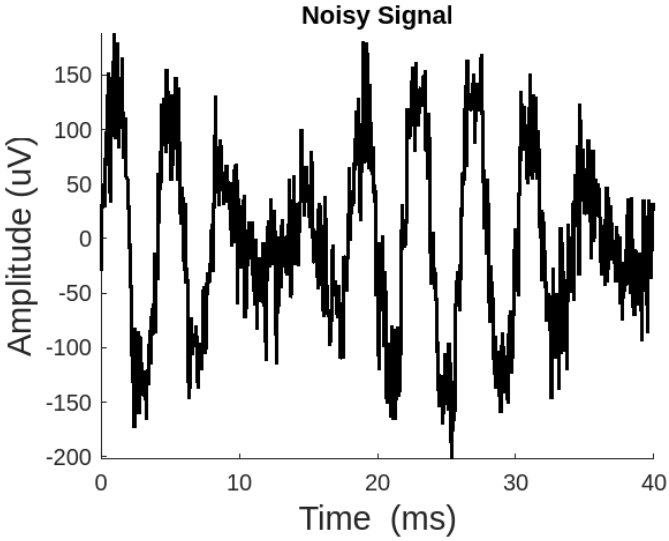

Figure 5.7: Signal with 25 % noise

the range of 0-1000 Hz and if they are true peaks in our signal.

We then compared the original and dirty signals to find the true modes of the dirty signals, this resulted with peaks at frequencies within the same frequencies of our original signal with a slight change in amplitude and latency. figure 5.10 to 5.15.

Prior to running the inverse FFT we added a threshold to the signal to eliminate all frequencies that were not prominent or potentially part of the true signal. Thresholding FFT of the noisy signal is done to complete the denoising process. We set the modes with absolute value less than 5% of the maximum mode magnitude to be 0. BandPass Filtering was done to account for aliasing.

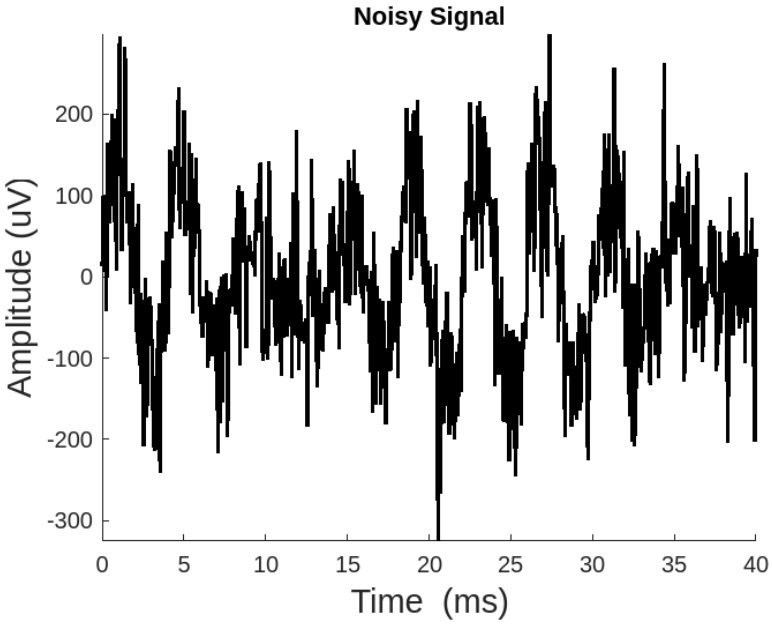

Figure 5.8: Signal with 50 % noise

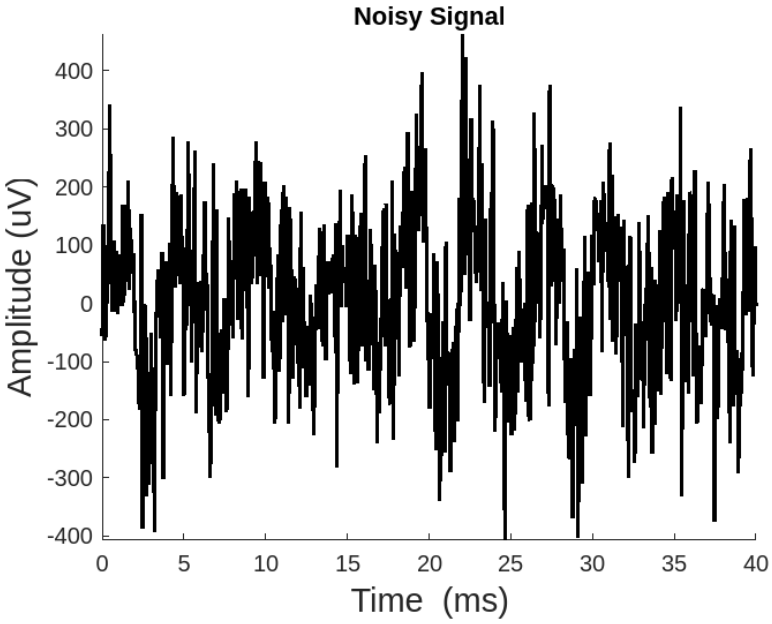

Figure 5.9: Signal with 90 % noise

We took the bandpass filter at symmetric points of the mode. All modes for frequencies greater than 1500 Hz were set to zero, figures 5.16 to 5.18.

The inverse FFT was taken of the dirty signal to go from frequency domain back to our time domain aiming to recover our original signal. Taking the inverse `iFFT` of our noisy signal with just

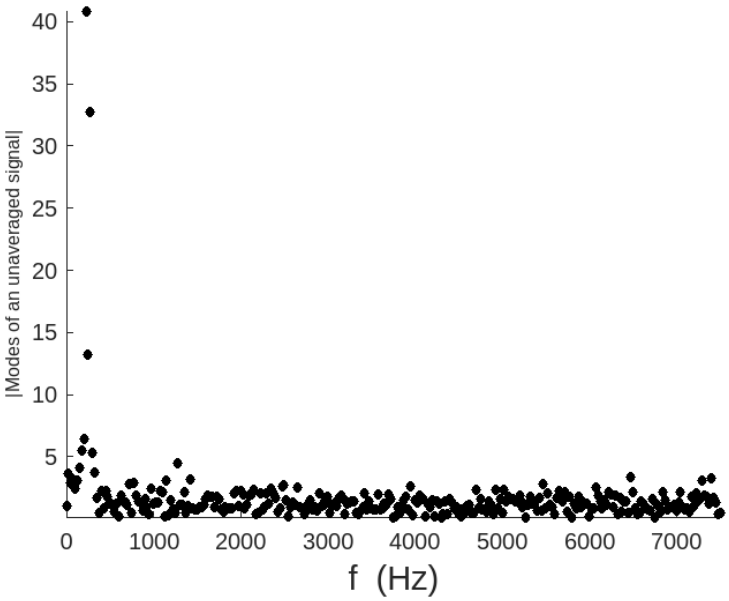

Figure 5.10: FFT of true noisy signal no threshold or averaging, 25% noise

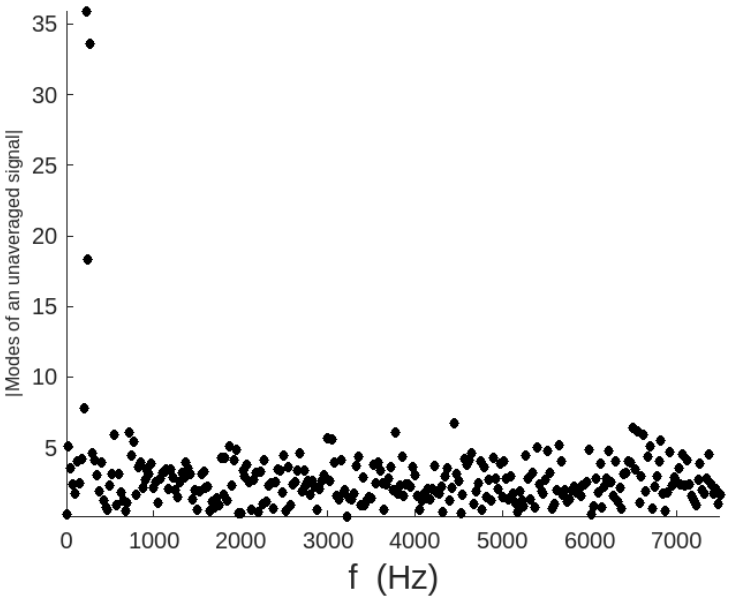

Figure 5.11: FFT of true noisy signal no threshold or averaging, 50% noise

thresholding resulted as demonstrated in the figures above. While hen resulted taking the inverse `iFFT` of our noisy signal with just averaging resulted as demonstrated in the figures 5.19 to 5.21.

It is noted that the signal was comparable to our original signal with the exception being changes in latency (time) and amplitude, figure 5.22.

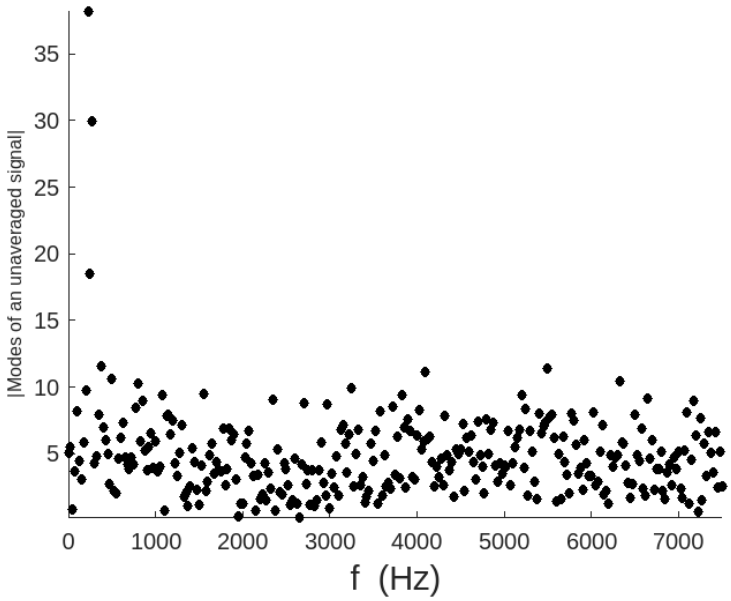

Figure 5.12: FFT of true noisy signal no threshold or averaging, 90% noise

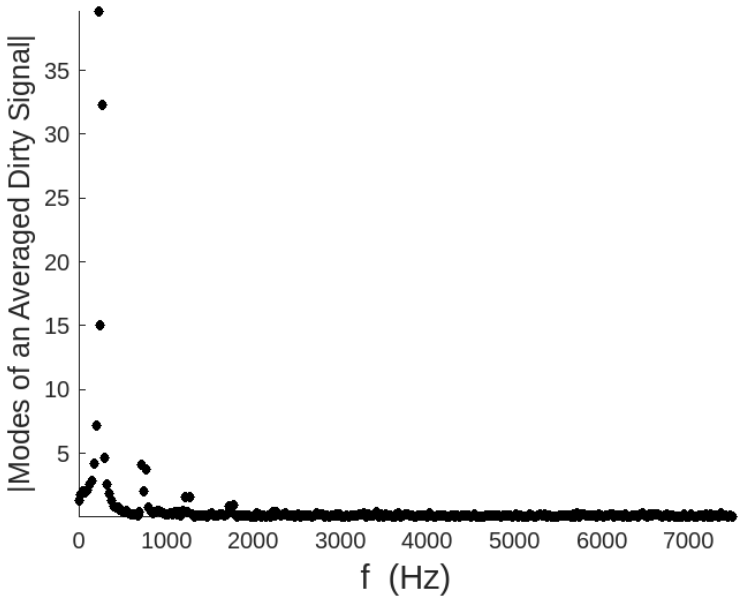

Figure 5.13: FFT with averaging, 25% noise

5.1 Change of passive cable equation Parameters

Along with evaluating along different points of (x,t), we later evaluated the parameters used for our equation. The change in capacitance, rep rate and pulse width in particular changed the resulting signals, while length did not drastically change the values. All values were assumed in particular for capacitance, since as mentioned above there is not yet a set capacitance for the dorsal

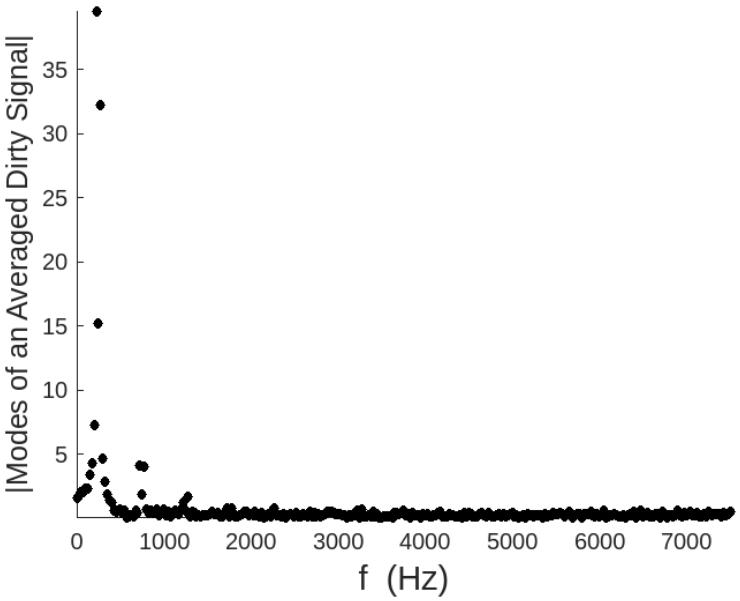

Figure 5.14: FFT with averaging, 50% noise

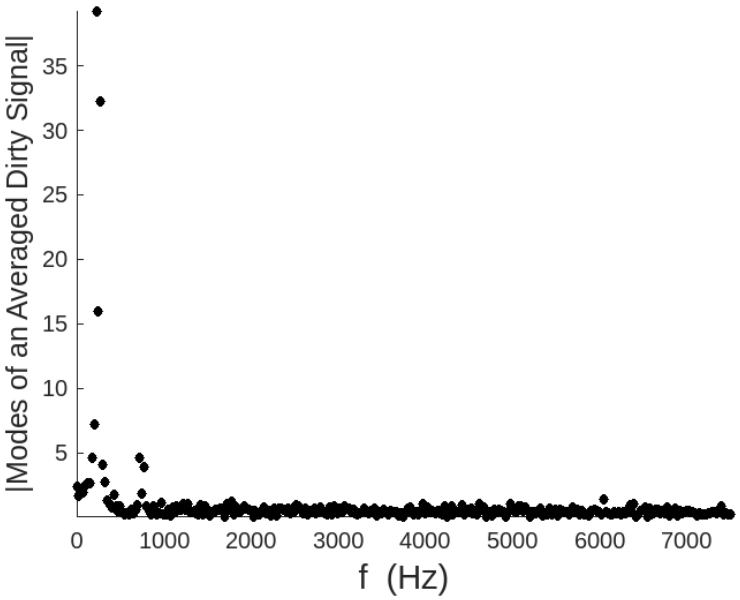

Figure 5.15: FFT with averaging, 90 % noise

horn, the ventral horn capacitance demonstrated the signal produced in figure 5.2.

The values evaluated were for $U_1(t) = V(x_{site1}, t)$ and $U_2(t) = V(x_{site2}, t)$, as noted in figure 5.22. This is a detail specifically noted by neurotechnicians, as is noted by the guidelines that any shift in latency that is 10 % or greater and a reduction of amplitude 50 % or greater should be noted, and the surgical team must be made aware of such changes.

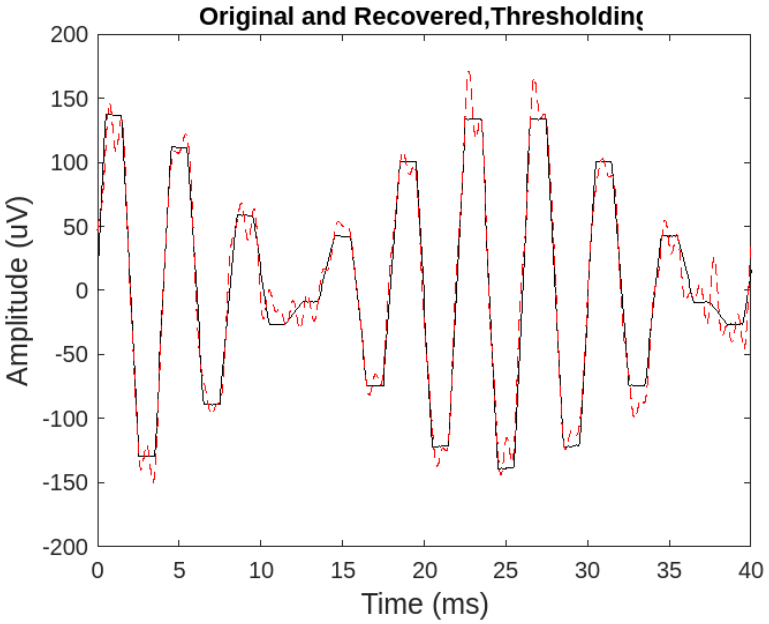

Figure 5.16: Thresholding and bandpass filter only, 25 % noise

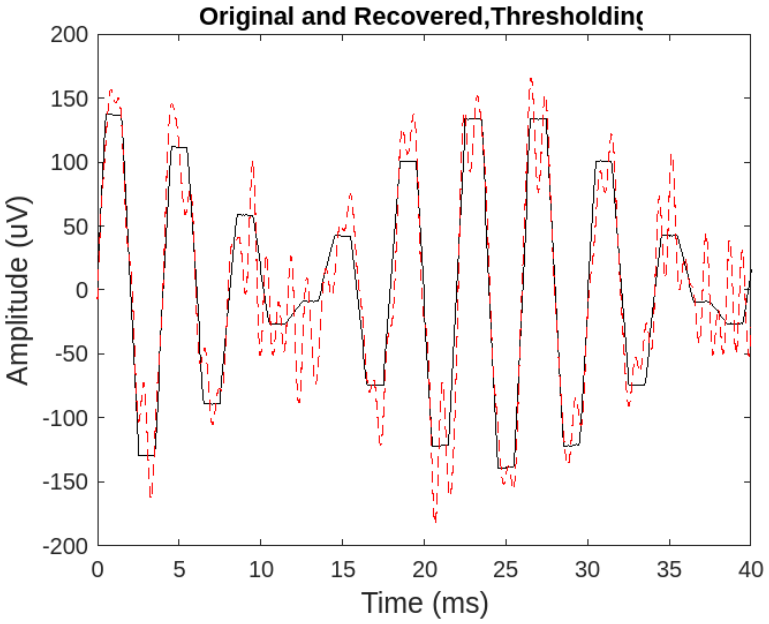

Figure 5.17: Thresholding and bandpass filter only, 50 % noise

Signals were also evaluated and recovered to show the importance of averaging and thresholding. It was found that when both are done our recovered signal matches our original signal in comparison to not having them, this is noted in the figures 5.23 to 5.26.

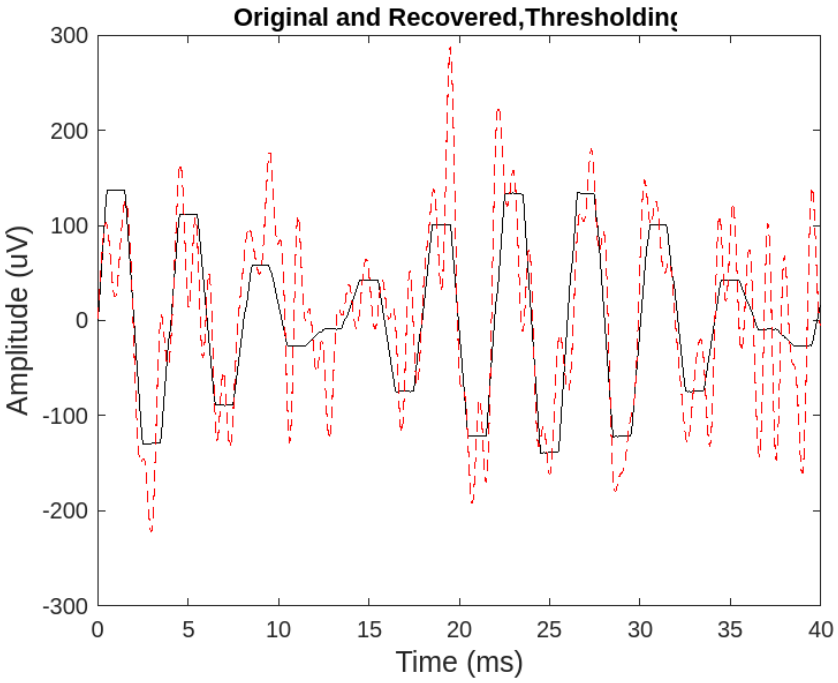

Figure 5.18: Thresholding and bandpass filter only, 90 % noise

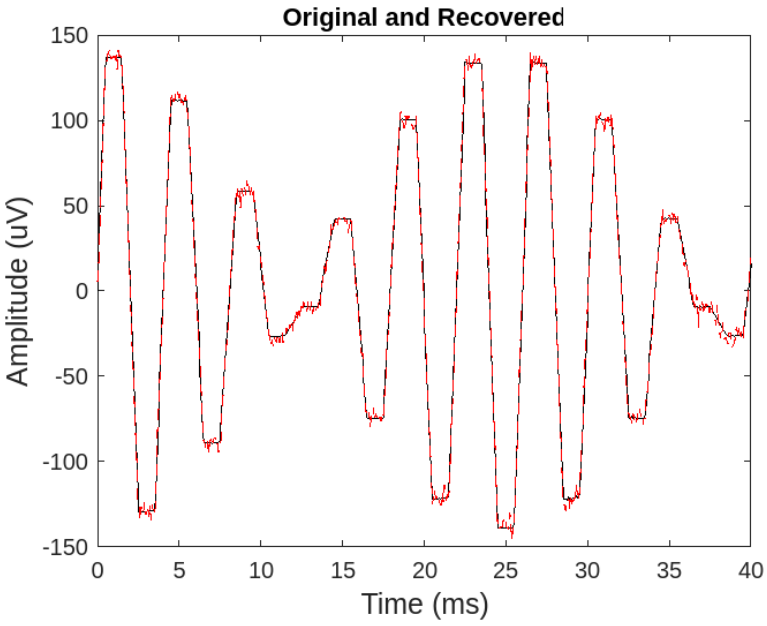

Figure 5.19: Averaging only, 25 % noise

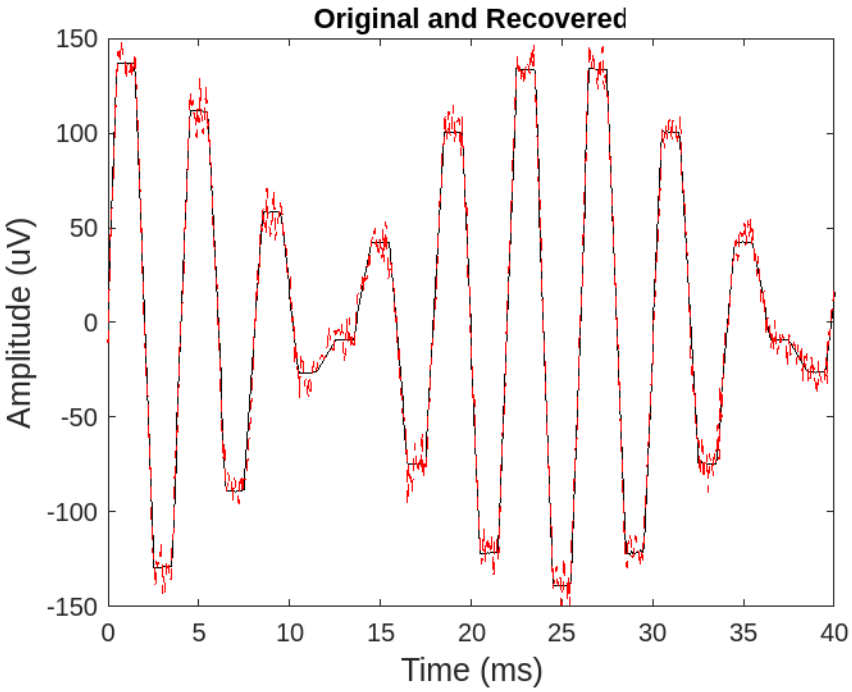

Figure 5.20: Averaging only, 50 % noise

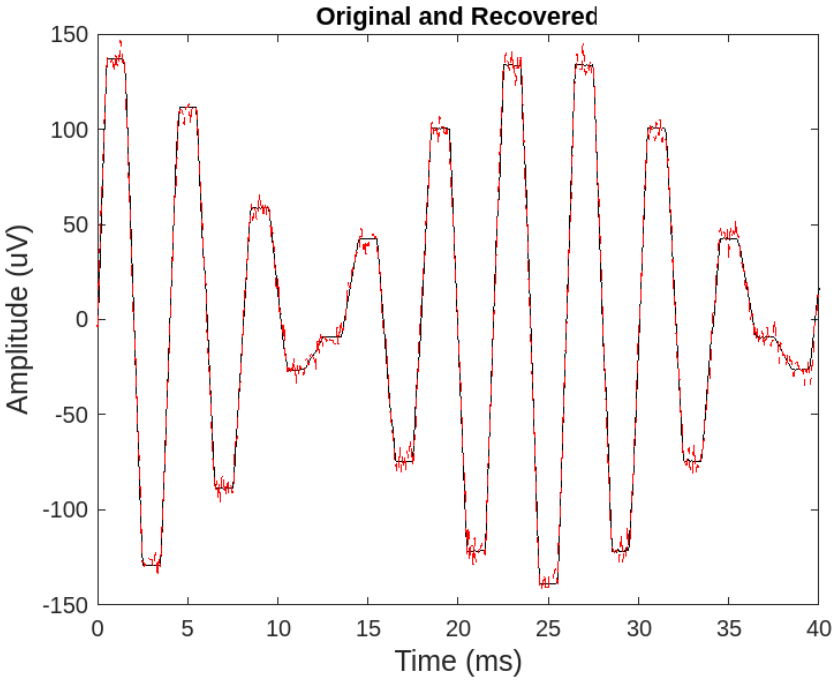

Figure 5.21: Averaging only, 90 % noise

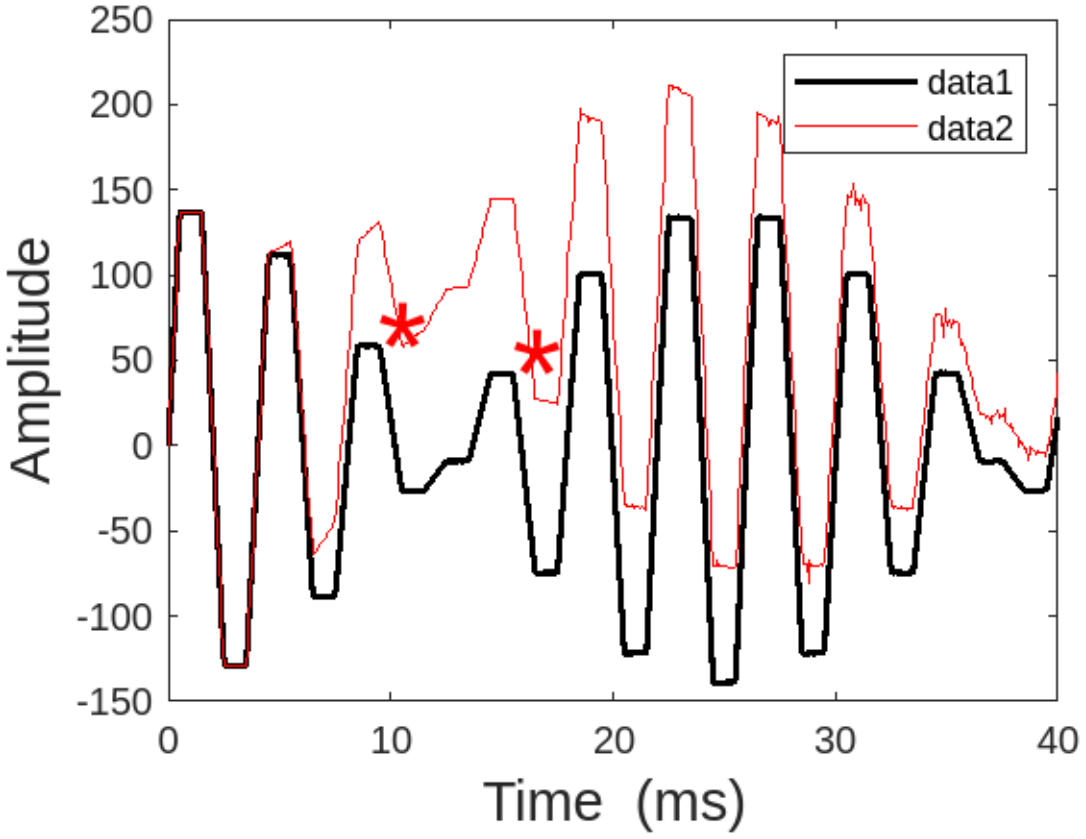

Figure 5.22: Original Signal with sites denoted $U_1(t) = V(x_{site1}, t)$ and $U_2(t) = V(x_{site2}, t)$. These sites we looked at were to compare and review the amplitude and latency, to show the importance of how an intraoperative neuromonitor accesses their data.

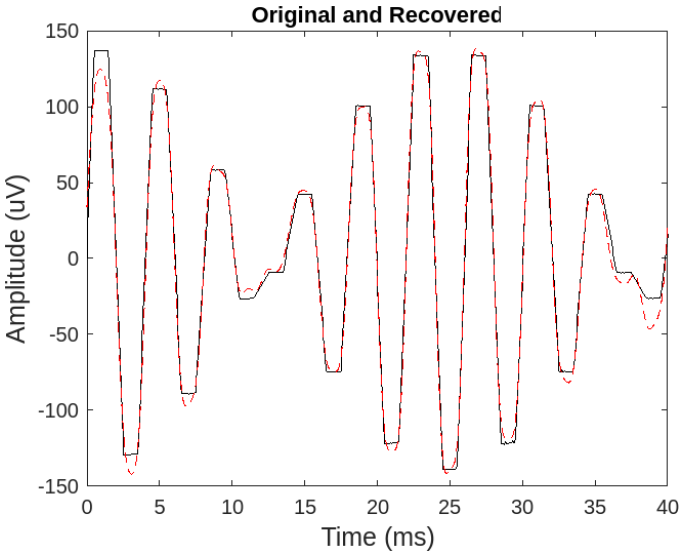

Figure 5.23: Combining Averaging, Thresholding and bandpass filter, 25 % noise

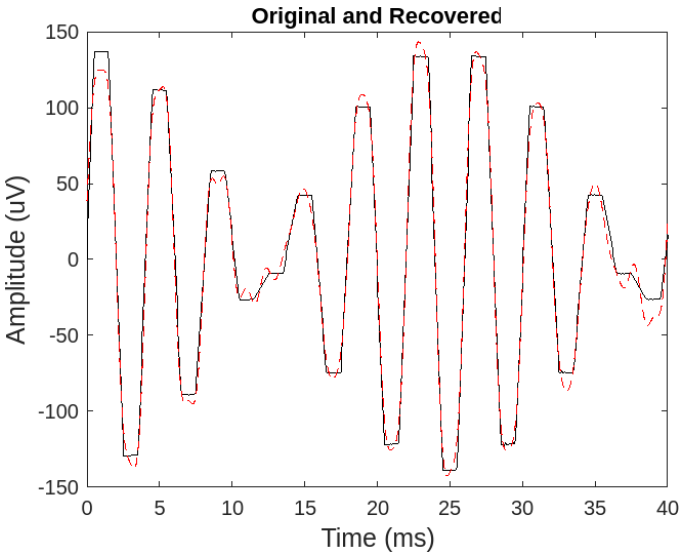

Figure 5.24: Combining Averaging, Thresholding and bandpass filter, 50 % noise

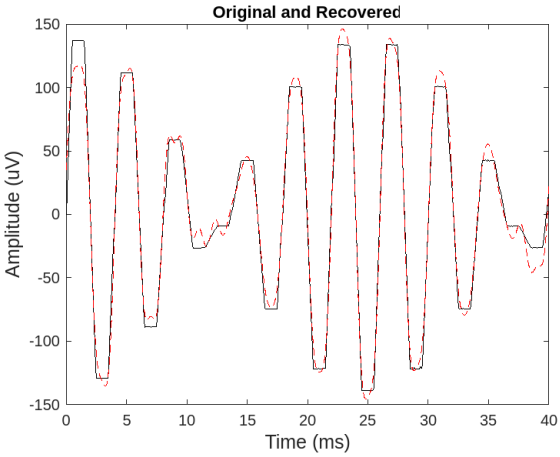

Figure 5.25: Combining Averaging, Thresholding and bandpass filter, 90 % noise

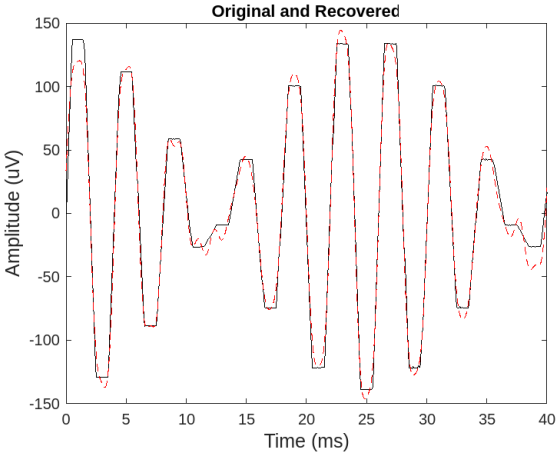

Figure 5.26: Combining Averaging at 1000, Thresholding and bandpass filter, 90 % noise

CHAPTER VI

CONCLUSION

The aim of this paper was to find a means of mathematically modeling the SSEP wave forms. Using the cable equation evaluated at it's interior points for the obligate peaks, and the resulting cosine waves due to the sealed end conditions of fourier and the exact eigenvalue solution. We coded a program in Matlab that invokes `rectpuls` and `pulstran` that gives a resulting waveform. This waveform was also manipulated to have a set thresholding and averaging to mimic OR conditions. FFTs were ran on the clean signal, signal without added noise, or averaging. An FFT was also done for the dirty signal. Where the dirty signal which contained the addition of noise, signal averaging and thresholding. After making adjustments to the period which we evaluated, then were we able to obtain FFTs with frequencies ranging from 0-1000 Hz, which is within the range of the guidelines 3 - 3000 Hz. The cause of this could have been the use of an assumed capacitance, resistivity and conductance that wasn't specific to the dorsal horn. We did however, find that the parameter used regardless of which point along x, $U_1(t) = V(x_{site1}, t)$, the most prominent frequencies remained consistent throughout. It was however noted, that the changes could play a potential role in determining the importance of having the correct capacitance and if the change in capactiance could cause a change in our overall waveform amplitude and latency, which is of concern for neurotechnicians. Can the change in capacitance, then show that there is damage to the nerve?

The use of intraoperative monitoring continues to play a large role in the operating room to help reduce the incidence of post operative deficits. While the technician does not interpret wave forms, they are online with a reading neurologist and relay information to the surgeon. A technician understanding the mathematical components of wave forms can ensure better acquisition of data in

a timely manner and help with troubleshooting.

With finding the mathematical model to SSEPs we can later evaluate and test the algorithm for different rep rates, add other variables that can affect an SSEP to help with faster troubleshooting. Such as adding a temperature component to the passive cable equation or finding how to add an anesthetic agent into the equation. Upon further understanding the full complexity and dynamic of the sensory pathway, we hope that the algorithm can help in teaching technicians how to determine the source of noise faster, or even helping the reading neurologist determine if the change that is occurring is indicative of a true change. Is the change due to a change in membrane resistance or capacitance after administration of anesthetics, changes in temperature, positional changes, or changes due to manipulation of the pathway itself.

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APPENDIX A

APPENDIX A

CODEPOSTPROCESS.M

```
%Parameters required to run passive cable theory to find an algorithm to
%obtain SSEPs using FFTs and passive cable equation
clear; clc



%Parameters required for passive cable theory
I0 = 40; %amplitude of the stimulus, if stimulating
% an Ulnar nerve between 10-40mA
%Istim = @(t) I0 * ( cos(t)>0);
%Istim = @(t) I0*(t<20);
%Istim = @(t) I0*(t<1);
%Istim = @(t) I0 * (cos(t*2*pi*1.77)>0);
%Istim = @(t);
l = 1; % need to correct this to an actual value l
%n = 1000; %compartments in total
%k = 80; %specific comparments (subset)?
%r = sqrt(5.9/pi); %radius of the ulnar nerve.
% Need to check correct radius and make adjustments for the units.
% Assumption is we are using a const r
r = 1e-4;
R = 0.3; %intracellular membrane resistivity,
```

```
% random value used need to input correct value
gcl = 1/15; % random value used need to input correct value
%C = 0.75;
C = 1;
%C = 2.4; % 1 microFarad (uF), switchced to 2.4
G = (2*pi*r)/(gcl); %need to double check
lambda = sqrt(r/(2*R*gcl)); %space constant
tau = C/G; % time constant
x = linspace(0,l);
%x = [0.05 0.2 0.8] * l;

%N = 100;
N = 600;
%N = 10;
%N = 1000;
%N = 3300;
%N = 6000;

%load data_all
load data1
load data2
load data3




%M = data1;%(t_iter);
```

```
figure(2); clf %clean signal


plot (linspace(0,40,N), data1, 'k-','linewidth',1.5)
hold on
xt = [9.41569 15.4925];
yt = [58.5096 42.2411];
plot(xt,yt,'.', 'markersize',14,...
    'color','r')
%plot((0:1/fs:40), data1)
hold on
%figure(21)
%plot (linspace(0,40,N), data2, 'r-')
%hold on
%figure (22)
%plot (linspace(0,40,N), data3, 'b--')
%hold on
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude','fontsize',14)
title('Original Signal')


T = 40;
dt = T/(N-1);
t = 0:dt:T;


%take this signal add the noise and get the average of this signal
%noiseY = 0.25 * max(data1);
```

```
%noiseX = 0.25 * max(data2);
%noiseZ = 0.25 * max(data3);

noiseY = 0.50 * max(data1);
noiseX = 0.50 * max(data2);
noiseZ = 0.50 * max(data3);

%noiseY = 0.90 * max(data1);
%noiseX = 0.90 * max(data2);
%noiseZ = 0.90 * max(data3);

%noiseY = 10 * max(clean);
%noiseY = 0.10 * clean;
%noiseY = 0.60 * clean;
%noiseY = 1 * max(clean);
%noiseY = 0.05 * max(clean);
%noise = noiseY .* randn(size(data1)); %guassian
%noise1 = noiseX .* randn(size(data2));
%noise2 = noiseZ .* randn(size(data3));
%ekg = ekgnoise (1,N)

figure(31); %dirty signal no averaging
noise0 = noiseY .* randn(size(data1));
udirty0 = data1 + noise0;
plot(t, udirty0, 'k-', 'linewidth', 1.5)
hold on
axis tight
```

```
box off
xlabel( 'Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)
title('Noisy Signal')

figure(3); clf %dirty signal, data1 averaged
%plot(t,data1,'k');
for H = 1:100
    noise = noiseY .* randn(size(data1)); %guassian
    udirty(H,:) = data1 + noise; %make the noise different
end
    udirty_avg = sum(udirty,1)/100;
%udirty = clean + noise + ekg....
%hold on
plot(t,udirty_avg,'k-','linewidth',1.5)
hold on
axis tight
box off
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)
title('Averaged Noisy Signal')
%legend ({'V20', 'V5', 'V80'}, 'location','bestoutside');

figure(3); clf %dirty signal, data2 averaged
%plot(t,data2,'k');
for H = 1:100
    noise = noiseX .* randn(size(data2)); %guassian
```

```
    udirty2(H,:) = data2 + noise;
end
    udirty_avg2 = sum(udirty2,1)/100;
%udirty = clean + noise + ekg....
%hold on
plot(t,udirty_avg2,'r-','linewidth',1.5)
hold on
axis tight
box off
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)

% figure(3) %dirty signal, data3
% plot(t,data3,'k');
% for H = 1:100
%     noise = noiseY .* randn(size(clean)); %guassian
%     udirty3(H,:) = data3 + noise;
% end
%    udirty_avg3 = sum(udirty3,1)/100;
% %udirty = clean + noise + ekg....
% %hold on
% plot(t,udirty_avg3,'r-','linewidth',1.5)
% hold on
% axis tight
% box off
% xlabel('Time  (ms)','fontsize',14)
% ylabel('Amplitude (uV)','fontsize',14)
```

```
figure(40); clf %fft of dirty signal, data 1 unaveraged
f = (0:N/2)*25;
udirty0 = fft(udirty0)/N;
plot(f,abs(udirty0(1:1+N/2)),'k.','markersize',14)
hold on
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|Modes of an unaveraged signal|','fontsize',8)
```

```
figure(4); clf %fft of dirty signal, data 1 averaged
f = (0:N/2)*25;
udirtyhat = fft(udirty_avg)/N;
plot(f,abs(udirtyhat(1:1+N/2)),'k.','markersize',14)
hold on
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|Modes of an Averaged Dirty Signal|','fontsize',12)

%take fft of each data set that was added
figure(42); clf %fft of dirty signal averaged
f = (0:N/2)*25;
udirtyhat2 = fft(udirty_avg2)/N;
```

```
plot(f,abs(udirtyhat2(1:1+N/2)),'r.','markersize',20)
hold on
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|u_{dirty}hat|','fontsize',14)



% %take fft of each data set that was added
% figure(4) %fft of dirty signal
% f = (0:N/2)/(T*N);
% udirtyhat3 = fft(udirty_avg3)/N;
% plot(f,abs(udirtyhat3(1:1+N/2)),'bx-', 'linewidth', 1)
% hold on
% axis tight
% box off
% xlabel('f  (Hz)','fontsize',14)
% ylabel('|u_{dirty}hat|','fontsize',14)

figure(5); clf %fft of clean signal, data1

f = (0:N/2)*25;
cleanhat = fft(data1)/N;
plot(f,abs(cleanhat(1:1+N/2)),'.','markersize',20)
axis tight
box off
```

```
xlabel('f  (Hz)','fontsize',14)
ylabel('|Modes of Original Signal|','fontsize',14)



% figure(15) %fft of clean signal, data1
%
% f = (0:N/2)*25;
% cleanhat = fft(data1)/N;
% plot(f,abs(cleanhat(1:1+N/2)),'g-')
% axis tight
% box off
% hold on
% xlabel('f  (Hz)','fontsize',14)
% ylabel('|{clean}hat|','fontsize',14)



figure(15); clf %fft of clean signal, data2

f = (0:N/2)*25;
cleanhat2 = fft(data2)/N;
plot(f,abs(cleanhat2(1:1+N/2)),'r.','markersize',20)
axis tight
box off
hold on
xlabel('f  (Hz)','fontsize',14)
ylabel('|{clean}hat|','fontsize',14)
```

```
% figure(15) %fft of clean signal, data3
%
% f = (0:N/2)/(T*N);
% cleanhat3 = fft(data3)/N;
% plot(f,abs(cleanhat3(1:1+N/2)),'r-')
% axis tight
% box off
% hold on
% xlabel('f  (Hz)','fontsize',14)
% ylabel('|{clean}hat|','fontsize',14)
figure(19); clf %no averaging no thresholding
plot (linspace(0,40,N), data1, 'k')
recoveredA = ifft(udirty0);
hold on
plot (t, N*recoveredA, 'r--')
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
title('Original and Recovered')
%legend ('data1','recovered')




figure(20); clf %averaging no thresholding
plot (linspace(0,40,N), data1, 'k')
recoveredA = ifft(udirtyhat);
hold on
```

```
plot (t, N*recoveredA, 'r--')
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
title('Original and Recovered')
%legend ('data1','recovered')


maxnode1 = max(abs(udirty0));
maxnode = max(abs(udirtyhat));
maxnode2 = max(abs(udirtyhat2));

udirty0(abs(udirty0) < 0.05 * maxnode1) = 0;
udirtyhat(abs(udirtyhat) < 0.05 * maxnode) = 0;
udirtyhat2(abs(udirtyhat2) < 0.05 * maxnode2) = 0;

ff = [f(1:end-1) fliplr(f(1:end-1))];
udirty0 = udirty0 .* (ff < 1500);
udirtyhat = udirtyhat .* (ff < 1500);
udirtyhat2 = udirtyhat2 .* (ff < 1500);
%udirtyhat3 (abs(udirtyhat3)<150) = 0;

%udirtyhat (abs(udirtyhat)<100) = 0;

figure(61); clf
plot(abs(udirty0),'bx-')

figure(6); clf
```

```
plot(abs(udirtyhat),'bx-')
hold on
plot(abs(udirtyhat2),'g-')
% hold on
% plot(abs(udirtyhat3),'o-')

%figure(2); %clf
%recovered = ifft(udirtyhat);
%hold on
%plot (t,N*recovered, 'r--')
figure(23); clf %thresholding, no avg
plot (linspace(0,40,N), data1, 'k')
recovered0 = ifft(udirty0);
hold on
plot (t, N*recovered0, 'r--')
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
title('Original and Recovered,Thresholding')
%legend ('data1','recovered')


figure(24); clf %avg, thresholded recovered signal
recovered = ifft(udirtyhat);
hold on
plot (t,N*recovered, 'k--')
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
```

```
title('Original and Recovered,Thresholding')

figure(24); clf %avg, thresholded recovered signal data2
recovered2 = ifft(udirtyhat2);
hold on
plot (t,N*recovered2, 'r--')

% figure (24)
% recovered3 = ifft(udirtyhat3);
% hold on
% plot (t,N*recovered3, 'g--')

figure(25); clf %clean, data1
plot (linspace(0,40,N), data1, 'k')
recovered = ifft(udirtyhat);
hold on
plot (t,N*recovered, 'r--')
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
title('Original and Recovered')
%legend ('data1','recovered')

figure(26); clf %data2
plot (linspace(0,40,N), data2, 'k')
hold on
recovered2 = ifft(udirtyhat2);
plot (t,N*recovered2, 'b--')
```

```
xlabel('Time (ms)','fontsize',12)
ylabel('Amplitude (uV)', 'fontsize', 12)
title('Original and Recovered')
%legend ('data2','recovered')

% figure(27) %data3
% plot (linspace(0,40,N), data3, 'k')
% recovered3 = ifft(udirtyhat3);
% hold on
% plot (t,N*recovered3, 'g--')
% xlabel('Clean and ifft, data3','fontsize',14)
```

APPENDIX B

APPENDIX B

PREPROCESSCODE.M

```
%Parameters required to run passive cable theory to find an algorithm to
%obtain SSEPs using FFTs and passive cable equation
clear all; clc



%Parameters required for passive cable theory
I0 = 40; %amplitude of the stimulus, if
% stimulating an Ulnar nerve between 10-40mA
%Istim = @(t) I0 * ( cos(t)>0);
%Istim = @(t) I0*(t<20);
%Istim = @(t) I0*(t<1);
%Istim = @(t) I0 * (cos(t*2*pi*1.77)>0);
%Istim = @(t);
l = 1; % need to correct this to an actual value l
%n = 1000; %compartments in total
%k = 80; %specific comparments (subset)?
%r = sqrt(5.9/pi); %radius of the ulnar nerve.
% Assumption is we are using a const r
r = 1e-4;
R = 0.3; %intracellular membrane resistivity,
gcl = 1/15; % random value used need to input correct value
```

```
C = 1;
%C = 2.4; % 1 microFarad (uF), switched to 2.4
G = (2*pi*r)/(gcl); %need to double check
lambda = sqrt(r/(2*R*gcl)); %space constant
tau = C/G; % time constant
x = linspace(0,l);

N = 100;
%N = 600;
%N = 1000;
%N = 3300;
%N = 6000;



%for loop that takes the time iteration
% to evaluate the passive cable
%equation using the Istim Function with a rep rate at 1.77
%for t = 0:4
t_iter = 0;
for t = linspace(0,40,N)
%fs = 1.77;
%for t = 0:1/fs:40

    t_iter = t_iter +1;
    V = 0;
    for n = 0:100
```

```
    %for n = 0:1000
        theta = (-n^2*pi^2)/(l^2);
        zeta = (lambda^2*theta-1)/tau;
        if n == 0
            q = 1/sqrt(l);
        else
            q = sqrt(2/l)*cos((n*pi*x)/l);
        end
            V = V + ((q*sqrt(2/l))/(C*2*pi*r)) * integral(@(s) ...
            Istimfunc(s, 1.77).*exp((t-s)*zeta), 0,t);
        %V = V + ((q*sqrt(2/l))/(C*2*pi*r)) * integral(@(s)
        % Istimfunc(s).*exp((t-s)*zeta), 0,t);

        sum(V)
    end
%    plot (x,V)
%   title(['t=' num2str(t)])
%  ylim ([0 1e8])
   % ylim ([0 2e7])
   %ylim ([0 1e7])
   %ylim ([0 1e5])
%    pause(0.01)
%if(mod(t_iter, 10) ==0)
%figure(1);
%plot (x,V)
%title(['t=' num2str(t)])
%ylim([-1e4 1e4])
```

```
%drawnow
% % pause (0.01)
%end



    data1(t_iter) = V(20);
    data2(t_iter) = V(5);
    % data3(t_iter) = V(80);
end


M = data1;%(t_iter);


figure(2) %clean signal
plot (linspace(0,40,N), data1, 'k')
%plot((0:1/fs:40), data1)
hold on
%figure(21)
plot (linspace(0,40,N), data2, 'k--')
hold on
%figure (22)
% plot (linspace(0,40,N), data3, 'k--')
% hold on
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude','fontsize',14)
%lgd = legend ({'V20', 'V5','V80'},'location', 'bestoutside');
%lgd.FontSize = 8;
```

```
if ( ~exist('N') )
    disp('N is the number of samples');
    disp('       using N = 100 (default).');
   N = 100;
    %N;

end

T = 40;
dt = T/(N-1);
t = 0:dt:T;
clean = M;
%take this signal add the noise and get the average of this signal
noiseY = 0.25 * max(clean);
%noiseX = 0.25 * max(data2);
%noiseZ = 0.25 * max(data3);
%noiseY = 10 * max(clean);
%noiseY = 0.10 * clean;
%noiseY = 0.60 * clean;
%noiseY = 1 * max(clean);
%noiseY = 0.05 * max(clean);
noise = noiseY .* randn(size(clean)); %guassian
%noise1 = noiseX .* randn(size(data2));
%noise2 = noiseZ .* randn(size(data3));
%ekg = ekgnoise (1,N)

figure(3); clf %dirty signal, data1
```

```
plot(t,clean,'k');
for H = 1:100
    noise = noiseY .* randn(size(clean)); %guassian
    udirty(H,:) = clean + noise; %make the noise different
end
    udirty_avg = sum(udirty,1)/100;
%udirty = clean + noise + ekg....
%hold on
plot(t,udirty_avg,'r-','linewidth',1.5)
hold on
axis tight
box off
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)
%legend ({'V20', 'V5', 'V80'}, 'location','bestoutside');



figure(3); clf %dirty signal, data2
plot(t,data2,'k');
for H = 1:100
    noise = noiseY .* randn(size(data2)); %guassian
    udirty2(H,:) = data2 + noise;
end
    udirty_avg2 = sum(udirty2,1)/100;
%udirty = clean + noise + ekg....
%hold on
```

```
plot(t,udirty_avg2,'r-','linewidth',1.5)
hold on
axis tight
box off
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)



% figure(3); clf %dirty signal, data3
% plot(t,data3,'k');
% for H = 1:100
%     noise = noiseY .* randn(size(data3)); %guassian
%     udirty3(H,:) = data3 + noise;
% end
%    udirty_avg3 = sum(udirty3,1)/100;
%udirty = clean + noise + ekg....
%hold on
% plot(t,udirty_avg3,'r-','linewidth',1.5)
% hold on
axis tight
box off
xlabel('Time  (ms)','fontsize',14)
ylabel('Amplitude (uV)','fontsize',14)

figure(4) ;clf%fft of dirty signal, data 1
f = (0:N/2)*25;
%f = (0:N/2)/(T-N);
```

```
udirtyhat = fft(udirty_avg)/N;
plot(f,abs(udirtyhat(1:1+N/2)),'kx-')
hold on
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|u_{dirty}hat|','fontsize',14)

%take fft of each data set that was added
figure(4) ;clf %fft of dirty signal
%f = (0:N/2)/(T*N);
f = (0:N/2)*25;
udirtyhat2 = fft(udirty_avg2)/N;
plot(f,abs(udirtyhat2(1:1+N/2)),'k-')
hold on
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|u_{dirty}hat|','fontsize',14)

% % %take fft of each data set that was added
% % figure(4) ;clf %fft of dirty signal
% % %f = (0:N/2)/(T*N);
% % f = (0:N/2)*25;
% % udirtyhat3 = fft(udirty_avg3)/N;
% % plot(f,abs(udirtyhat3(1:1+N/2)),'bx-', 'linewidth', 1)
% % hold on
```

```
% % axis tight
% % box off
% % xlabel('f  (Hz)','fontsize',14)
% % ylabel('|u_{dirty}hat|','fontsize',14)

figure(5) ; clf%fft of clean signal, data1

%f = (0:N/2)/(T*N);
f = (0:N/2)*25;
cleanhat = fft(clean)/N;
plot(f,abs(cleanhat(1:1+N/2)),'kx-')
axis tight
box off
xlabel('f  (Hz)','fontsize',14)
ylabel('|{clean}hat|','fontsize',14)

figure(15) ;clf%fft of clean signal, data1

%f = (0:N/2)/(T*N);
f = (0:N/2)*25;
cleanhat = fft(clean)/N;
plot(f,abs(cleanhat(1:1+N/2)),'g-')
axis tight
box off
hold on
xlabel('f  (Hz)','fontsize',14)
ylabel('|{clean}hat|','fontsize',14)
```

```
%figure(15);clf  %fft of clean signal, data2

%f = (0:N/2)/(T*N);
f = (0:N/2)*25;
cleanhat2 = fft(data2)/N;
plot(f,abs(cleanhat2(1:1+N/2)),'kx-')
axis tight
box off
hold on
xlabel('f  (Hz)','fontsize',14)
ylabel('|{clean}hat|','fontsize',14)

% figure(15) ;clf%fft of clean signal, data3
%
% %f = (0:N/2)/(T*N);
% f = (0:N/2)*25;
% cleanhat3 = fft(data3)/N;
% plot(f,abs(cleanhat3(1:1+N/2)),'r-')
% axis tight
% box off
% hold on
% xlabel('f  (Hz)','fontsize',14)
% ylabel('|{clean}hat|','fontsize',14)

udirtyhat (abs(udirtyhat)<150) = 0;
```

```
udirtyhat2 (abs(udirtyhat2)<150) = 0;
% udirtyhat3 (abs(udirtyhat3)<150) = 0;

%udirtyhat (abs(udirtyhat)<100) = 0;

figure(6)
plot(abs(udirtyhat),'bx-')
hold on
plot(abs(udirtyhat2),'g-')
hold on
plot(abs(udirtyhat3),'o-')



figure(2)
recovered = ifft(udirtyhat);
hold on
plot (t,N*recovered, 'r--')

figure(24)
recovered = ifft(udirtyhat);
hold on
plot (t,N*recovered, 'k--')
xlabel('IFFTs','fontsize',14)



figure (24)
recovered2 = ifft(udirtyhat2);
```

```
hold on
plot (t,N*recovered2, 'b--')

figure (24)
recovered3 = ifft(udirtyhat3);
hold on
plot (t,N*recovered3, 'g--')

figure (25) %clean, data1
plot (linspace(0,40,N), data1, 'k')
recovered = ifft(udirtyhat);
hold on
plot (t,N*recovered, 'r--')
xlabel('Clean and ifft, data1','fontsize',14)

figure(26) %data2
plot (linspace(0,40,N), data2, 'k')
hold on
recovered2 = ifft(udirtyhat2);
plot (t,N*recovered2, 'b--')
xlabel('Clean and ifft, data2','fontsize',14)

% figure(27) %data3
% plot (linspace(0,40,N), data3, 'k')
% recovered3 = ifft(udirtyhat3);
% hold on
% plot (t,N*recovered3, 'g--')
```

```
% xlabel('Clean and ifft, data3','fontsize',14)
```

APPENDIX C

APPENDIX C

ISTIMFUNC.M

```
function y1 = Istimfunc(t, reprate)
%function y1 = Istimfunc(t)
%d =[0:reprate:40;cos(2*pi*25*(0:reprate:40))]';
d =[0:2:40;cos(2*pi*reprate*(0:2:40))]';
%d =[0:250e-6:40;cos(2*pi*10*(0:250e-6:40))]';
y1 = pulstran(t,d,@rectpuls);
%y1 = pulstran(t,@rectpuls);
```

BIOGRAPHICAL SKETCH

Maribel C. Gomez. Bachelor's of Science Major: Neuroscience, Minors: Biology and Biochemistry, 2013. Certified Clincial Neuro-physiologist (Certified Intraoperative Neuro-monitor) CNIM, 2015. Certified Personal Trainer, 2018. Master of Science in Applied Mathematics, 2023. Email Address: maribelcgomez212@gmail.com or mcgome12.20@gmail.com. Academic Experience: Prior research done in Autism and Epilepsy for B.S. in Neuroscience with two published articles. Obtained certifications as a nurse assistant and physical therapy tech. Behavioral Therapy Certification. Her current in progess certifications are as follows: Kinesiology Taping Practitioner Certification, IASTM Practitioner Certification, Myofascial Cupping Practitioner Certification, Vestibular Rehab Certificate Course, Functional Neurology: Harness the Power of Technology and Neuroplasticity to Reach Goals Faster than Traditional Rehab. Her professional Experience invovled working in the operating room from 2015-2017. Intraoperative Neuromonitoring Certification was obtained through a fellowship done with National Neuromonitoring. After obtaining her CNIM, she, in addition to working in the operating room took on the role of preceptor, and further primary preceptor to help in educating and training new fellows to obtain their certification. Her current employment is as a certified personal trainer focusing on functional movements to help alleviate pain, weight loss and overall health and wellness.