

Quantification of Motion and Cry Characteristics of NAS Newborns

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ABSTRACT

Neonatal abstinence syndrome (NAS) is a condition caused by in-utero exposure to opioids, and its occurrence is increasing nationwide. NAS patients are newborns who can experience withdrawal symptoms including tremors, poor feeding, and respiratory distress. Presently, the Finnegan Scoring System, a subjective rating scale, is commonly used to judge the patient's condition and determine appropriate treatment methods. This project sought to develop a sensor system that is capable of objectively assessing symptoms of withdrawal, including tremors and high pitched cry. The system developed is composed of five wireless accelerometers, for attachment to a subject's limbs and chest, and an external microphone. The sensor system is targeted toward quantifying limb movements of the subject and recording audio information that includes samples of the subject's cry.

The sensor system was used as part of a research study, and data was collected from recruited participants. A total of 29 out of 30 desired participants were enrolled and studied as part of the data collection process. Gathered data was analyzed using MATLAB, with motion data being searched for tremor activity in NAS participants, and cry samples searched for unique characteristics. Results generated indicate that detection of tremors was successful, and that the average fundamental frequency of cry differs between the NAS and non-NAS participants. Future considerations for this project include expanding to measure more symptoms, and system refinement to minimize the number of sensors.

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GENERAL AUDIENCE ABSTRACT

Neonatal abstinence syndrome (NAS) is a condition affecting newborns, caused by exposure to opioids before birth, and its occurrence is increasing nationwide. NAS patients are newborns who can experience withdrawal symptoms including tremors, poor feeding, and respiratory distress. Presently, the Finnegan Scoring System, a manual scoring method, is commonly used to judge the patient's condition and determine appropriate treatment methods. This project sought to develop a sensor system that is capable of measuring symptoms of withdrawal, specifically tremors and high pitched cry. The system developed is composed of five wireless accelerometers, for attachment to a subject's limbs and chest, and an external microphone. The sensor system is targeted toward quantifying limb movements of the subject and recording audio information that includes samples of the subject's cry.

The sensor system was used as part of a research study, and data was collected from recruited participants. A total of 29 out of 30 desired participants were enrolled and studied as part of the data collection process. Gathered data was analyzed using MATLAB, with motion data being searched for tremor activity in NAS participants, and cry samples searched for unique characteristics. Results generated indicate that detection of tremors was successful, and that the average cry for NAS participants was higher pitched than those of non-NAS participants. Future considerations for this project include expanding to measure more symptoms, and minimizing the number of sensors used. If successful, such a system could be used to assist medical personnel and continuously monitor NAS newborns.

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Chapter 1: Overview

Chapter 1.1 - Introduction

Introduction to NAS

Neonatal abstinence syndrome (NAS) is a condition that can be experienced by newborns after in-utero exposure to opioids. Loss of access to opioids, due to birth, can cause the newborn to go through withdrawal, displaying symptoms such as tremors, poor feeding, respiratory distress, and trouble sleeping. [1] For newborns identified as having NAS, the current treatment method involves medical personnel observing the newborn at set time intervals (commonly 4 hours), and manually completing a scoring sheet for their symptoms. Based on the newborn's condition, as indicated by their score, pharmacological treatment may or may not be applied.

The tool most widely used, as a basis for a scoring method, is the Finnegan neonatal abstinence scoring system, which was originally developed by Dr. Loretta Finnegan. A scoring sheet is completed by medical personnel, based on their ranking of symptom severity, for each symptom listed on the sheet. The modified Finnegan scoring sheet, Figure 1, includes a range of indicators and symptoms that are grouped into three categories: central nervous system disturbances, gastrointestinal disturbances, and metabolic/vasomotor/respiratory disturbances.

Based on procedure published for Ohio Children's' Hospitals, a pharmacological treatment is deemed appropriate for those patients receiving scores of at least 8 for three consecutive scoring periods, or a score of 12 at two scorings. [2] Morphine and methadone are two common medications used to help ease progression through withdrawal for these patients. For those patients that pharmacological treatment is deemed appropriate for, dosages are influenced by scores received and scaled based on the patient's body weight.

Between 2000 and 2012, Occurrence of NAS increased nationwide, from 1.2 to 5.8 per 1,000 hospital births. Concurrently, average costs have gone from about \$39,400 to \$66,700 for NAS patients. In comparison, the average price of a "normal" birth in 2012 was \$3,500. [3, 4] While individual families have been impacted by the rising costs of treatment, the government has also been affected, as roughly 81% of NAS patients were covered by Medicaid in 2012, a cost of approximately \$1,170,206,600. [3]

Modified Finnegan Neonatal Abstinence Score Sheet ¹												
System	Signs and Symptoms	Score	AM			PM			Comments			
Central Nervous System Disturbances	Excessive high-pitched (or other) cry < 5 mins	2										
	Continuous high-pitched (or other) cry > 5 mins	3										
	Sleeps < 1 hour after feeding	3										
	Sleeps < 2 hours after feeding	2										
	Sleeps < 3 hours after feeding	1										
	Hyperactive Moro reflex	2										
	Markedly hyperactive Moro reflex	3										
	Mild tremors when disturbed	1										
	Moderate-severe tremors when disturbed	2										
	Mild tremors when undisturbed	3										
	Moderate-severe tremors when undisturbed	4										
	Increased muscle tone	1										
	Excoriation (chin, knees, elbow, toes, nose)	1										
	Myoclonic jerks (twitching/jerking of limbs)	3										
Generalised convulsions	5											
Metabolic/ Vasomotor/ Respiratory Disturbances	Sweating	1										
	Hyperthermia 37.2-38.3C	1										
	Hyperthermia > 38.4C	2										
	Frequent yawning (> 3-4 times/ scoring interval)	1										
	Mottling	1										
	Nasal stuffiness	1										
	Sneezing (> 3-4 times/scoring interval)	1										
	Nasal flaring	2										
	Respiratory rate > 60/min	1										
	Respiratory rate > 60/min with retractions	2										
Gastrointestinal Disturbances	Excessive sucking	1										
	Poor feeding (infrequent/uncoordinated suck)	2										
	Regurgitation (≥ 2 times during/post feeding)	2										
	Projectile vomiting	3										
	Loose stools (curds/seedy appearance)	2										
	Watery stools (water ring on nappy around stool)	3										
	Total Score											
	Date/Time											
Initials of Scorer												

Figure 1: Categories and possible scores for symptoms according to the modified Finnegan scoring system. [1]

Project Purpose

With the large and growing presence of NAS, this project aimed to be a step towards making a positive impact on the issue. Consisting of sensor development and real data collection, this project involved the making and testing of a system, capable of being used as the framework for a more refined product. One purpose of the project was to gather quantitative information on symptoms of NAS, using an internally developed sensor system to collect data continuously. It was hoped that information within the data could be used to identify the presence and severity of

multiple withdrawal symptoms that could be occurring. Reporting of informative results would also serve to expand the publically available knowledge, possibly being of use to future related efforts.

Having a system that could be worn by a newborn or left in their presence was necessary to achieve project goals. Such a system would reduce the system interaction time and burden on medical personnel, while also allowing for continuous data collection. One possible benefit gained from continuous data collection was the ability to search for the occurrence of noticeable symptoms, which could have occurred when medical personnel weren't present. The Finnegan scoring is based on observations made every four hours, not necessarily taking into account any of the symptoms displayed in between scorings. This brings up an underlying question of interest, would knowledge of patients' behavior between observations change their scores, and if so, would that have an impact on the effectivity of treatment?

This project builds off of a previous study that investigated tremor activity displayed by NAS newborns, and so an interest in tremors was maintained. While there are multiple known symptoms such as accelerated respiration, high pitched cry, and others listed on the Finn Scoring sheet, it was not feasible to attempt to quantify all of them. [1] In addition to tremors, the indicators/symptoms we hoped to be able to quantify included: high-pitched cry (pitch and duration), sleep pattern, Moro reflex, tremors, myoclonic jerks, generalized convulsions, and respiratory rate. In addition to items included on the Finnegan scoring sheet, we also hoped to gain information on heart rate variability, and occurrence rate of cries. It was expected that sensing of cries would require a separate sensor, but the other symptoms would all be able to be captured by the same sensor that could track tremors. But, later in the project, once the initial data sets were gathered and investigated, it was determined that our system would only allow us to reliably gather information on a newborn's cries and tremors. Additional sensors were not added for the other symptoms due to the developmental nature of this project. Incrementally increasing coverage of symptoms would allow for gradual refinements and improvements to be made to the system as the complexity increased.

Long term hopes would be to develop a sensor suite that can aid medical personnel in the evaluation of a patient's condition, ideally resulting in an improved treatment process, reduced length of stay, and lower costs. This project is motivated by the trend of increasing NAS occurrence and the growing need of newborns in need of help. If the long term goals were to be

achieved and a product implemented, it would be expected to directly influence the patient's health and well-being, the parents emotionally and financially, and the government financially.

Background

Among other important background information for this project, research was completed to gather knowledge about the accessible NAS symptoms of interest, tremors and cries. Using reported values for other ailments to generate expectations for the NAS newborns allowed for expedited data analysis by focusing processing on regions of interest. Within the available literature, limited numbers of NAS-specific studies were found, so searches were expanded to include other ailments.

Upon researching tremors, information was found about multiple types of tremors and the associated characteristics. Physiologic tremors are considered to be normal and displayed by all people, and while they are not always visible, they can be amplified by factors such as cold, fear, or excitement. Based on the magnitude of tremors displayed by newborns with NAS, we are led to look towards unordinary tremors, which are usually a symptom of conditions affecting the brain or nervous system.

While there are multiple known types of tremors, such as resting, action or postural, we are unable to classify the tremor type of newborns with NAS. This limitation is due to an inability to communicate with the newborn, as classification depends on what the individual is doing, or attempting to do, when the tremor occurs. Resting tremors can occur when an individual relaxes their muscles, action tremors occur when attempting to use the afflicted muscles, and postural tremors occur when the individual is using muscles to hold a position, such as sitting or standing. [5] With regard to newborns having NAS, their intention at the moment a tremor occurs is unable to be determined, preventing us from classifying the tremor type and finding more information from available literature.

Even though tremor type is unknown, limiting use of available resources, some information is available regarding characteristics of their tremors. According to verbally conveyed information, the frequency of motion in tremors exhibited by newborns ranges between 5 and 8 Hz. This rate of motion exceeds that of normal movements, which should be in the range of 0-1 Hz.

According to verbal accounts from medical personnel who work with NAS infants, there is a noticeable difference in the pitch of cry between healthy and NAS newborns. Guided towards searching for a difference in pitch, values were gathered from literature regarding pitch of cry for healthy and ailing newborns. While values were not able to be found for NAS newborns, papers were found related to studies on Wessel's colic and autism spectrum disorder. From these papers, fundamental cry frequencies were found to be 591 (s=208) and 504.87 (s=57.42). The control newborns used in these papers displayed fundamental frequencies of 498 (s=78) and 420.28 (s=40.32) respectively. [6, 7] The pattern of higher fundamental frequencies for ailing newborns agreed with the verbal reports from medical personnel, thus guiding our project towards an investigation into fundamental frequencies.

Project Approach

To achieve our proposed aim, investigating the feasibility of quantifying the NAS symptoms of tremors and high pitched cry, it was chosen to use two sensor types and conduct a research study. The sensor set used for this project was composed of wireless accelerometers and an external microphone. An individual microphone, in the vicinity of the newborn, would be used to collect auditory information, ideally containing multiple cry samples. Five wireless accelerometers, would be used to collect motion data, aiming to gather information relevant to tremor activity. One consideration of note is, while the previous iteration of this project made use of wired accelerometers, the shift to wireless was a mandated change, intended to improve the visually acceptability of the sensor system to parents.

The sensor system developed was put to use during the study to collect real data from newborns, with an intended sample of 15 newborns with NAS, and 15 control newborns. Each participant was to be instrumented for 8 hours continuously, and gathered data transferred to personnel at Virginia Tech. Study subject recruitment and data collection were completed by medical personnel, adding the challenge of requiring non-technical personnel to operate the sensor system. To assist with operation of the sensor system, an instruction guide was created, covering all steps of sensor operation.

Within the overall scope of the project, the primary tasks personnel at Virginia Tech would be responsible for included design of a method to instrument newborns with accelerometers and processing of collected data. Design of an instrumentation method was an iterative process, with the mounting method for accelerometers being undertaken as a team effort. My primary contribution and the focus of this thesis, was to process the data gathered during this project. The central processing tool used for both data types was a discrete Fourier Transform, which allowed for conversion from the time domain to the frequency domain. Separate MATLAB programs were developed to search the motion data for tremor content, and the audio data for cries.

Chapter 1.2 – Upcoming Content

Chapter 2: Design Process

Chapter 2 covers the design process that was completed during the project. Design was centered on procuring appropriate sensors, development of mounting methods and system testing. With the aim of gathering motion data and audio information, a set of accelerometers and a microphone were selected. While safety considerations were most important, runtime was also an significant factor, as study trials were to be eight continuous hours.

Chapter 3: Research Study Execution

A general overview of the data collection process will be covered in chapter 3. Conducted by medical personnel outside of Virginia Tech, participants were recruited and studied at Carilion Roanoke Memorial Hospital in Roanoke, VA. The intention during this process was to study 30 individuals, 15 NAS newborns and 15 non-NAS control newborns.

Chapter 4: Data Handling Tools

A brief introduction to two important tools used during data processing will be provided in this chapter. The first topic discussed will be the Fourier transform, a tool used to convert information from the time domain to the frequency domain. The second topic to be covered will be a statistical test used during analysis of the data. These tools were applied to all of the processed data, both motion and audio data.

Chapter 5: Motion Analysis

Information regarding analysis of motion data will be provided within chapter 5. This chapter will present a summary of the methods used to process the data and what the output formats would be. Results from the analysis of data will also be included, supported by some discussion of the results and conclusions that can be made.

Chapter 6: Audio Analysis

Coverage of data analysis for audio data will take place in chapter 6. Similarly to the presentation of motion data analysis, the methods used for data handling will be covered. Graphical outputs from processed data will be presented, along with the results of statistical tests that were ran on comparisons between data sets.

Chapter 7: Summary

Chapter 7, the final chapter, will be composed of summaries of previously presented material. For both motion and audio data, summaries will be provided for the approaches used and results found. Brief discussions on project challenges, recommendations and future work will also be incorporated.

Chapter 2: Design Process

Chapter 2.1 – Introduction

Within this chapter, we will delve into aspects of the design processes required to bring the sensor system to an operational status and ready for data collection. We aimed to develop a sensor suite capable of collecting motion and audio data from participants in a research study. The plan for collecting motion data called for the attachment of wireless accelerometers to each of a participant's limbs, as well as to their chest. An external audio recorder would be used to gather audio information, ideally only collecting information from the current participant. From the data gathered, we hoped to have motion information including tremors that occurred and audio information containing cry samples from the participant.

After covering general design notes, applicable to the whole system, separate sections will be devoted to focusing on development of the motion and audio sensors. This chapter will cover the bulk of the design process, with particular attention to the equipment used in the final designs. In addition to the designs themselves, considerations such as design constraints and objectives will be further discussed.

Chapter 2.2 – Design Notes: General

Creation of the sensor system proved to be a combination of off-the-shelf and custom components. Generally speaking, the electronic sensing components were purchased as a complete unit, while the mounting method was custom-made. Central to the system was a laptop computer that would be used for managing sensors and data during the data collection progression. A second computer was used for analysis and processing of the data.

System design was a joint effort, involving assistance from multiple individuals. Primarily for the motion sensing components, designing for mounting was a highly iterative process. Commonly motivated by safety concerns, suggestions for design alterations were received from team members as well as external individuals who were shown design prototypes. The design process was an iterative process, affected by both the addition of constraints and procurement of new materials for use.

Design Process

During the design process, there was a collection of constraints that applied to both audio and motion sensor design. Conducting the study in 8 hour long trials set the minimum run-time for the sensors. This time constraint highlighted the importance of making any worn sensors comfortable and considering battery life when selecting sensors. Additionally, physical exposure of equipment to newborns motivated the need to prioritize safety during the design process. An aim was to disallow the possibility of causing visually noticeable pain in the form of bruises or bleeding, and less obvious issues, such as soreness or discomfort. In parallel, the ideal design would not add obtrusive sensors to the environment, possibly making the newborn participant uncomfortable. As sanitation plays an important role in the maintenance of a healthy environment, the sensor system was designed to allow for equipment to stay clean or be disposable.

Design aesthetics played an important role in the design process, along with functionality and safety, due to the application being designed for. Visual presentation played a role in acceptability when displaying the equipment to experienced team members and the parents of participants. An intentional shift from wired to wireless accelerometers assisted in this process, as the presence of wires was an aspect that the parents did not approve.

With consideration for the medical personnel and study operators, ease-of-use also became an objective during design. However, the purchasing of contained sensors, electronic and software interfaces could not be modified. Limited to the external and physical characteristics of the design, modifications were confined to mounting and enclosure hardware. An operation guide was also written, providing a walkthrough of sensor usage. The guide could be used for instruction or reference, and included a check-sheet to track progress.

Chapter 2.3 – Design Notes: Motion

Motion Sensor

The motion sensing aspect of the design was meant to be capable of sensing the occurrence of tremors in a newborn's limbs. The desired sensor system was intended to include synchronized 3-axis accelerometers (± 3 g's) sampling at 50Hz, capable of running for at least eight hours and fifteen minutes. Whether storing data on board or streaming to an external node, wireless operation was a firm requirement.

Purchased for the project were twelve, Modular Signal Recorder (MSR) 145 3-axis wireless accelerometers (Figure 2). These sensors achieved wireless operation through on-board storage, requiring the sensor to be accessed through a computer to offload data. Provided with a software interface, sensor usability was controlled by the options available in the program. The acceleration measurement range could be set to +/- 2 or 16 g's, and the sampling rate could be set to 1, 2, 5, 10, 20, or 50 Hz. Based on expected accelerations and to improve resolution, the range was set to +/- 2 g for data collection. At a sampling rate of 50 Hz, the on-board storage was not sufficient to collect data for 8 hours, so the collection rate was lowered to 20 Hz. Sampling at 20 Hz allowed each sensor to collect data for 10 hours continuously, meeting the 8.25 hour minimum time requirement.



Figure 2: Modular Signal Recorder (MSR) 145 3-axis accelerometers purchased for use on this project.

The original sensors were larger than ideal, so two steps were taken to reduce the size and weight of the sensor. The main reduction in size was achieved by removing the circuit board and battery from their plastic enclosure, to be repackaged in heat shrink. Weight was also decreased by replacing the provided lithium polymer batteries with smaller batteries (Figure 3). Estimated calculations were done to confirm the new batteries would still allow for sufficient run-time, and a single sensor was modified then tested before the others were altered. At the end of this process, 2 out of 12 sensors were no longer usable, due to an unresponsive board and an overheated battery.

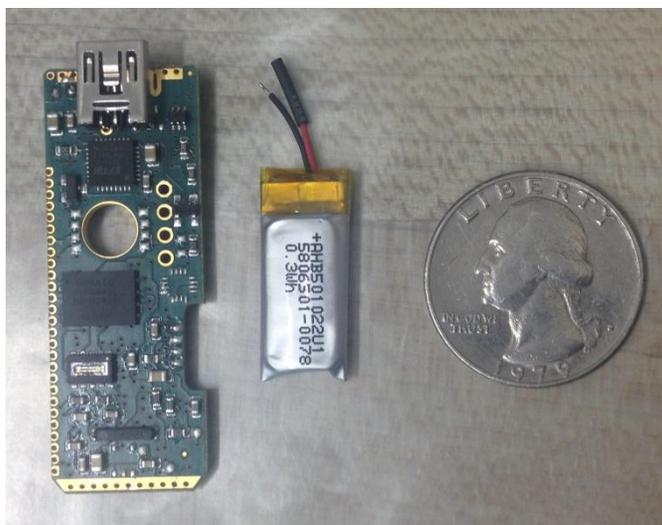


Figure 3: Accelerometer circuit board shown with replacement battery and quarter for size reference.

Hardware/Dressing Design Process

Accommodating repackaged sensors, holders were designed to allow for the accelerometers to be worn by newborns. The intended application dictated many of the constraints which had to be met by the developed holders. To meet the wear-time requirement of 8.25 hours, a securely attached holder was needed, without being restrictive to the newborn or a hassle to use. The sensitivity of a newborn's skin ruled out the possibility of directly adhering anything, and guided designs away from use of rough materials that could be abrasive to the skin. Along with rough edges, exposed circuitry and sharp corners would also need to be minimized in designs. Targeted toward improving safety, these goals would also serve to improve acceptability among parents and medical personnel. With respect to sanitation, the aim was to make the accelerometers cleanable and the holders disposable.

In addition to securing the exchanged battery to the sensor board, repackaging sensors with heat shrink helped in the design process by providing a level of safety. Conforming to the shape of the sensor, the heat shrink served as a low-profile enclosure, while also covering sharp edges that could have been a scratching hazard. The need to access sensors through a USB port prevented the sensors from being completely enclosed, but the seal provided by the heat shrink did reduce the amount of exposed circuitry. Initially, black heat shrink was used on the sensors, but holes had to be cut into the heat shrink to allow indicator LEDs on the boards to be visible (Figure 4). While the holes allowed the lights to be visible, they also served as access points for

moisture that could damage the board. As an improvement, the boards were re-enclosed using clear heat shrink, allowing the lights to be seen without the need to cut holes (Figure 5). The method of applying heat shrink was also refined by Vy Nguyen to improve moisture coverage of the board, solely leaving access at the USB port.



Figure 4: Initial heat shrink wrapped sensors. Use of black heat shrink required holes to be cut for indicator LED's, in the upper right-hand corner, to be seen.



Figure 5: Re-enclosed sensors, wrapped in clear heat shrink to improve seal and allow LED's to be seen without holes.

With the ten available accelerometers, two full sets of accelerometers were available, so the group was split in half and labeled for organizational and record-keeping purposes. In each

group of five, the sensors were assigned to the location they would be placed during testing and labeled with the intended limb or chest placement. Arrows were also placed on each sensor to be an orientation reference, standardizing sensor direction during multiple uses. In combination with the physical label, the labels were added within the software, providing a reference that could be used in combination with a serial number for identifying sensors. To physically organize the sensors for use in the study, two containers were set-up to organize and store the accelerometers. Inclusion of a USB hub allowed each container to hold five accelerometers, as needed for an individual study. The hub would serve to help in the process of working with the accelerometers, as plugging in a single cord to the computer would allow all five accelerometers to be accessed, instead of connecting each accelerometer individually (Figure 6).



Figure 6: One of two containers set up to organize accelerometers. A USB hub beneath the foam allowed for all accelerometers to be charged and accessed through a single connection to a computer.

Based on initial brainstorming of ways to hold the accelerometers, it was decided that adjustable length bands would be an acceptable design. Provided with Beta Pile II Loop, to be used as the foundation of the band, a student team composed of Vy Nguyen, Lucy Epshteyn and myself, developed the bands used in the research study. The Beta Pile II Loop provided is approved for medical use, and has a fiber structure that is compatible with Velcro for fastening purposes, working as the softer loop component. The initial band design included a slot for

holding the sensor, and a strip of hook Velcro that the band could wrap around and stick to (Figure 7). Progressing from this design based on feedback and new ideas, later iterations of the design included redesign components such as an elastic pouch and alternative set-ups for securing the band closed (Figure 8 and Figure 9).



Figure 7: Initial band design featuring an external pouch and section of Velcro hooks for closure.



Figure 8: An iteration of the band design, including an elastic material to form a pocket.

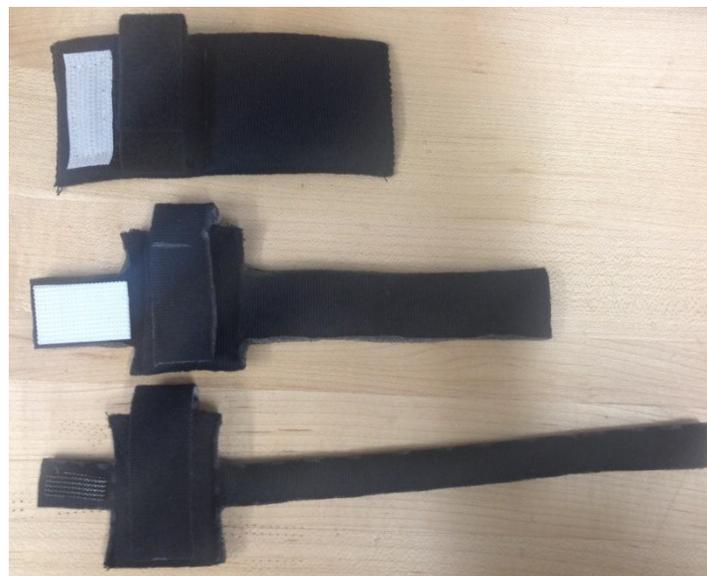


Figure 9: Further iterations of band designs, including the final design at the bottom.

For the final band design, we were able to reduce the weight of the band by internalizing the space for holding the accelerometer. Instead of attaching additional material to the outside of the band to form a pocket, we created a cavity by splitting the band open and sewed an outline to hold the desired shape. A strip of Beta Pile II Loop with a patch of Velcro hooks was sewn into the edge of the opening, as a way of securing an accelerometer in the pocket. The remainder of the band, intended to encircle the limb, was narrowed to a strip of material and patch of Velcro hooks was added to hold the band closed. To accommodate a variety of limb sizes, the strip of band material was intentionally made to be an excessive length, so that it could be cut to the correct length when used (Figure 10). Along with bands for limb sensors, a pouch was made to hold the chest sensor. By including a patch of hook Velcro on the back of the pouch, it was able to be mounted to a separate band that would encircle the participant's chest (Figure 11).



Figure 10: Final band design with flap for sensor cavity open.



Figure 11: Sample of pouch designed for chest sensor, mounted on band that would be wrapped around participants.

Testing and Sample Data

Control of the MSR 145 accelerometers was completed using the associated software, included with the purchase of sensors. Select settings within the program, controlling how data would be handled when downloaded from a sensor, were set to have data be saved as “.csv” files. A helpful capability of the program, assisted by organizing accelerometers on hubs, was being able to save the data from multiple sensors to an individual file. Using the software, setting up the accelerometers to collect data was a relatively short process, but downloading the eight hour data sets from all five sensors took nearly an hour to complete.

During preparations for the research study, the accelerometers were tested repeatedly to confirm proper operation. Endurance testing, limited by storage capacity, was conducted by having the sensors run for as long as possible, up to about 10 hours. These trials were conducted multiple times, and in various conditions, such as with the sensors being worn by numerous individuals.

More controlled testing was also completed, using a shaker to excite the accelerometers at known frequencies. Metal plates were used to make a rig for holding the accelerometers, allowing simultaneous mounting to the shaker (Figure 12). Excited at 1, 2, 5, 7, 10, and 15 Hz, the accelerometers were tested across the needed coverage range and past the usable limit. Limited to sampling at 20 Hz, as they would be in the study, the highest frequency the accelerometers would be capable of properly recording was 10 Hz. Expected to result in aliasing, exciting the accelerometers at 15 Hz was done to ensure the sensors and processing method would still display the expected results. In addition to performance testing, sample data, especially results from the shaker testing, was able to be used to test processing methods since there was an expected output for the known inputs.



Figure 12: Accelerometers mounted to small shaker for testing.

Tested in their final configurations, both the accelerometers and bands were able to perform satisfactorily during testing. The required 8.25 hours was able to be met without the sensors shutting off or the bands failing when worn by adults. Processing of sample data from the shaker displayed the appropriate frequency content, covering the range of frequencies expected for tremors.

Chapter 2.4 – Design Notes: Audio

Audio Sensor

Collection of audio data was completed using a digital recorder in combination with a lavalier microphone. The primary recorder used, a TASCAM DR-44WL, had two on-board microphones and sampled at a rate of 48 kHz. But, the set-up planned for the research study prevented use of the two on-board microphones. The lavalier microphone provided was a MOVO cardioid lavalier microphone LV4-C, and served as an external microphone, connected to the recorder. This set-up allowed the recorder to gather audio information, saved as “.mp3” files, without needing to be in the bassinet with the newborn. But, the addition of the external microphone required the addition of a battery pack, as discovered during testing.

Mounting Design Process

Limited design occurred for the audio sensor, as it was not intended for the newborn to wear or be directly attached to the microphone. Rather, the focus of the design around the microphone was to protect the sensor itself from damage. Of the dangers presented, the two primary concerns were moisture damage from bodily fluids and physical damage if left exposed. Initial brainstorming pointed towards creation of an enclosure for the recorder, able to prevent damage while also allowing sound to reach the on-board microphones. Instead, the chosen solution was to use an external microphone that would be more exposed and replaced if needed, while the recorder was more protected (Figure 13).

The recorder itself was to be placed in a small lock box that would be stored under the newborn's bassinet. Exiting from the side of the lock box would be the external microphone that would be clipped to the edge of the bassinet near the newborn. In the event the external microphone was rendered unusable by soiling or damage, a second was available as a replacement.



Figure 13: Recorder and external microphone used, turned on and collecting sample data.

Testing and Sample Data

Collection of sample audio data was completed on multiple occasions, both before and after the external microphone was attached. Various sounds were recorded, including silence within a closed box, ambient noises in an empty room, and normal conversation within an occupied room. These samples were used as a way to check the clarity of recordings, along with

how well softer sounds were able to be discerned. Generated using the speaker on a cell phone, a sweep through frequencies from 20 to about 15,000 Hz was also recorded as sample audio data. The frequency sweep was useful for testing processing methods, confirming the correct output was found for the known input.

The audio recorder underwent endurance testing to confirm it would be able to collect data for at least 8.25 hours. While the recorder was originally able to run for the desired amount of time, adding the external microphone increase the rate of battery drain, causing the system to stop well before 8 hours. The four AA batteries within the recorder were not sufficient, so they were supplemented with an external battery pack. The final combination of recorder, external microphone and external battery pack were confirmed to be capable of running for over 11 hours during further testing (Figure 14).



Figure 14: Recorder, external microphone, and external battery placed in lock box, as intended during data collection.

Chapter 3: Research Study Execution

Chapter 3.1 - Overview

The research study was conducted in the newborn nursery/NICU ward at Carilion Roanoke Memorial Hospital in Roanoke, VA. Managed and executed by medical personnel, their responsibilities included recruiting subjects, applying sensors to collect data, and organizing the data for transferal to Virginia Tech. For the study, the desired sample size was 30 newborns, half control newborns and half newborns with NAS. Each newborn was to be instrumented with five accelerometers and recorded with a microphone for eight continuous hours. During the eight hours of observation, the Finnegan scoring was to be completed three times, at the beginning, middle and end. At the conclusion of trials, data was to be organized on a computer and external hard drive, pending transfer to Virginia Tech.

Chapter 3.2 - Data Collection Procedure

In possession of two sensor systems from Virginia Tech, medical personnel began participant recruitment by seeking appropriate newborns. Once a newborn was identified, parents/guardians were approached, informed of the study, shown the sensing system and asked for consent. Assisted by a reference guide detailing use of the sensors, the process of data collection was completed entirely by medical personnel.

For the newborns consent was obtained for, the data collection trial likely took closer to nine hours due to set-up and clean-up time. In preparation for conducting a study, the accelerometers would be connected to a computer and assigned the appropriate start and end time for collecting data. The software interface allows for different modes of operation, but an assigned start and stop time works best for this application. With the times assigned, the accelerometers could be disconnected from the computer, ready to be placed into bands. The recorder used did not have the same functionality, so recording had to be manually started at the correct time. Around the time of beginning the study, a Finnegan scoring should have been conducted for all 30 study participants.

During the trial, another Finnegan scoring should have been completed at the mid-point, four hours after the trial began. The third and final Finnegan scoring used in this study should have been conducted at the end of the data collection period, eight hours after starting. After

approximately eight hours had elapsed, the recorder should have been stopped and the accelerometers removed from the participant. Participant interaction completed, the accelerometers and recorder would store the collected data until erased. Downloaded from the sensors after each study, a computer was used to store the data sets and an external drive was used to back-up the data. After each trial, the memory on the accelerometers would also need to be cleared, as the on-board memory is not sufficient to store the data from two trials. Periodically, the external hard-drive was brought to Virginia Tech, and the downloaded to a second computer that would be used for processing.

Chapter 3.3 - Resulting Data

At the conclusion of the study, data had been gathered on a total of 29 participants, 15 control newborns and 14 NAS newborns. But, while 29 trials were conducted, complete and usable data was not collected for all participants due to various issues. For the accelerometer data, 28 usable sets were collected, and for the audio data, 19 usable sets were collected. While some of the unusable content is due to missing files, other files contain content that was unable to be processed using the developed programs. For example, some of the audio files recorded are very quiet, due to the microphone being connected to a channel on the recorder that did not have the proper sensitivity setting. The resulting files are audible, and some content can be seen in the data, but the low magnitudes cause the desired information to be highly affected by the noise in the data. While almost all accelerometer data sets are present, some are incomplete, containing data from four out of five sensors. Also, some of the accelerometer data is complicated, due to activities such as the accelerometers being removed from the participant for a period of time.

Summarized in Table 1 and Table 2, a log of data files was kept to track the progress of data collection. The log contains information about which data had been collected, as well as the lengths of audio recordings provided, due to variations between trials. Some notes are also included for data files that did not appear as expected.

Table 1: Log of data files provided for non-NAS participants. A total of 15 non-NAS participants were recruited.

Non-NAS			
Subject #	Accelerometer	Audio	Note
44	Present	Multiple Files	
83	Present	Multiple Files	
49	Present	None	No audio file.

54	Present	8:12:33	
85	Present	8:09:23	
40	Multiple Files	0:36:14	
68	Present - RA	2:15:12	Right arm data missing.
61	Present - RL	6:58:53	Right leg data missing.
77	Present	8:01:23	
64	Present - C	7:37:56	Chest data missing.
55	Present	8:23:14	
70	Present	8:28:24	
72	Present	7:58:18	
57	Present	8:21:41	Blank audio file.
99	Present	8:43:08	Blank audio file.

Table 2: Log of data files provided for NAS participants. A total of 14 NAS participants were recruited.

NAS			
Subject #	Accelerometer	Audio	Note
74	Present	6:38:26	
88	Present	9:48:10	Very quiet audio
76	Present	8:32:19	Very quiet audio
62	Present	8:44:12	Very quiet audio
86	Present	2:15:12	
53	Present	8:34:15	
78	Present	9:49:59	
60	Present	7:56:59	Chest accel unused.
80	Present	7:52:34	
58	Present	8:20:37	
66	Present	Multiple Files	
65	Present	8:29:27	
81	Present	8:13:21	
90	Present	6:53:42	Blank audio file.

Chapter 3.4 - Chapter Summary

Data collection for this project was completed at Carilion Roanoke Memorial Hospital, and conducted by the medical personnel. In this part of the project, medical personnel were responsible for recruitment of participants, collection of data, and organization of data before transferal to Virginia Tech. Of the 30 desired participants, 29 were recruited and studied, including 15 control newborns and 14 NAS newborns. Gathered during the 29 trials, 28 sets of accelerometer data and 19 sets of audio data were provided containing usable data.

Chapter 4: Data Handling Tools

Chapter 4.1 – Discrete Fourier Transform

Central to the processing conducted on the data gathered in this project, a discrete Fourier transform is used to convert information from the time domain to the frequency domain.

Mathematically, the Fourier transform is intended to be applied to continuous, stationary data. Stationary data is cyclic over time, maintaining the same statistical properties, such as mean and variance. Repetition within the time data after a set interval allows for an accurate transformation of the data using this method.

For the Fourier transform, equation 1 is used to convert from time to frequency information while equation 2 converts from frequency to time information. The idea that any time signal can be represented by a specific combination of sinusoidal functions is reflected by using Euler's formula (equation 3) in combination with equation 2. Written concisely using a summation, equation 2 equates time information to a set of sinusoids at various frequencies, each with separate amplitudes and phases. A listing of variable definitions is provided in Table 3 as a reference. [8]

$$X_k = \sum_{n=0}^{N-1} x_n * e^{-\frac{i2\pi kn}{N}} \quad (1)$$

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k * e^{\frac{i2\pi kn}{N}} \quad (2)$$

$$e^{ix} = \cos(x) + i * \sin(x) \quad (3)$$

Table 3: Summary of variable definitions for equations related to Fourier transform.

Variable	Definition
X_k	Fourier Transform of data signal, complex coefficients
x_n	Data signal
N	Number of data samples
n	Indexed value of samples
k	Indexed value of complex coefficients
e	Euler's number
i	Imaginary number, square root of negative one

When the Fourier transform is applied to time data, a set of real numbers, output frequency information will be of the same length, but composed of complex numbers. Use of complex numbers allows for inclusion of magnitude and phase information. The frequency value each complex number is associated with depends on the sampling rate and length of time data used. Using the inverse transform, equation 2, this information can be used to recreate the time signal.

The sampling rate of time information also dictates the range of frequency information that can be found. The frequency information found using the Fourier transform provides results up to the frequency equal to half of the sampling rate. For example, if time data is sampled at a rate of 50 Hz, frequency information for signal content up to 25 Hz can be found. The audio sensor we used sampled at a rate of 48 kHz, allowing pitch content up to 24 kHz to be discerned. Motion data was sampled at 20 Hz, providing information about motion content up to 10 Hz. When applied to real data, software is commonly used to complete the required calculations.

Chapter 4.2 - Statistical test

With results gathered during this project, outputs from various groups would be compared to determine if a difference is present. Instead of relying on visual comparisons to determine differences, statistical testing was incorporated to confirm the presence or lack of significant differences. The statistical tests conducted for comparisons made within this project were two-sample t-tests for difference of means, at a confidence level of 95%. An appropriate test for the data under consideration would be the Welch's t-test, as we are comparing independent data sets and unable to assume equal variances. For use of the Welch's t-test, equation 4 makes use of sample means, sample standard deviations, and sample sizes to determine the test statistic. Equation 5, the Welch-Satterthwaite equation, is used to determine the correct degrees of freedom for use in the test.

$$t_s = \frac{(\bar{x} - \bar{y})}{SE_{\bar{X} - \bar{Y}}} = \frac{(\bar{x} - \bar{y})}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \quad (4)$$

$$df = \left(\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y} \right)^2 / \left(\frac{\left(\frac{s_x^2}{n_x} \right)^2}{n_x - 1} + \frac{\left(\frac{s_y^2}{n_y} \right)^2}{n_y - 1} \right) \quad (5)$$

The null hypothesis for tests was that the true mean for the two comparison groups was approximately the same. The alternative hypothesis was that the true mean of one group was higher than the other. Due to having expectations regarding which group should possibly have the higher mean, results were interpreted in terms of one-sided tests. Decisions to reject or fail to reject the null hypothesis were based on the output p-values. At a confidence level of 95%, evidence indicates we should reject the null hypothesis if a p-value smaller than 5% (0.05) is found. In terms of the hypotheses used, when a p-value smaller than 0.05 is found, the data indicates a difference of means between the comparison groups.

Chapter 5: Motion Analysis

Chapter 5.1 – Motion Processing

Intentions/Overview

The primary question to be investigated using the accelerometer data was whether or not tremor activity could be identified, solely using numerical data. Processing of the accelerometer data applies some of the tools mentioned in Chapter 5, in an attempt to identify tremor activity. If successful in identifying tremors, a secondary topic of interest is the possibility of reducing the number of sensors, without missing necessary information. Processing and analysis of the accelerometer data was completed using a series of programs in MATLAB. The programs I developed for use on this project made use of many built-in MATLAB functions, but were designed specifically for this application.

Analysis Program

Using built in MATLAB functions, accelerometer data is read in from CSV files. Each CSV file contains a single time column displaying absolute time, and four additional columns for each accelerometer. The four columns for each sensor include acceleration values, in units of g's, for the X, Y, and Z axes, and the fourth column holds the voltage level of the battery, which is checked every five minutes. Column identification information is contained in the text that makes up the header section of each file.

While the CSV file includes a time column containing absolute date and time, these values are unable to be used due to the format being incompatible with MATLAB functions. Instead of being deleted when the data is imported, these values are replaced with a column of indexed values, counting the number of rows. These indexed values will later be replaced with relative time values for each sensor. Relative time values are generated for each accelerometer separately, as arrainging readings from multiple accelerometers, relative to a single time column, can result in the data appearing staggered (Figure 15). This stagger is due to the sensors sampling at slightly different times, even though they were programmed to start at the same time. As a result, when X, Y and Z columns are extracted for a single sensor from the data file, an unknown number of blank rows will also be present.

11	NAME	Chest	Chest	Chest	Chest	Right Arm	Right Arm	Right Arm	Right Arm	Left Leg	Left Leg	Left Leg	Left Leg
18	*CHANNEL												
19	TIME	ACC x	ACC y	ACC z	BAT	ACC x	ACC y	ACC z	BAT	ACC x	ACC y	ACC z	BAT
21	*UNIT												
22		G	G	G	V	G	G	G	V	G	G	G	V
38	*DATA												
39	7/1/2016 10:45												
40	7/1/2016 10:45					0.263	-0.914	0.26	3.87				
41	45:00.1	0.392	-0.018	-0.876	3.88								
42	45:00.1									0.718	0.718	0.157	3.86
43	45:00.1												
44	45:00.1					0.263	-0.925	0.284					
45	45:00.1	0.384	-0.054	-0.861									
46	45:00.1									0.741	0.694	0.145	
47	45:00.1												
48	45:00.1					0.302	-0.914	0.3					
49	45:00.2	0.396	-0.03	-0.904									
50	45:00.2									0.698	0.674	0.109	
51	45:00.2												
52	45:00.2					0.283	-0.91	0.28					
53	45:00.2	0.392	-0.038	-0.872									
54	45:00.2									0.706	0.706	0.125	

Figure 15: Sample of raw accelerometer data before importing into MATLAB, displaying an example of staggered data rows due to sampling timing. The time stamp format is also shown, with the “45:00.x” seen actually referring to an absolute time of “7/1/2016 10:45:00.x”.

Processing one sensor at a time, a new matrix, containing a time and data column, is made for each axis. The three matrices are searched for the presence of blank data rows, which are then removed. The indexed values in the time column are replaced with relative time values, having units of minutes, counting up from the beginning of the recording period. At the conclusion of this step, three separate two-column matrices will be present, each having a time column counting up from 0 minutes and a data column.

In the next section of the program, a “while” loop is used to process the data in manageable sections. Using one minute of data from each axis, a resultant is calculated, forming a single array of values. A discrete Fourier transform is applied to the array of resultant values, converting information from the time domain to the frequency domain. At this stage of the program, the power distribution of the frequency content is also calculated. The distribution of power within the frequency content can be used to indicate which frequencies were most common in the selected data. Processed in 0.5 Hz increments, the amount of content in each frequency range is found from 1 – 10 Hz in order to determine where the frequency content is concentrated. The high magnitudes of low frequency content (0 - 1 Hz), likely due to regular motion, can cause higher frequency content to be masked due to scaling issues. Since motion in

the 0 – 1 Hz range is not of interest in this project and causes other information to be masked, it is excluded when the power distribution is calculated.

Resulting from processing data in one minute increments, a multitude of frequency distributions are generated per sensor for the eight hours of data (Figure 16). When graphically displayed, this information can provide insight into the characteristics of motion for a single participant. One such insight is being able to determine the relative timing of a data segment containing high frequency content. But, having a multitude of distributions for a single sensor makes it difficult to compare results between different participants. As a remedy, the multiple frequency spectrums are combined into a single representative spectrum and converted to a power distribution for each sensor.

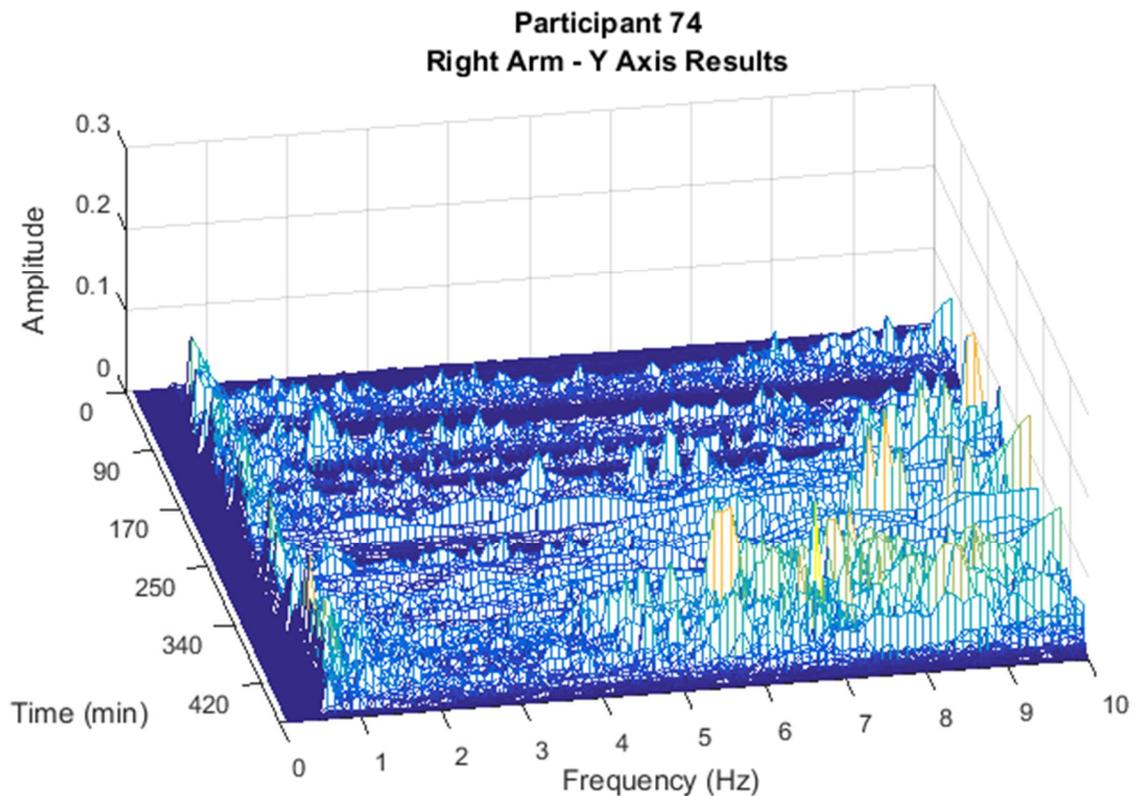


Figure 16: Sample of aeries of frequency spectrums resulting from processing a single axis of accelerometer data in one minute increments. The time axis allows the approximate timing of high frequency content to be estimated.

Possibly sensitive to the combination method used, the power distributions were combined in two different ways. The first method found the mean power content for each 0.5 Hz interval, and the second took the maximum value present for each 0.5 Hz interval. The second method was later altered to use an average of the top five percent of values, instead of the

maximum, to make the result less vulnerable to outliers (Figure 17). Visual analysis of results confirmed that each method resulted in different outputs. Without an indicator of which method is better, results from both are kept and used in the comparison process. Comparisons are made using the sensors that were placed on limbs, as it was found that the chest accelerometer did not gather much usable information.

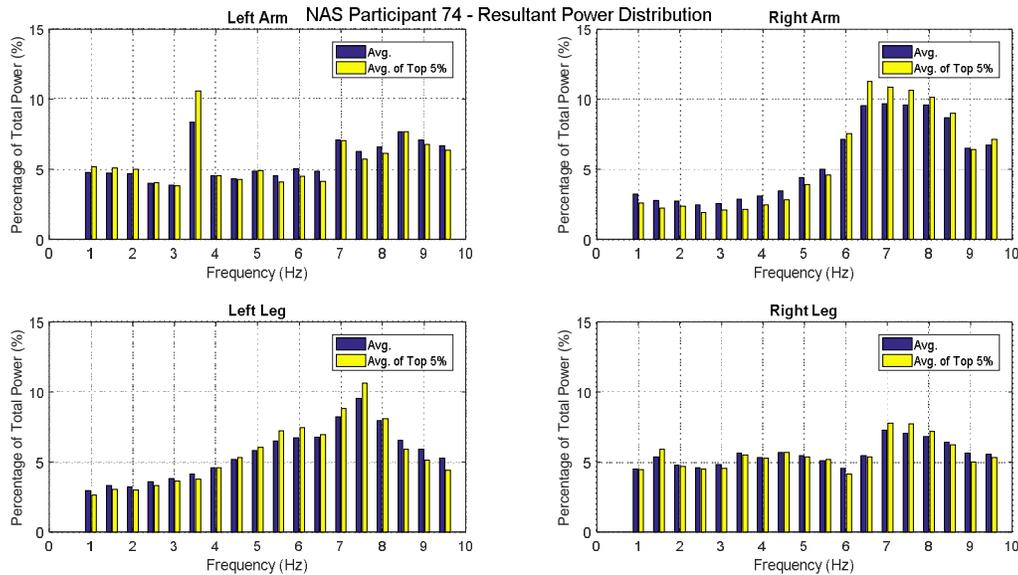


Figure 17: Example of power distributions for the resulting frequency spectrums using two combination methods. While general trends are similar, the results from each combination method are found to be different.

With results in a format that allowed for direct comparisons to be made, various comparisons of interest were tested. To help with making direct comparisons between plots, instead of showing magnitudes at each spectral line, the percentage of the total spectrum contained within 0.5 Hz intervals is shown. For example, if a bar at the 1 Hz mark shows a value of 8%, it means 8% of the total spectrum is contained within the range from 1-1.5 Hz. Along with individual comparisons of participants, the format of results made it possible to compare one group to another, or to an individual (Figure 18: Sample comparison of power distributions between two selected groups. The frequency spectrums used in this comparison were formed using mean values. Figure 18). This capability was used to make comparisons such as all NAS participants versus all non-NAS participants, or individual NAS participant vs all non-NAS participants. A visual comparison, in the form of an overlaid plot, was supported by the P-value of a statistical test. After rescaling the data, by removing a portion of the offset from zero common to all intervals, a 2-sample t-test was used to check for a difference of means. Each

sample would be a weighted frequency value, where the weighting is based on the percentage of content at that frequency. Testing using a 95% confidence interval, the resulting P-value is included in plot legends for reference (Figure 19).

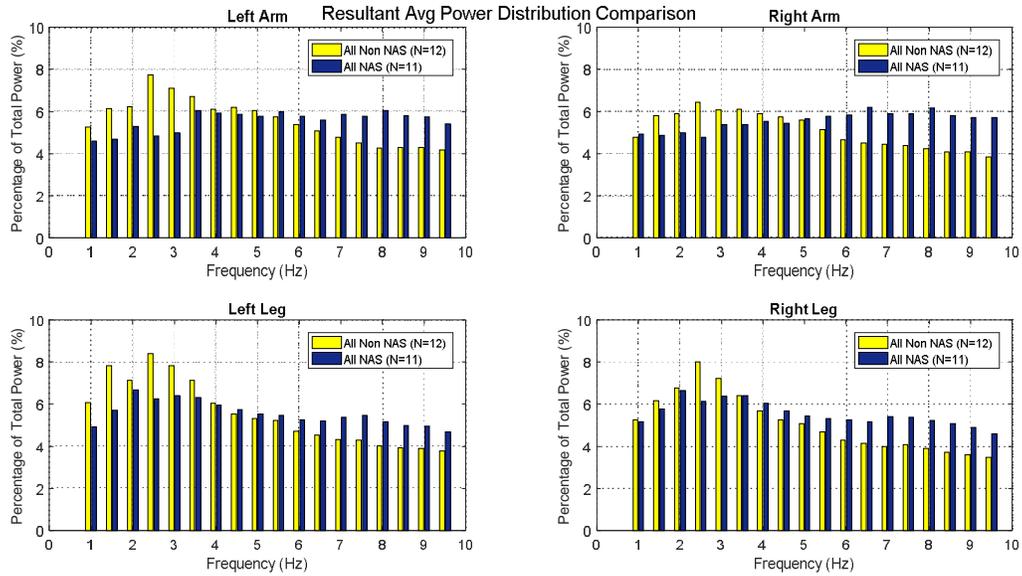


Figure 18: Sample comparison of power distributions between two selected groups. The frequency spectrums used in this comparison were formed using mean values.

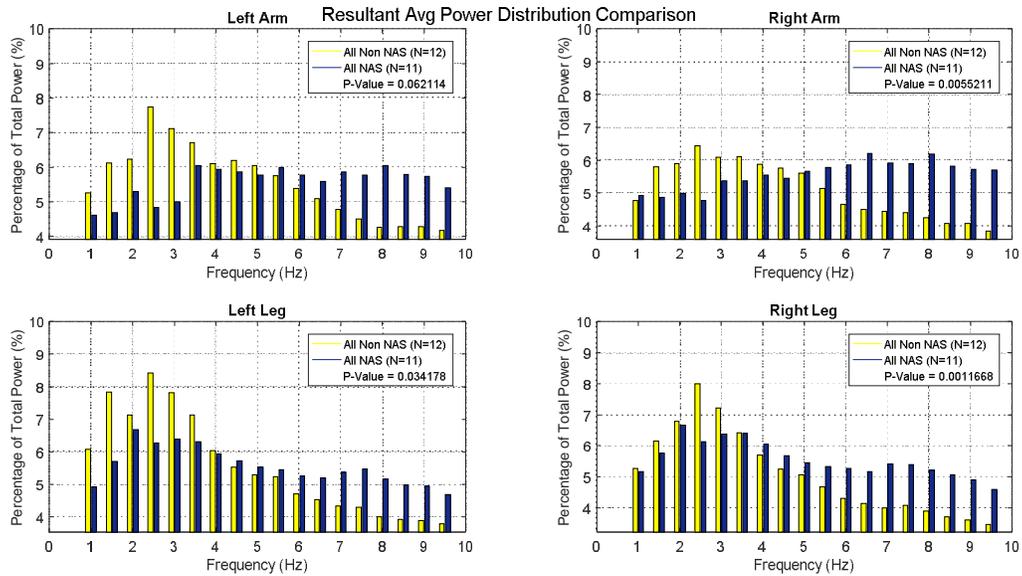


Figure 19: Building off of the comparison in Figure 18, a portion of the offset from zero has been removed from all bars. A statistical test is run on the modified values, and the resulting P-value is included in the legend for reference.

Chapter 5.2 – Motion Results

Results were analyzed with the intention of answering whether or not we would be able to observe the presence of tremors, and if it would be possible to do so with fewer sensors. In comparing the power distributions, it was expected that NAS newborns experiencing tremors would show greater proportions of content in the higher frequency region (5-8 Hz). For each comparison, power distributions resulting from both, finding the mean of frequency spectrums and averaging the top 5% of values, are provided.

Comparing the average power distributions of NAS newborns against control newborns, most results indicate a difference is present. Displayed in Figure 20 and Figure 21, all plots visually indicate more high frequency content among NAS newborns. Using a 95% confidence interval, seven out of eight comparisons indicate that the difference is statistically significant. A P-value of 0.052 is cause for failing to conclude there is a statistically significant difference for a left arm comparison, but its proximity to the threshold is to be noted. Also, the other test for left arm data, using frequency spectrums that were combined using the top 5% of values, is also close to the threshold, but does indicate that there is a statistically significant difference. With a difference confirmed, the results appear to indicate that the presence of tremor activity among NAS newborns is the cause for the separation.

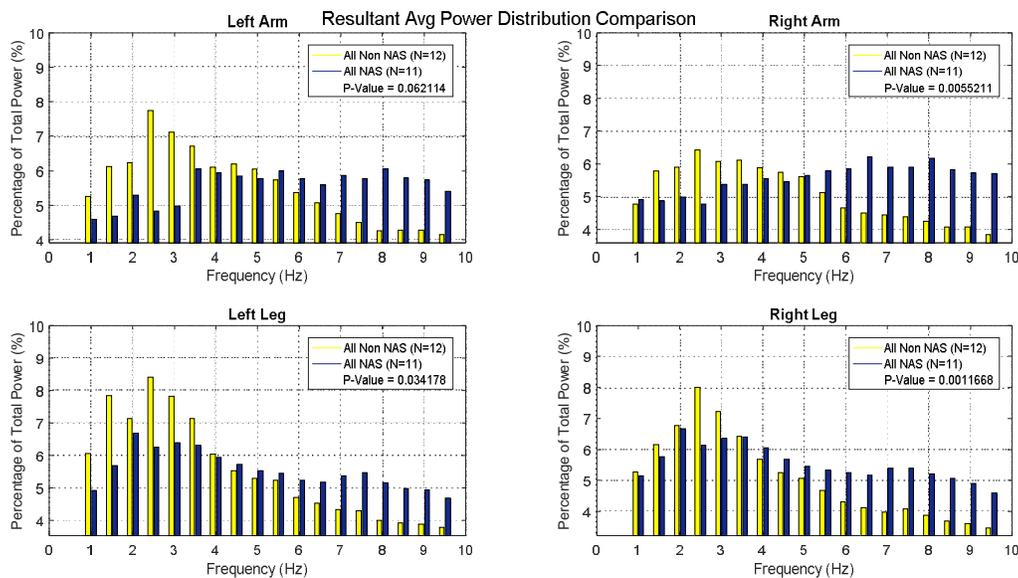


Figure 20: Three of four comparisons between NAS participants and non-NAS participants are found to result in statistically significant differences using this method of combining frequency spectrums.

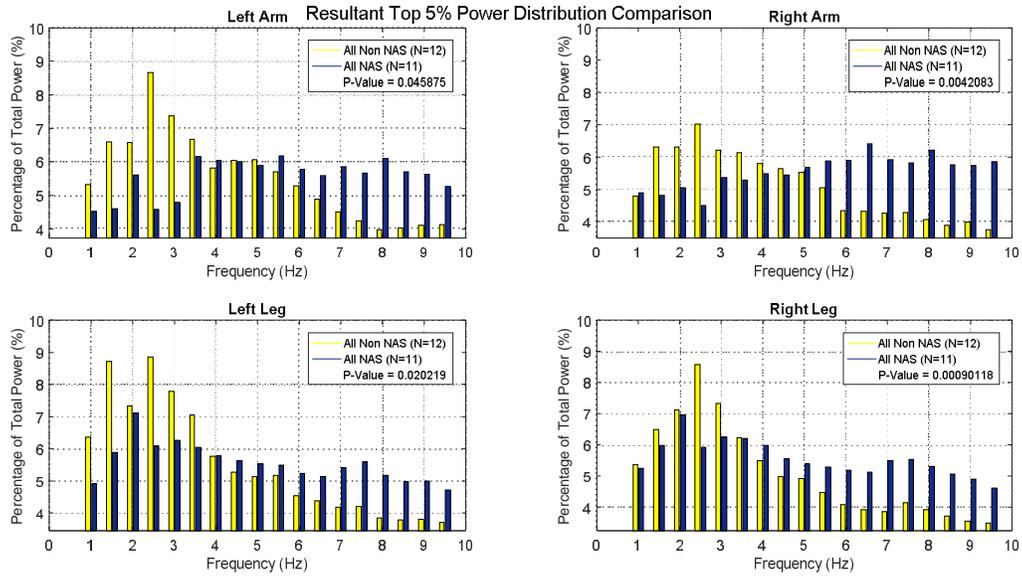


Figure 21: Four of four comparisons between NAS participants and non-NAS participants are found to be statistically different using this method.

To highlight and double check the comparison method, the non-NAS control newborns were compared to a single NAS newborn, known to have exhibited tremors (Figure 22 and Figure 23). Within these plots, these groups display an increased visual difference. But, based on the results of statistical testing, two of eight comparisons, the right leg tests, indicate a significant difference of means. In this case, the results from the different frequency spectrum combination methods are in agreement.

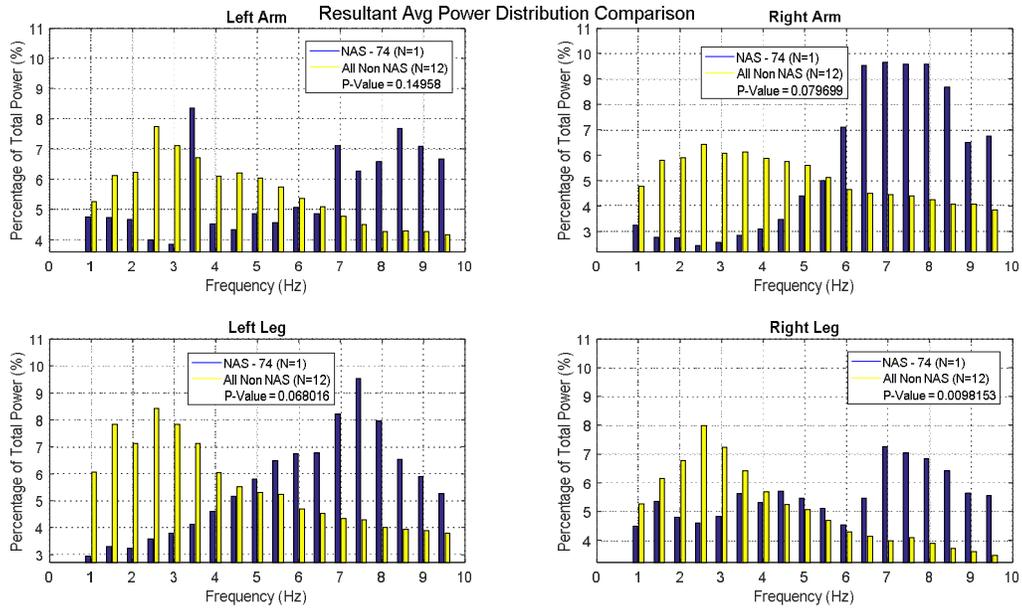


Figure 22: A statistical difference is found for the right leg when comparing non-NAS participants to NAS participant 74.

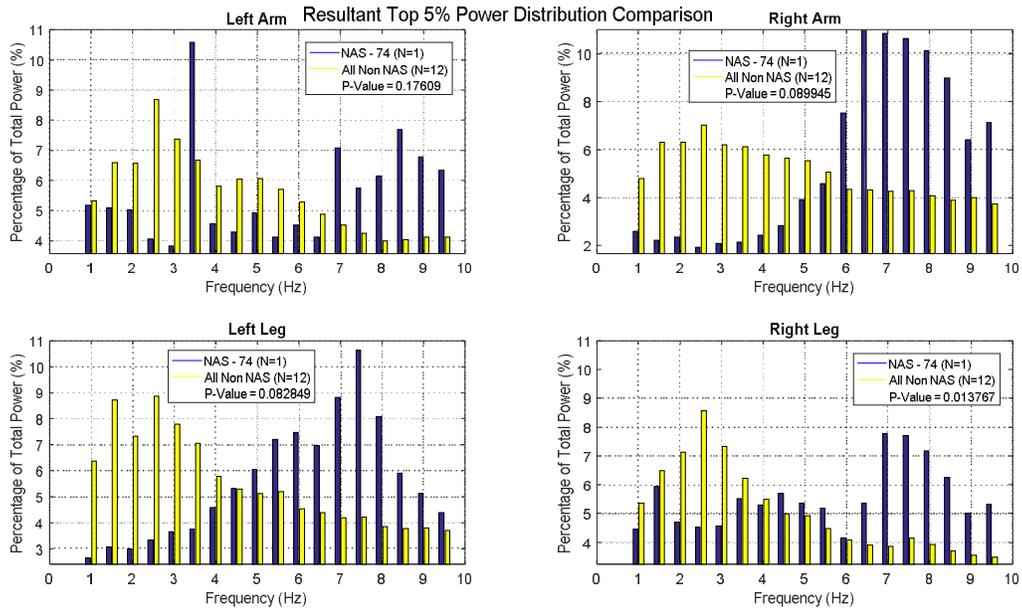


Figure 23: While all limbs appear different visually, comparison of non-NAS participants to NAS participant 74 results in a statistically significant difference for a single limb, the right leg.

In contrast to the previous comparison, the next compares NAS newborns to a single non-NAS control newborn. The control newborn visually shows a greater proportion of low frequency content as expected, and the difference is statistically significant for five of eight tests

at a 95% confidence level. There is a disagreement in the statistical test results for the right leg comparisons, with the top 5% method indicating a difference while the use of mean values does not (Figure 24 and Figure 25).

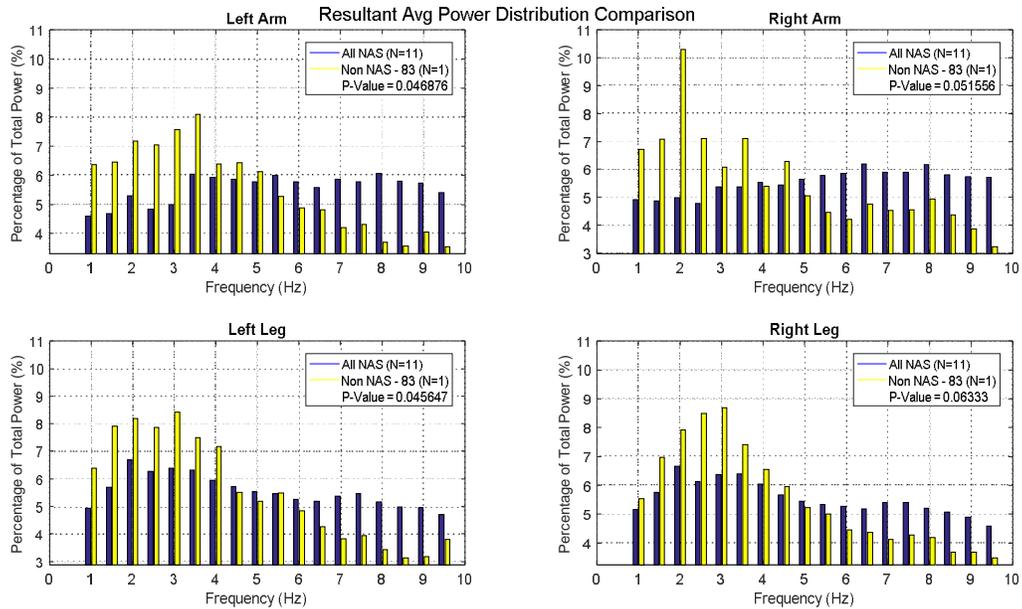


Figure 24: Using this method, two of four limbs are found to have a statistically significance for the comparison between NAS participants and non-NAS participant 83.

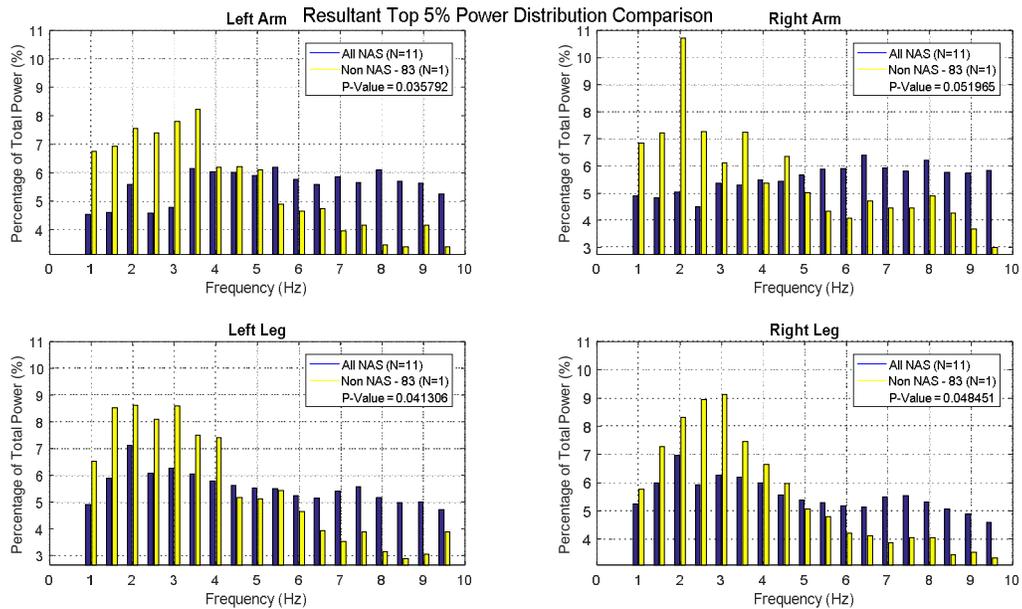


Figure 25: Without a sharp visual difference, a statistically significant difference is found for three of four limbs using this method to compare NAS participants to non-NAS participant 83.

Directly comparing the individual participants used continues the trend of showing an apparent visual difference that is not always reflected by the statistical tests. There appears to be a greater proportion of high frequency content for the NAS participant in all eight plots, but at the 95% level, a statistically significant difference is present in one of eight plots (Figure 26 and Figure 27).

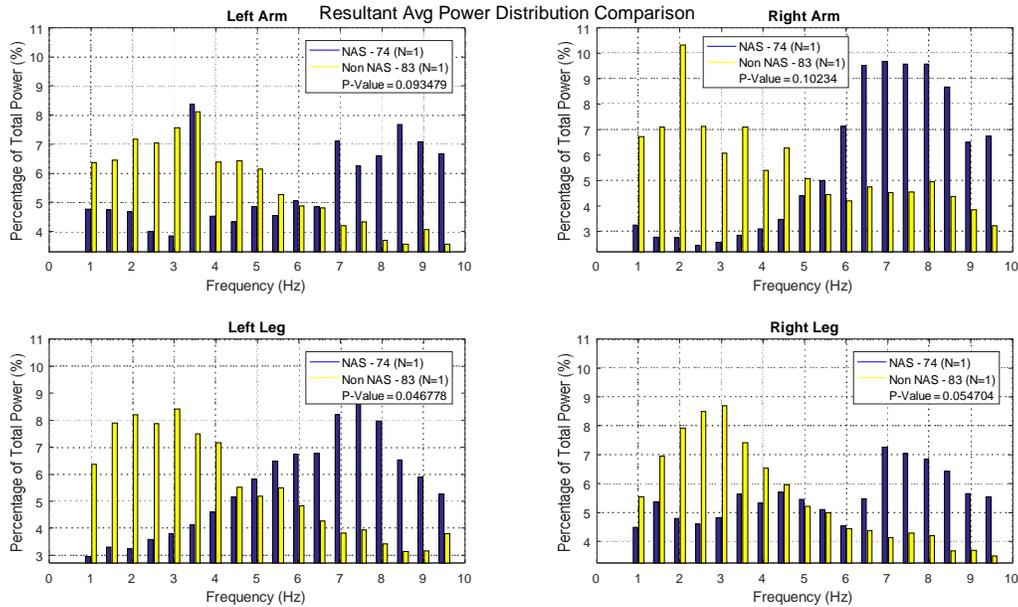


Figure 26: A statistically significant difference is found for left leg results between NAS participant 74 and non-NAS participant 83. Visual differences are present in all for plots.

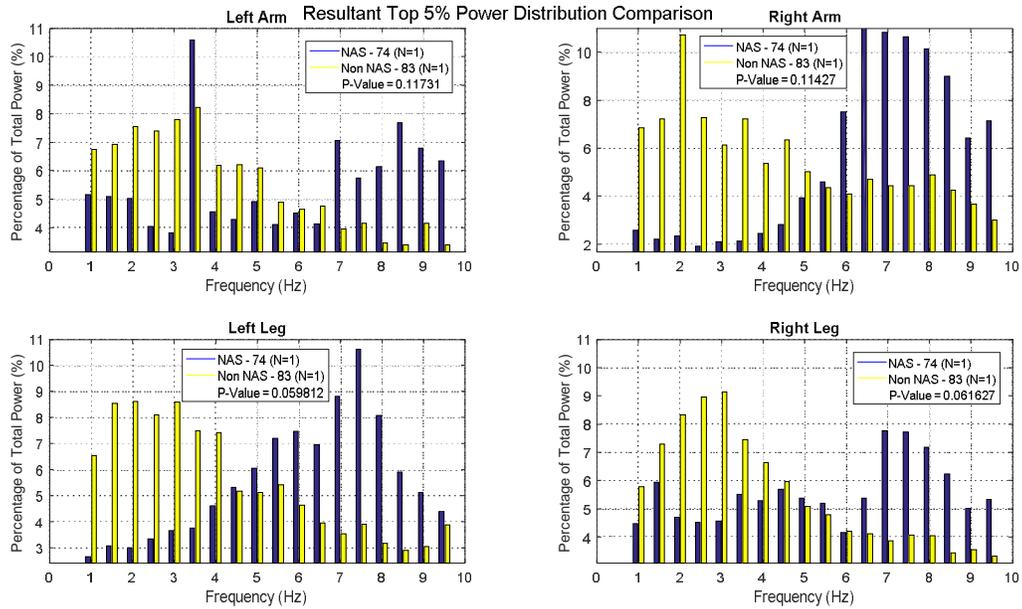


Figure 27: This method of comparing NAS participant 74 to non-NAS participant 83 does not result in statistically significant differences, but they do appear different visually.

Reported as not displaying tremors, according to the Finnegan scores provided, NAS participant 76 was compared to NAS participant 74, a newborn known to have exhibited tremors. While power distributions for participant 76 do appear to be more proportionally concentrated in the low frequency region, it does not appear to be as strongly concentrated as control participant 83, previously considered. According to the results from statistical testing, we are unable to conclude that there is a significant difference of means between means between participants 74 and 76 (Figure 28 and Figure 29). Even without statistical significance, there does generally appear to be a difference in the power distributions between NAS participants with and without tremors.

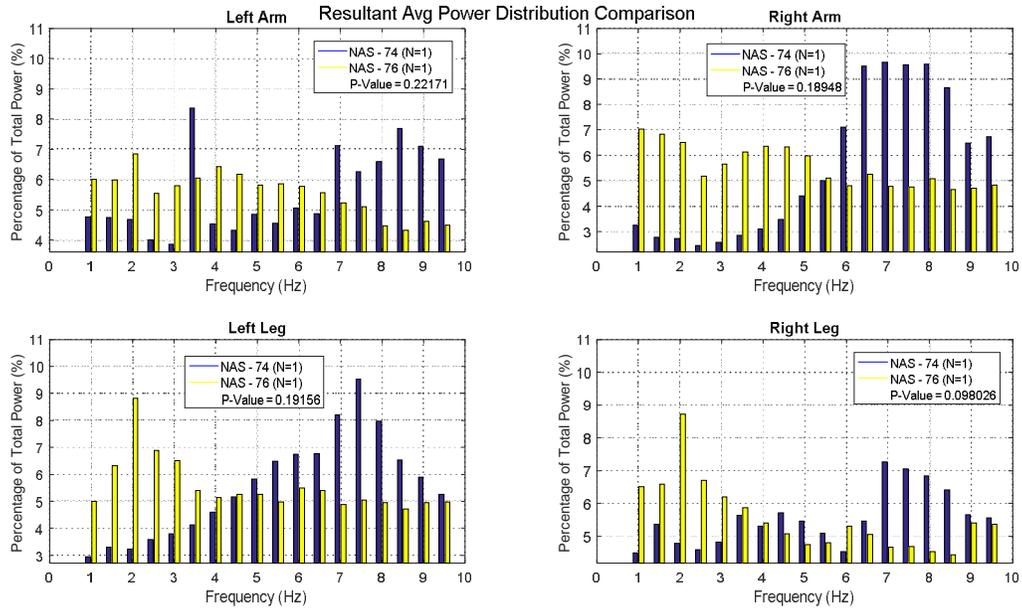


Figure 28: Visual differences can be seen when comparing NAS participant 74 to NAS participant 76, but statistical tests do not indicate that there is evidence of a difference.

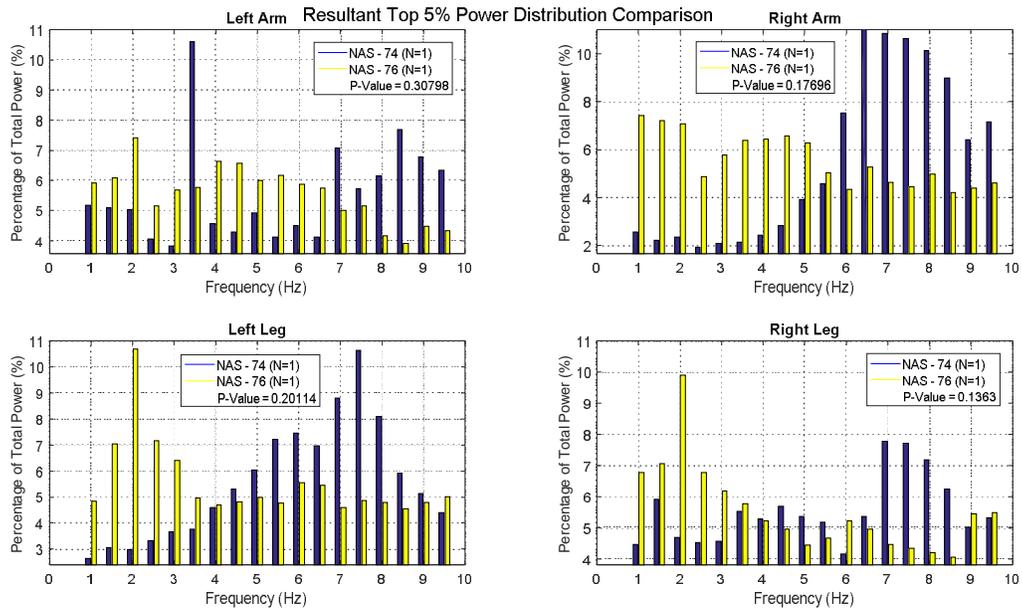


Figure 29: Comparison between tremor-positive NAS participant 74 and tremor-negative NAS participant 76 display differences visually, but not statistically.

Comparing non NAS participants to tremor-negative NAS participant 76 was also completed. Visually, both sides of the comparison display the same general trends in their power distributions, with a greater proportion of the content in the lower frequency region (Figure 30

and Figure 31). Statistical testing indicates that there is a difference in four of the eight plots, the plots for the right arm and leg. Within the plots for the right leg, the results do indicate the presence of some high frequency content in the 9-10 Hz area, possibly the cause of statistical tests indicating a difference.

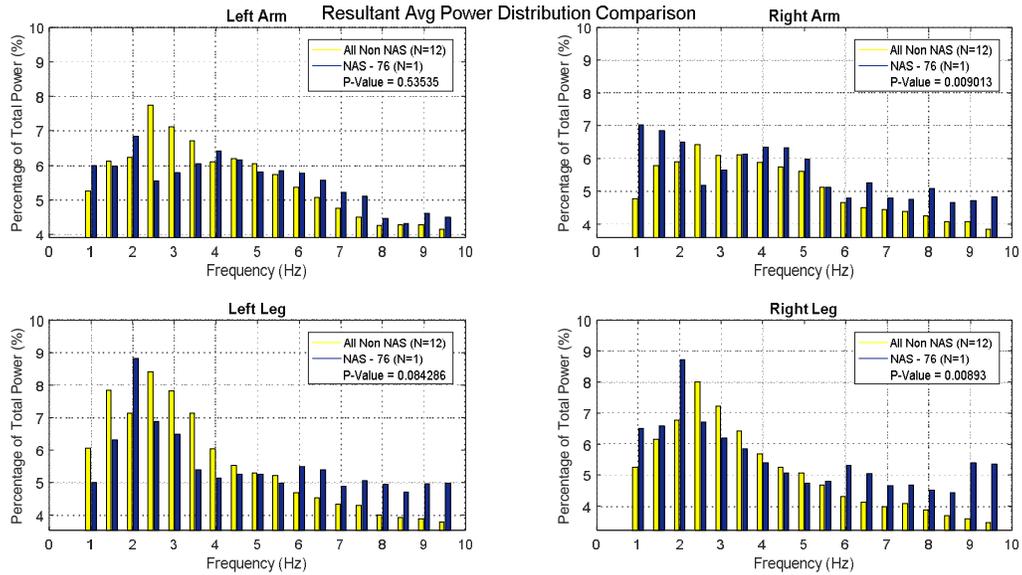


Figure 30: Comparison between non-NAS participants and NAS participant 76 indicates statistically significant difference of means for right arm and leg data.

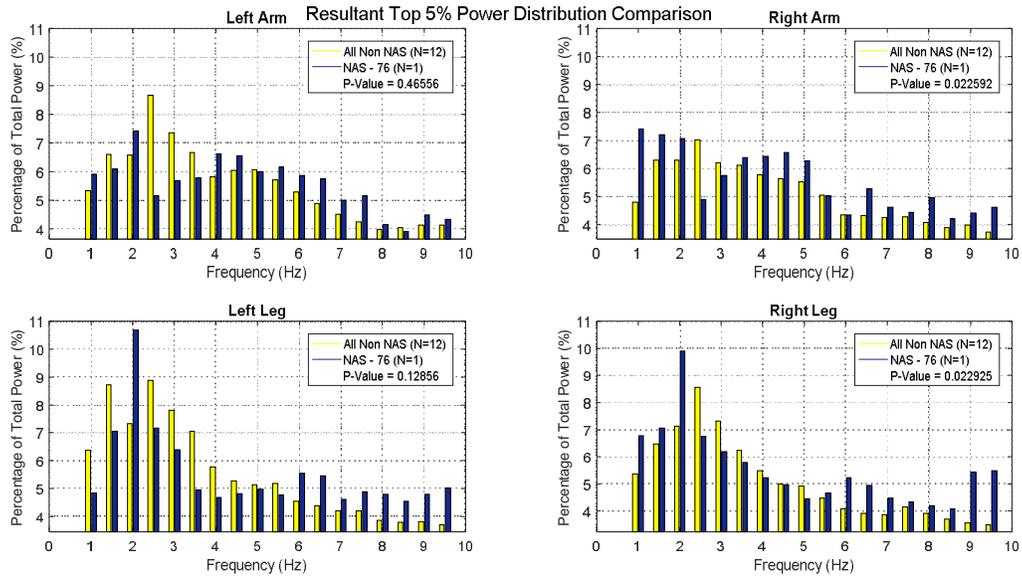


Figure 31: Non-NAS participants compared to NAS participant 76, not reported to have shown tremors, have generally overlapping trends, but display statistically significant difference in right arm and leg data.

Non-NAS participants were also compared to non-NAS participant 85, due to participant 85 displaying the presence of 5-7 Hz content. The 5-7 Hz content is visually noticeable for participant 85 and could be influencing the results of tests using an average of all non-NAS participants (Figure 32 and Figure 33). Preserving the group used in other comparisons, data for participant 85 is still included in the group of non-NAS participants used in these comparisons. Even with data for participant 85 being on both sides of these comparisons, a statistically significant difference is found for right arm and leg comparisons, four of eight plots.

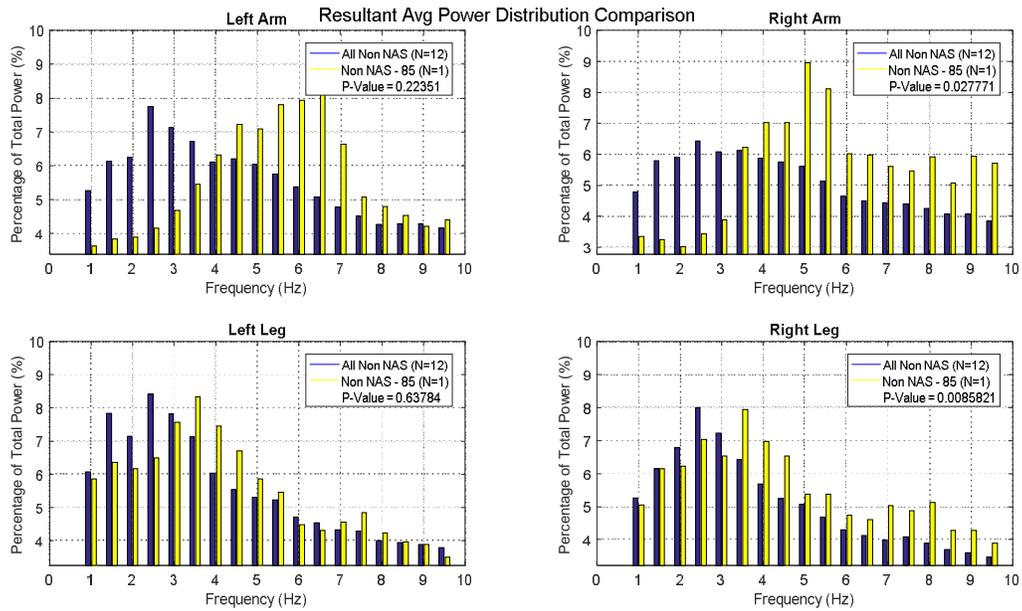


Figure 32: Statistically significant difference found for right arm and leg power distribution from comparison between non-NAS participants and non-NAS participant 85.

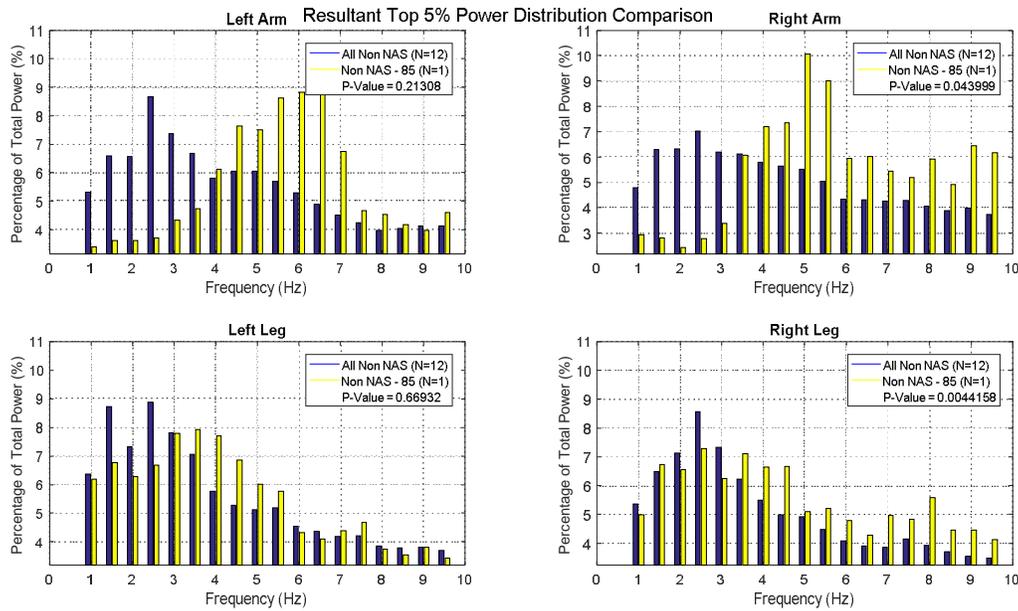


Figure 33: Comparison of non-NAS participants to non-NAS participant 85, chosen due to apparent presence of 5-7 Hz content. Statistically significant difference found for results of right arm and leg.

Chapter 5.3 - Chapter Discussion and Summary

In search of motion data indicative of tremors, a MATLAB program was developed to handle the data from our accelerometers and convert information from the time domain to the frequency domain. For each sensor, output frequency information was combined into single spectrums using two different methods and converted to displays of power distribution. The power distributions were the chosen format for making comparisons in search of results. In combination with visual analysis of results, statistical tests were run to check for significant differences between power distributions.

Results from NAS participant 74, who was known to have experienced tremors, displayed high frequency content in the range of 6-8 Hz. Various comparisons were also conducted to gather more information, such as comparing the outputs between NAS participants and non-NAS participants, which were found to be different. It was found that statistically significant differences could be found between groups when it was not visually apparent. Also, some contrasts that appeared markedly different did not show statistical significance. Another factor of note is that the method used to combine frequency spectrums for each participant did have an impact on results.

The possibility of comparing results to Finnegan scores was considered, but not completed. On the Finnegan scoring system, there are four scores that can be assigned for tremors. The lower two scores are for tremors that occur when the newborn is disturbed, and the higher two for undisturbed tremors, with the separation at each level being whether the tremor was mild or moderate-severe. With the available information, it is not possible to determine whether or not the newborn was disturbed, by sound or contact, when a tremor occurs. In terms of a tremor being mild versus moderate-severe, more data would need to be collected in a controlled manner to directly correlate data to a score. Observed tremors that were scored for participants could provide a limited number of samples, but we lack a definite way of knowing the exact portion of data covering the time scoring was completed.

Based on the results gathered, it appears that our sensor system and processing method is able to detect tremors. But, before a well-defined identification method can be developed, more data should be collected and analyzed. If interpreting tremors based on visual analysis, the numbers of accelerometers would be able to be reduced. There were multiple power distributions that appeared different when visually compared, but did not show statistical significance when tested. Since statistically significant differences were found for different limbs in different comparisons, the presently available information does not appear to be sufficient for definitively choosing if and which sensors can be removed.

Chapter 6: Audio Analysis

Chapter 6.1 – Audio Processing

Intentions/Overview

Examination of audio data was targeted toward investigating ways to distinguish the cries of NAS newborns from non-NAS newborns. Prompted by accounts of individuals able to pick out NAS newborns based on sound alone, it was inferred that unique characteristics should be present in audio recordings as well. Described as a higher pitched cry, processing of the audio data was focused on a frequency analysis of cry samples.

In addition to investigating the frequency characteristics of cries, information was sought regarding the rate of cry occurrence and length of cries. It was predicted that NAS newborns would cry longer, more often, and at a higher pitch than non-NAS control newborns. Sampling at a rate of 48 kHz allowed for frequency content up to 24 kHz to be detected, exceeding the human hearing range, which can go up to about 20 kHz. Eight hours of recording was sufficient to cover multiple cries, providing some insight into rate of cry occurrence and the length of cries. It was hoped that useful information could be gleaned from the recorded cries, even though additional information, such as cause of cry, would not be available.

Analysis Program Considerations

Mainly provided in “.mp3” format files, data from the recorder-microphone combination used was available as a single channel of audio information. Due to the size of the files and computing limitations, it was discovered that the computer used would not be able to import an entire audio file into MATLAB at once. To remain within system capabilities, importing of data was reduced to fifteen minute increments. A loop within the program would be used to increment through the entire data file, expected to be about eight hours, in fifteen minute increments.

Unable to work with an entire data file at once, a way to reduce the amount of information to be processed was needed. Recording for multiple hours continuously meant that there would likely be many stretches of time when no cries were occurring. Taken as a feasible solution, a method of reducing information to just the cry content was sought.

To begin development of way to extract cries, known cries had to be found first and investigated for identifying characteristics. At an accelerated playback speed, two audio files were listened to, one from a NAS participant, and the other from a non-NAS participant. Files were listened to in search of cries, and when heard, an approximate start and end time was recorded. Manually applying a discrete Fourier transform, the chosen samples were converted to the frequency domain and visually analyzed to search for unique characteristics. Frequency information from other non-cry sounds was also used in contrast, to help in selecting characteristics of cry spectrums that were not shared with other sounds.

Using this method, an estimated threshold was selected to separate cries from non-cries in the frequency domain. Frequency spectrums containing content at 6.5 kHz or higher, at a minimum magnitude of 0.0005, would be considered to likely contain a cry. As the thresholds were estimated, testing was conducted using variations in values to reach a reasonable balance between selecting too many audio and too few audio snippets.

Analysis Program

Processing of the audio data in MATLAB was achieved using a series of programs, rather than a single process. These separations are due to new components being added later in time, and to give the user more control over handling of data. Processing one second audio snippets at a time, the initial program was used to convert data from the time to frequency domain and select which audio snippets were expected to contain cries. Applying the chosen thresholds to frequency information, some snippets were kept for processing. For the chosen snippets, the information preserved was raw time data, frequency spectrum information, and which second within the recording it was. Figures generated at this step often included some audio snippets that did not actually contain a cry (Figure 34 and Figure 35).

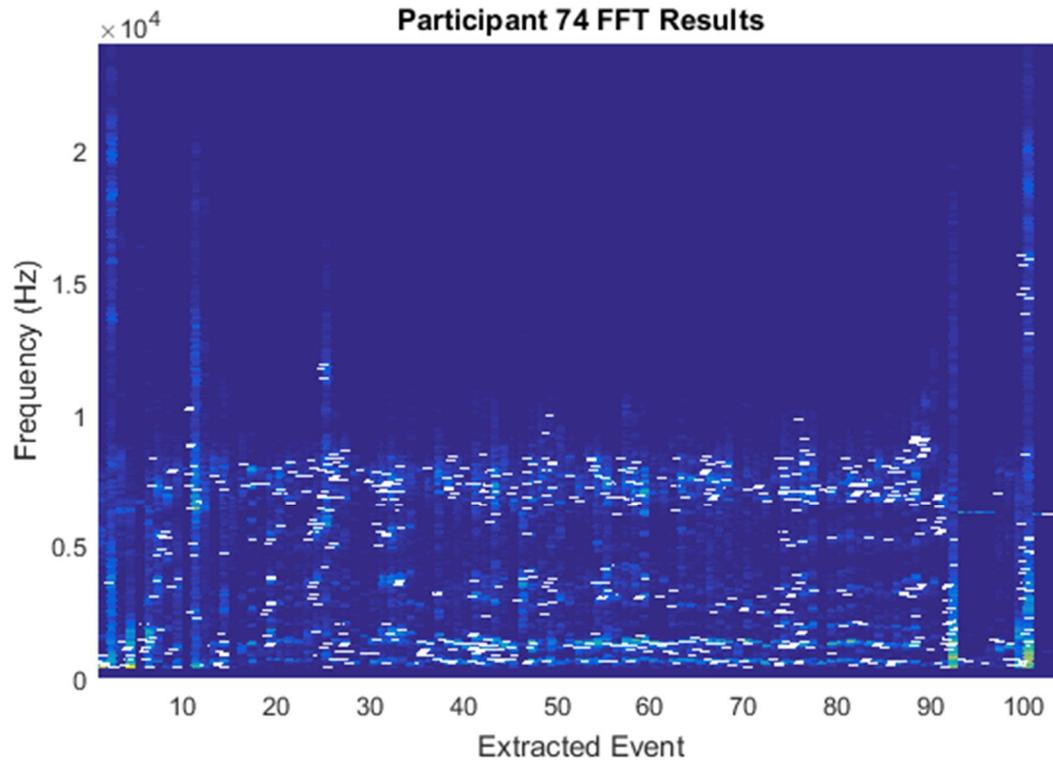


Figure 34: Sample series of frequency spectrums for audio snippets chosen by the program, expected to contain cry information. In this example, roughly 100 one second audio snippets were expected to contain cry information.

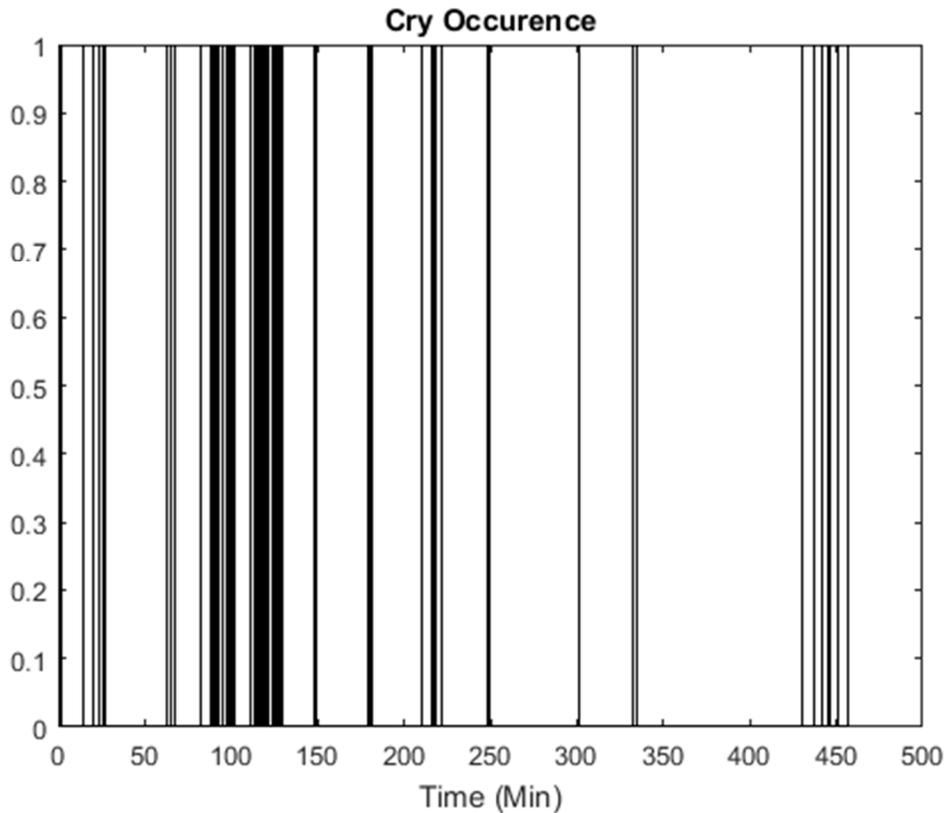


Figure 35: Graphic depicting the timing of audio snippets expected to contain cry information, as chosen by the program using input thresholds.

Knowing the selected audio snippets would likely contain false positives, a separate program was used to manually filter the data. Within this step, a user would play through the previously selected audio snippets and select which, if any, were not cries. Some of the non-cry sounds heard included things like cans opening, phones ringing, or machines beeping. Time and frequency information for the maintained cry snippets would be used to create updated data plots, and kept for further analysis (Figure 36). The multiple frequency spectrums from the cry samples were also combined into representative spectrums, using two methods (Figure 37). For each spectral line in the frequency spectrum, one method took the median of values seen, while the other selected the maximum magnitude.

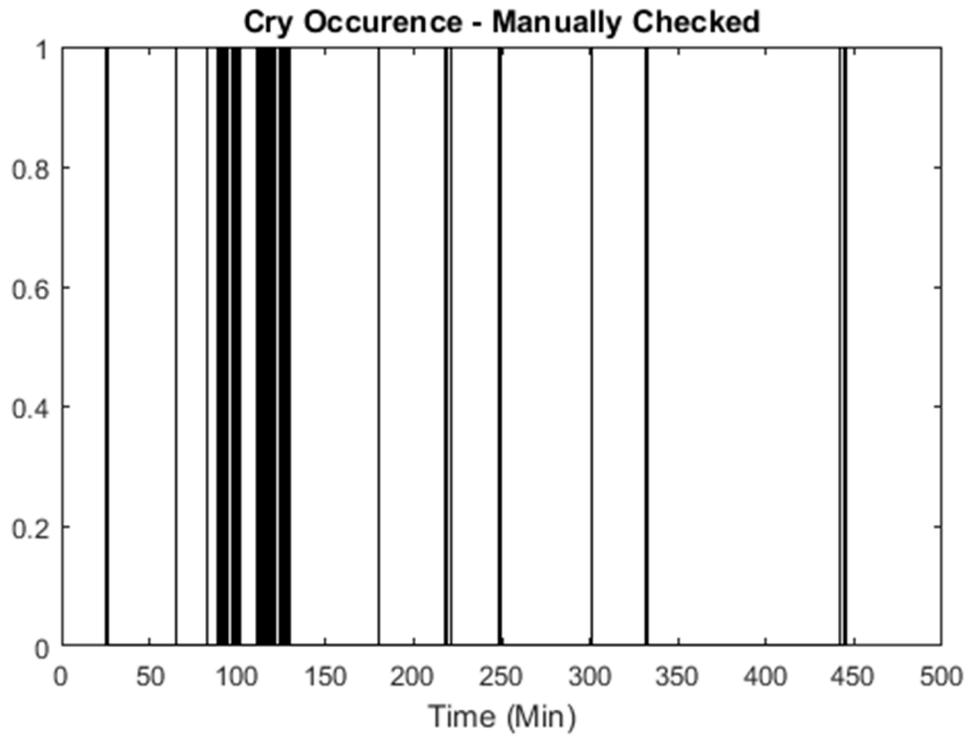


Figure 36: A sample of an updated graphic depicting the location of cry events. The reduction in lines relative to the marker plot above is due to non-cry events being removed.

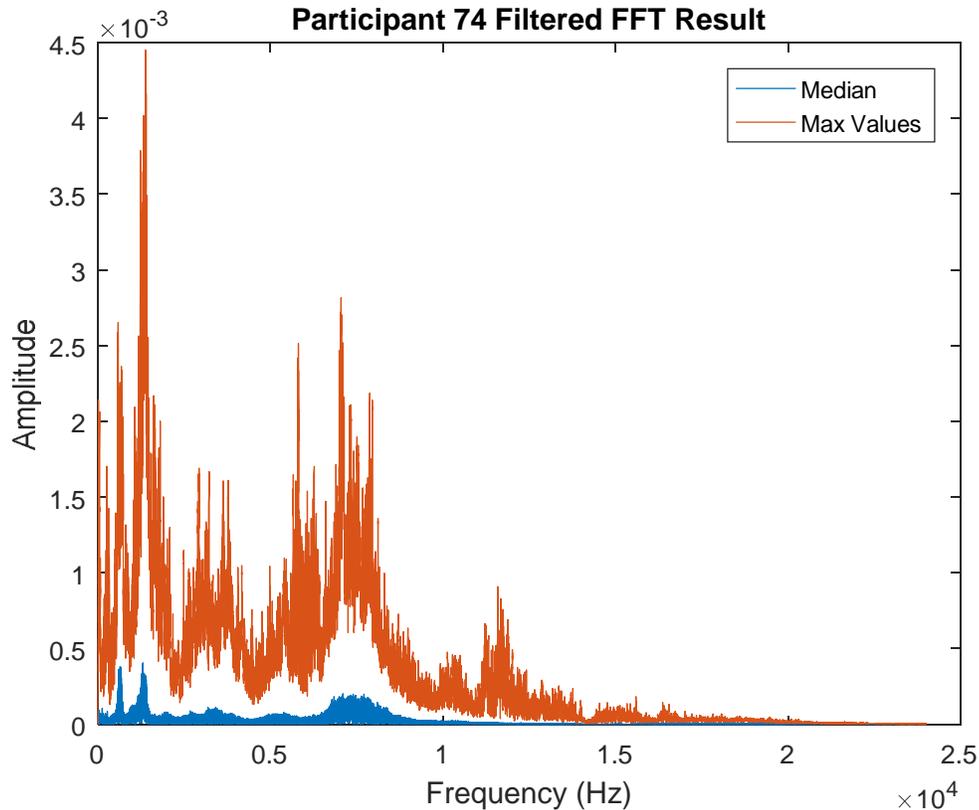


Figure 37: Visual display of the two methods used to combine frequency spectrums into single representative spectrums. For each spectral line, one method uses the median of all values seen at that spectral line over time, while the other method retains the maximum value found.

Counting of cries was completed using the stored time values, indicating which second in the recording a snippet took place. The thresholding method used to extract cries does not pick out the inhales while a newborn is crying, so gaps are expected to be present between snippets containing cries for a single period of crying. To bridge these gaps, snippets were considered to be part of a continuous cry if they occurred within five seconds of each other. This condition was applied when counting the number of cries and when determining how long a cry lasted.

For comparison of frequency content, one method attempted made use of power distributions. The representative frequency spectrums, generated using median or maximum values, were converted to power distributions for each participant. Working with audio data, the range of frequencies was separated into one-third octave bands. The spacing of full octave bands allows for a doubling of the center frequency when progressing from one band to the next, but one-third octave bands were used for greater resolution. Octave bands are used with audio data because human hearing is sensitive to the doubling of a frequency. Comparisons made using this

method were possible, but did not display a clear visual difference (Figure 38 and Figure 39). Several plots were visually analyzed, but trends were not found that could be used to distinguish NAS participants from the non-NAS control participants.

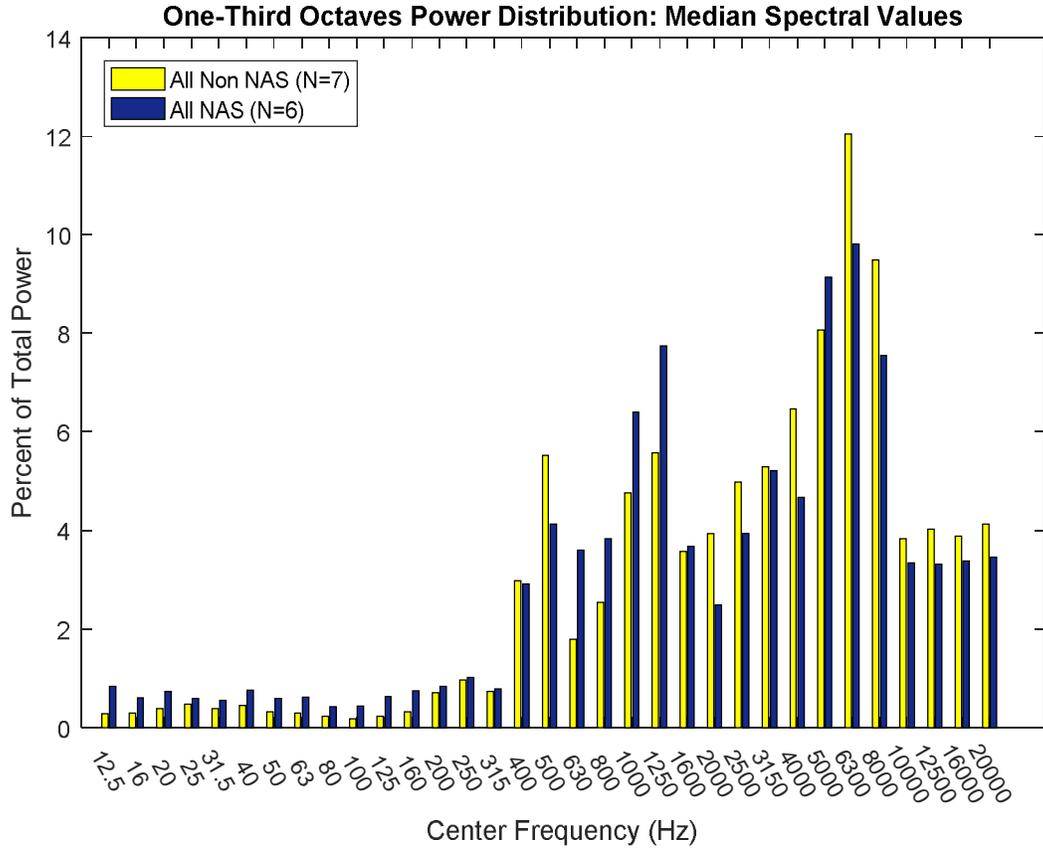


Figure 38: Sample power distribution comparison using one-third octave spacing. The frequency spectrums for each participant were summarized by using the median value for each spectral line. Comparison of available NAS participants to non-NAS participants does not show a marked visual difference.

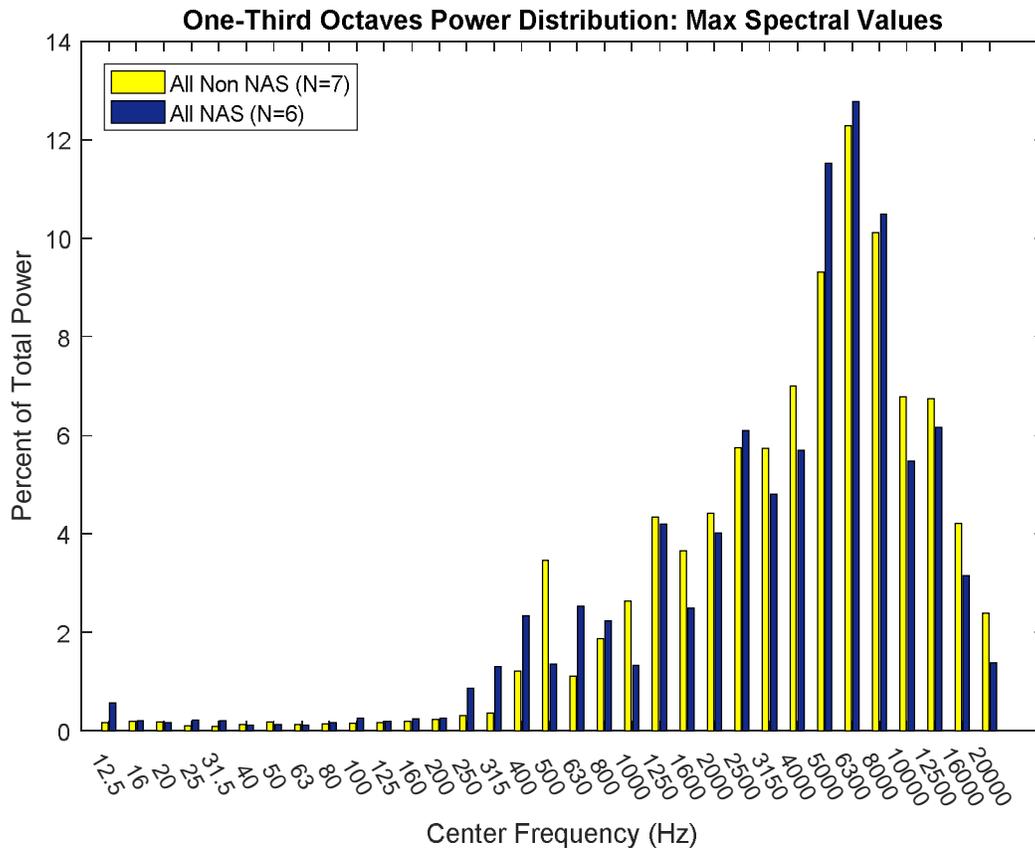


Figure 39: Sample power distribution comparison using one-third octave spacing. The frequency spectrums for each participant were summarized by using the maximum value for each spectral line. Comparison of available NAS participants to non-NAS participants does not shown a marked visual difference.

Comparing the fundamental frequency found within cry samples was the second comparison method attempted. Values found during literature searches indicated that the control newborns should exhibit fundamental frequencies in the range of 400-500 Hz. Based on this information; the search for fundamental frequencies was limited to the range of 100-900 Hz. Within this range, the frequency value having the highest magnitude would be taken to be the fundamental frequency (Figure 40). Individual cry snippets would be used for this method, instead of a combined representative spectrum, in order to increase the number of data points available.

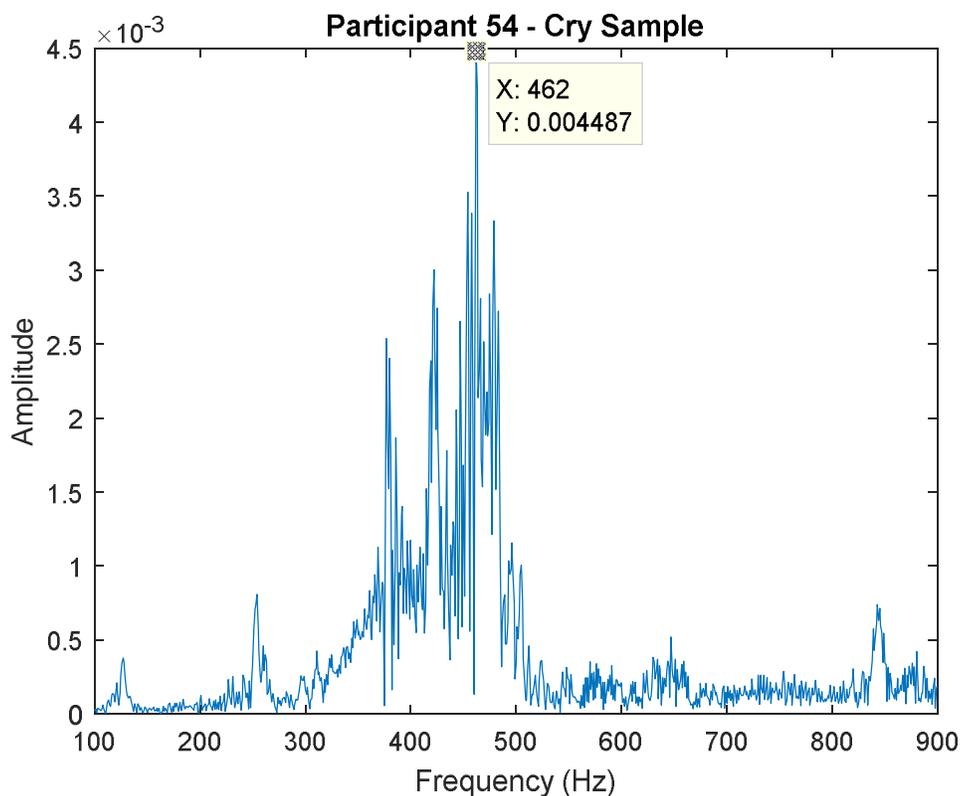


Figure 40: The frequency having the highest magnitude, in the range of 100 to 900 Hz, was taken to be the fundamental frequency for the cry sample.

Chapter 6.2 – Audio Results

Even though information was sought regarding length of cries, rate of cry occurrence, and pitch of cry, results will not be reported for length of cries. Using the previously mentioned methods, data regarding duration of cry was able to be gathered, but the validity of those values is called into question due to the known existence of false negatives. The cry extraction threshold was set to values that would reduce the number of wrongly selected snippets, which also caused some snippets containing cries to be missed. As the current method is not robust enough to capture entire cries at their true length, cry duration values found could be misleading. But, while the duration of cries will not be reported, information about the rate of cry occurrence will be. Even though every snippet containing cry was not extracted, an approximation of the number of cry events can be obtained. Bridging gaps of less than five seconds should serve to improve accuracy, and reduce overestimating the number of cries.

Counting of cry events was completed for a group of NAS and non-NAS participants, results of which are summarized in Table 4 and Table 5. Instead of being interesting in the total

number of cries found, the focus was shifted to cries per hour as a representative value. Variations in recording length prompted the change, with the shortest file being about 30 minutes in length and the longest being nearly ten hours long. Using the results of a 2-sample t-test, the available data does not indicate a difference in cries per hour between the two groups (Figure 41). Results from the data indicate an average of about six cries per hour for both NAS and non-NAS participants. Due to the small sample size and uncontrolled recording environment, these results should not be generalized as applicable to all newborns unless more data is collected and analyzed.

Table 4: Cry count results from recordings of NAS participants.

Status	NAS	NAS	NAS	NAS	NAS	NAS	NAS	NAS
Record length	6:38:26	8:34:15	9:49:59	7:56:59	7:52:34	8:20:37	8:29	8:13:21
# of hours	6.64	8.57	9.83	7.95	7.88	8.34	8.49	8.22
# of Cries	22	13	50	53	68	96	43	54
Cries per hour	3.31	1.52	5.08	6.67	8.63	11.51	5.06	6.57

Table 5: Cry count results from recordings of non-NAS participants. One value of note, 24.84 cries per hour, appears to be notably larger than the others.

Status	Non-NAS								
Record length	8:12:33	8:09:23	0:36:14	6:58:53	8:01:23	7:37:56	8:23:14	8:28:24	7:58:18
# of hours	8.21	8.16	0.60	6.98	8.02	7.63	8.39	8.47	7.97
# of Cries	33	35	15	16	16	43	36	10	44
Cries per hour	4.02	4.29	24.84	2.29	1.99	5.63	4.29	1.18	5.52

```

Two-sample T for C4 vs C5

      N   Mean   StDev   SE Mean
C4    8    6.04    3.10     1.1
C5    9    6.01    7.23     2.4

Difference =  $\mu$  (C4) -  $\mu$  (C5)
Estimate for difference: 0.04
95% CI for difference: (-5.79, 5.86)
T-Test of difference = 0 (vs  $\neq$ ): T-Value = 0.01  P-Value = 0.989  DF = 11

```

Figure 41: Portion of Minitab output providing output of statistical test on cry count results.

Comparing pitch of cry was completed with a focus on the fundamental frequency of the cry. Use of power distributions separated into one-third octave bands was attempted, but outputs generated did not appear as though they would be useful for drawing conclusions. Switching to an exploration of fundamental frequencies, the search was guided by existing literature indicating an expected frequency of 400-500 Hz for the control participants. Using manually filtered audio snippets known to contain cries, fundamental frequencies were chosen from frequency spectrums by finding the peak magnitude between 100 and 900 Hz. Each one second snippet was treated as a separate sample, and histograms were created to display differences between groups. The first of two comparisons completed compared results from NAS participants to non-NAS participants. The second comparison used a smaller sample size, using non-NAS participants and NAS participants who were scored for cry on a Finnegan sheet.

Starting with the full available population of cry samples from NAS participants, a histogram was created to visually compare to the non-NAS participants (Figure 42). From the image, it can be inferred that the NAS population displays a higher mean frequency and higher variance. Appearing to agree with expectations, a statistical comparison was used to confirm a difference of means (Figure 43 and Figure 44). The mean frequency for NAS participants was found to be 562.4 Hz ($s = 154.3$ Hz), and the mean for non-NAS participants was found to be 507.4 Hz ($s=145.5$ Hz). With an approximate difference of 55 Hz, the difference between the two groups is found to be statistically significant.

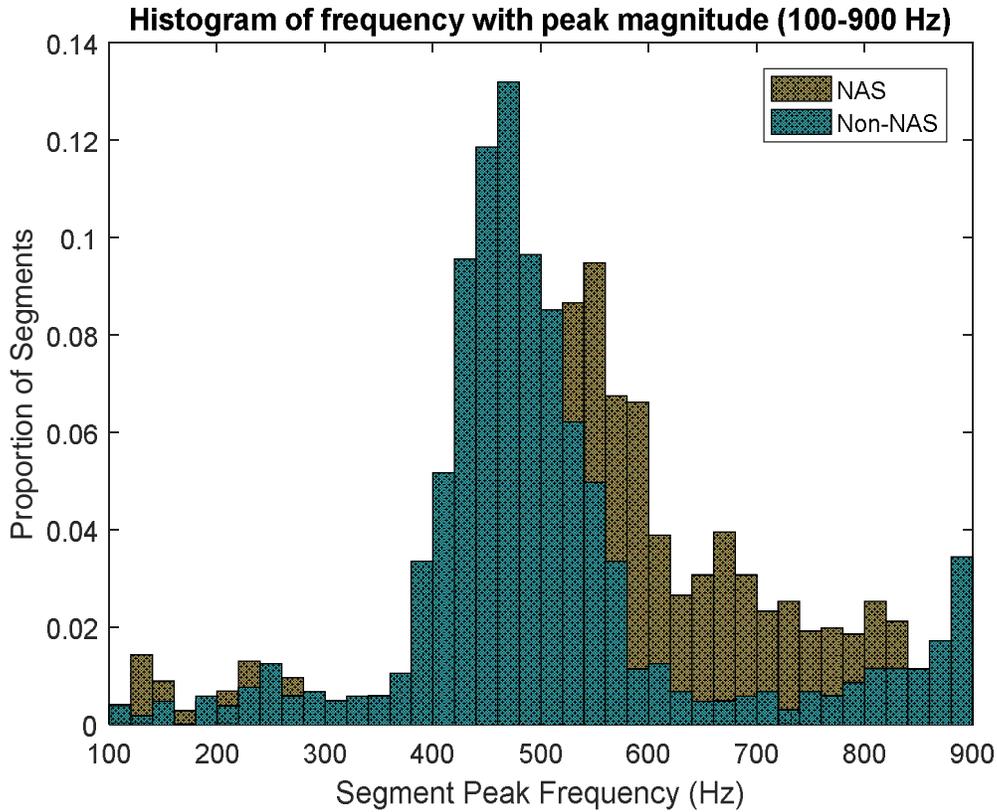


Figure 42: Histogram of peak frequencies found in the range from 100 to 900 Hz for cry samples from NAS participants and non-NAS participants. Based on the distributions of values, NAS participants appear to exhibit a higher mean fundamental frequency, along with greater variability in the fundamental frequency of their cries.

Two-Sample T-Test and CI: Freq_NAS, Freq_Non_NAS

Two-sample T for Freq_NAS vs Freq_Non_NAS

	N	Mean	StDev	SE Mean
Freq_NAS	1466	562	154	4.0
Freq_Non_NAS	1046	507	145	4.5

Difference = μ (Freq_NAS) - μ (Freq_Non_NAS)

Estimate for difference: 54.99

95% CI for difference: (43.14, 66.83)

T-Test of difference = 0 (vs \neq): T-Value = 9.10 P-Value = 0.000 DF = 2326

Figure 43: Summary of a two-sample t-test comparing the mean fundamental frequency values found for NAS and non-NAS participants. Test results indicate that the difference is statistically significant and approximately 55 Hz.

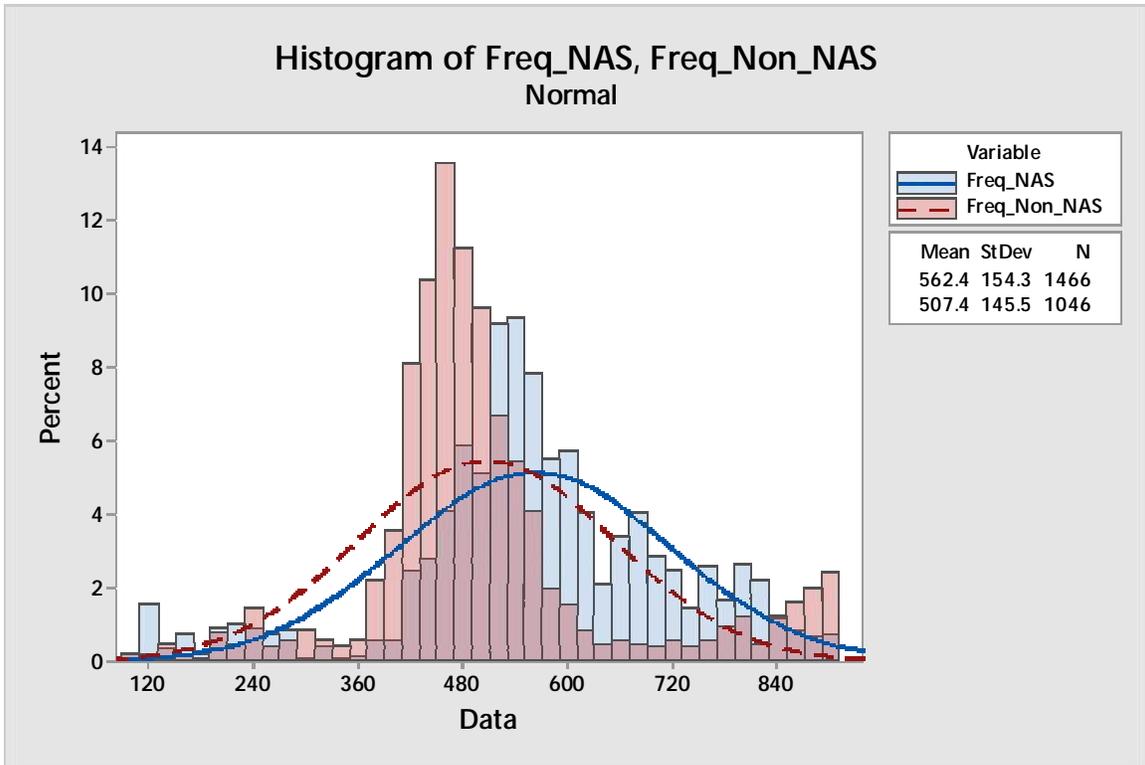


Figure 44: Alternative histogram display for the comparison between NAS participants and non-NAS participants with overlaid normal distributions.

A second comparison was completed to account for the possibility that results for NAS participants could have been impacted by data from participants that did not exhibit the characteristic cry. The current histogram, Figure 45, still indicates a higher mean frequency for the NAS participants, but it appears that the variability has decreased. Having a mean frequency of 576 Hz ($s=114$), the group of NAS participants with Finnegan scored cries was found to have a higher mean and lower variability than the full group of NAS participants. With an approximate difference of 68.5 Hz, the difference between the mean values of these groups is statistically significant (Figure 46 and Figure 47).

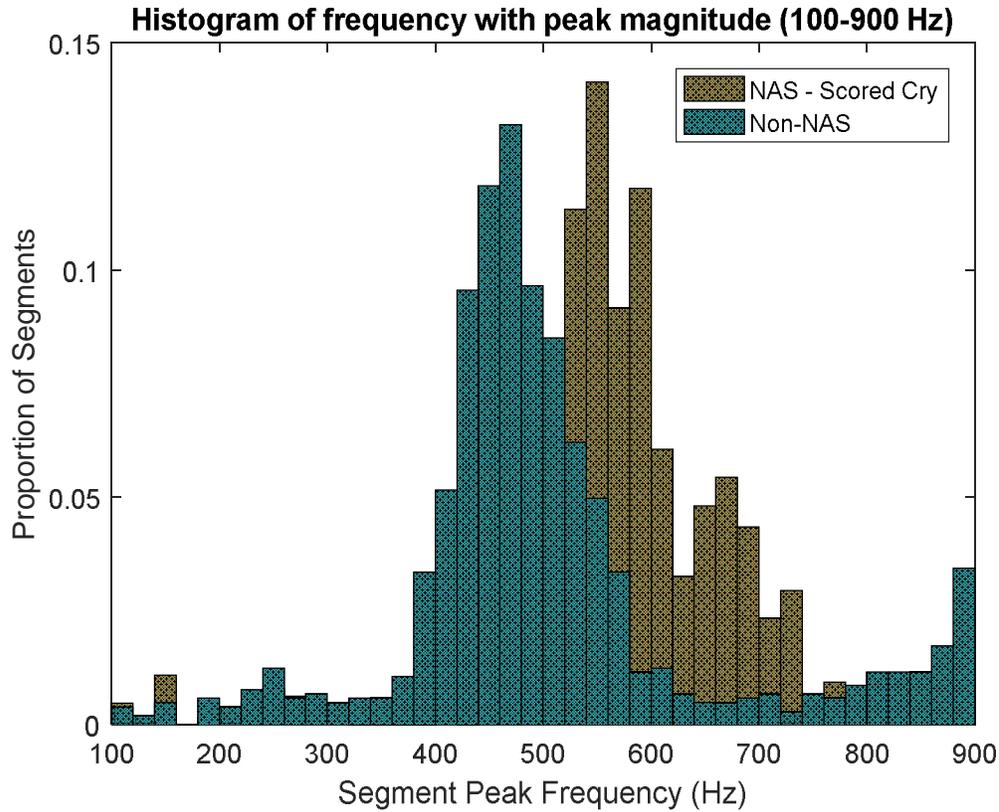


Figure 45: Histogram of peak frequencies found in the range from 100 to 900 Hz for cry samples from NAS participants scored with symptomatic cries and non-NAS participants.

Two-Sample T-Test and CI: Freq_Finn_NAS, Freq_Non_NAS

Two-sample T for Freq_Finn_NAS vs Freq_Non_NAS

	N	Mean	StDev	SE Mean
Freq_Finn_NAS	644	576	114	4.5
Freq_Non_NAS	1046	507	145	4.5

Difference = μ (Freq_Finn_NAS) - μ (Freq_Non_NAS)

Estimate for difference: 68.50

95% CI for difference: (56.02, 80.97)

T-Test of difference = 0 (vs \neq): T-Value = 10.77 P-Value = 0.000 DF = 1593

Figure 46: Two-sample t-test results indicating a statistically significant difference of means between the reduced set of NAS participants and non-NAS participants.

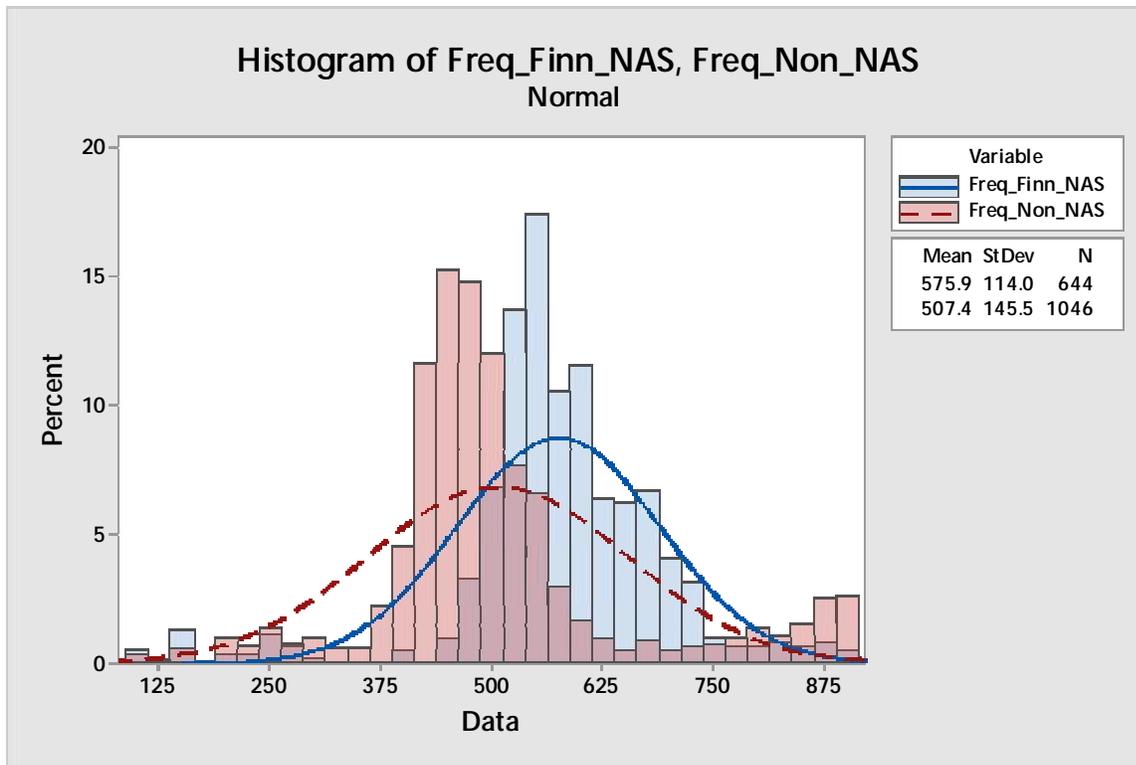


Figure 47: Secondary histogram display of comparisons between reduced set of NAS participants and non-NAS participants, with approximate distributions overlaid.

Chapter 6.3 - Chapter Discussion and Summary

Handling of audio data was completed using a MATLAB program created to process the data in search of information about length of cries, rate of cry occurrence and the pitch of cries. Results on cry duration have not been reported due to lack of an accurate way to determine cry length. With the available data indicating about 6 cries per hour, the rate of cry occurrence was found to be similar for NAS participants and non-NAS participants tested. Pitch comparisons involved three groups, non-NAS participants, NAS participants, and NAS participants that were scored as exhibiting symptomatic cries. From the comparisons made, both sets of NAS participants were found to exhibit cries having a statistically significant difference in fundamental frequency when compared to non-NAS participants. Evaluated cries were found to have a mean fundamental frequency of 507.4 Hz ($s=145.5$ Hz) for non-NAS participants, 562.4 Hz ($s = 154.3$ Hz) for NAS participants, and 576 Hz ($s=114$) for the reduced set of NAS participants (Figure 48). Lacking results on cry duration, and with rates of cry occurrence being similar for both groups, the data available solely confirms expectations of higher pitched cries among NAS newborns.

Descriptive Statistics: Freq_NAS, Freq_Finn_NAS, Freq_Non_NAS

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Freq_NAS	1466	0	562.41	4.03	154.33	104.00	492.00	553.50	659.00	900.00
Freq_Finn_NAS	644	822	575.92	4.49	114.04	104.00	527.25	569.00	631.75	898.00
Freq_Non_NAS	1046	420	507.42	4.50	145.49	101.00	436.75	477.00	538.00	900.00

Figure 48: Summary statistics for fundamental frequency analysis of non-NAS participants, NAS participants, and NAS participants scored with cries. Both groups of NAS participants were found to have mean fundamental frequencies that differed statistically from the non-NAS participants.

Using the results gathered, it appears that fundamental frequency of cry can be a way to distinguish between the cries of NAS and non-NAS newborns. To gain more information on differences in duration and occurrence rate of cry, additional data should be collected in a more controlled manner. The observational aspect of the current study allowed for the possibility of cry information gathered to be impacted by multiple unknown factors, such as response time of caregivers. Other factors, such as the cause of a cry, would likely influence the intensity of the cry event and how easily the newborn can be calmed, directly impacting duration of cry. In combination with collecting more data, another analysis method would be needed, capable tracking cry events with improved accuracy. The use of such resources should be used for a large study, capable of providing enough data to make general inferences about NAS newborns as a whole.

Chapter 7: Summary

Chapter 7.1 - Motion

Approach

The sensors used to track motion for this project were 3-axis MSR 145 accelerometers, set to record accelerations in a +/- 2 g range, at a sampling rate of 20 Hz. Provided with dedicated software, the accelerometers were assigned start and stop times at the beginning of each study trial. With each study trial intended to be eight hours in length, the wireless accelerometers needed to be comfortably worn by the newborns taking part in the study. For this application, bands were designed to fit the needs of the study population, while also being compatible with the hardware selected for use.

Accelerometers were worn on each limb and the chest for the study trials completed. The sensor worn on the chest was intended to gather information that could be used to determine respiratory rate, but this endeavor was unsuccessful. Worn on each limb, the other four sensors were meant to gather information on any tremor activity that occurred. Analysis of tremor activity was primarily achieved by converting information from the time domain to the frequency domain, allowing discovery of higher frequency content.

Results

Analysis of the accelerometer data was completed using a program in MATLAB, designed to investigate the frequency content of provided data. While the desired information was not able to be gained from the accelerometer placed on the chest, higher frequency content, indicative of tremor activity, was able to be found from the other accelerometers. Results from a NAS newborn, known to have displayed tremors during the study trial, display high frequency content, in the range of 6-8 Hz. For comparisons to be made between different data sets, the format of information was converted from frequency spectrums to power distributions in 0.5 Hz increments. Collecting results from NAS participants and non-NAS participants into separate groups, statistically significant differences were able to be found. These results, and the results from additional comparisons conducted, confirmed an ability to detect higher frequency content resulting from tremor activity.

Comparing results to Finnegan scores gathered was also investigated, but found unable to be completed. Information required to properly assign a Finnegan score for tremor activity, whether or not the newborn was disturbed when the tremor occurred, was not available. Collection of data using the methods applied could allow for a distinction to be made between mild and moderate-severe tremors, but more data would need to be available.

Chapter 7.2 - Audio

Approach

Recording of audio information was achieved through the combination of a recorder and external microphone. The chosen set-up made use of an external microphone, instead of the recorder's on-board microphones, to protect the recorder from exposure and allow for better control of sensor placement. Requiring manual starting and stopping, recording of audio was controlled by the medical personnel who carried out the data collection aspect of the research study. From the recordings gathered, we sought samples of cry to investigate the possibility of distinguishing between the cries of NAS and non-NAS newborns.

Guided by reports of individuals describing the cries of NAS newborns as high-pitched, the frequency content of cries was investigated. Due to the collection of several continuous hours of data, much of the content was not useful, due to not containing cry information. To reduce the amount of content and improve processing, a thresholding method was used to extract cry snippets from the data. As false positives were present in the extracted snippets, the snippets were double-checked by a user, keeping cries and removing other sounds.

Results

Using the manually filtered cry samples, information was desired regarding duration of cries, rate of cry occurrence and pitch of cries. With the processing method implemented, a sufficient level of accuracy was not able to be achieved, so information regarding the duration of cries was not reported. With the available data, the rate of cry occurrence was found to be about six cries per hour for both NAS participants and non-NAS participants. For the investigation into cry pitch, the fundamental frequencies found within cry samples were used to compare the groups. A statistically significant difference was found between the fundamental frequency for non-NAS participants 507.4 Hz ($s=145.5$ Hz) and NAS participants 562.4 Hz ($s = 154.3$ Hz), in agreement with expectations of higher pitch for NAS newborns. Also statistically different from

the non-NAS group, the fundamental frequency for NAS participants scored as having symptomatic cries was found to be 576 Hz (s=114).

Chapter 7.3 – Project Challenges

Recording for eight hours limits us to analyzing what happens in that time frame, leaving us blind to activity that occurs when the sensors are not running, such as tremors or additional cries. In terms of the movement data, it does appear that we have been able to identify tremor content, but we lack a way of confirming that a tremor actually occurred for all but one participant. No verification method also means that we are unable to determine if any tremors were missed during processing.

Literature also suggests that a newborn's time since birth can play a factor in the presence of withdrawal symptoms. Within this study, the time since birth for participants was recorded, but it was not able to be standardized, resulting in the shortest time since birth being about 10 hours, while the longest was approximately 65 hours. Determining an impact of age on symptom display for NAS newborns would need a greater supply of collected data to be analyzed.

One of the primary challenges to developing programs and processing the data for this project was being blind to the data collection. As the data collection was conducted by medical personnel, knowledge of notable events that occurred during data collection was limited. Timings of events such as diaper changings, feedings, or movement of the participant from one location to another were unknown, but capable of impacting the data gathered. It is unclear if knowledge of these events would have impacted results, but knowledge of external activities could have assisted in making sense of unexpected content in the motion data.

Chapter 7.4 – Recommendations

Sensor Alterations

Sensors used in this project functioned as needed and were capable of generating usable results, but some changes can be recommended for future endeavors. Even though the motions of newborns are not expected to exceed 10 Hz, a sampling rate higher than 20 Hz would be preferable. In the current application, requiring instrumentation of newborns, minimizing the size and number of sensors would also improve the design. To expand on the results gathered, use of 6-axis accelerometers instead of 3-axis accelerometers would allow for some level of motion reconstruction. Having a graphical display of motions would allow for data and represented

motions to be visualizing, helping in the analysis process, along with presentation of results. In terms of audio recordings, some way of providing more control over what is recorded would allow for a reduction in extraneous content.

Future work

Building on the data gathered as part of this project, collection of more data would improve the accuracy of results found. Focusing on the audio information, collection of more samples would allow stronger conclusions to be drawn and more controlled data would assist with processing. Controlling data samples, such as recording for a set amount of time after a newborn receives a shot, would result in shorter data files that can be processed in full and known to contain desired information. Another aspect to consider would be the possibility of differing results based on the cause of a cry. Having a known input, resulting in a cry, would improve the level of standardization between samples. In combination with, or in place of, altered data collection, a refined data processing method could also improve results. Implementation of cry extraction with improved accuracy would allow for more useful data to be extracted, along with reducing the time required for processing.

For future studies that are completed, one pursuit of interest would be development of ways to quantify additional symptoms from the Finnegan scoring sheet. Whether requiring improved sensors or additional sensors, greater Finnegan score coverage would improve the possibility of being able to map quantitative data to Finnegan scores. Looking into additional symptoms can likely be done in parallel with gathering information on tremor occurrence and cry characteristics, serving to collect new information while also double-checking the results on this project.

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Appendix A – MATLAB Program: Motion

```
%Collection of programs used to process motion data from MSR acclerometers
clc; clear;

d=input ('Input number of file to start at: ');
path='D:\1 NAS Data\CSV Data'; addpath(path); %Adds path to
what matlab can access
filenames=dir([path '\*.csv']); filecount = length(filenames(:,1)); %Find and count
chosen file type

while d < (filecount+1)
    file=filenames(d).name; fprintf(file); %Display file name
    for user
        Resp=input(' Do you wish to analyze this data file? Please input y or n: ','s');

        close all; tic;
        D1 =[]; D2 =[]; D3 =[]; %Initializing
        matricies
        if(Resp=='y');
            [Datainfile,words]=xlsread(filenames(d).name); %Read data from
            file, to access text
            xcols=find(strcmp(words(19,:), 'ACC x')); %Find X axis columns
            for each sensor
                clear Datainfile; %Clear variable to
            save space
            numdata=importdata(file, ',', 38); DataIN=numdata.data; %Import numerical
            set without time column
            tt=transpose(1:length(DataIN(:,1))); DataIN=[tt, DataIN]; %Add counting column
            hold place of time

            h(1)=figure('units','normalized','outerposition',[0 .05 1 .95]); hold on;
            %Figure set-up
            suptitle([file(1:end-4) ' - Resultant Power Dist.']);
            Pwrdata=zeros(18,8); %Reset/preallocate
            matrix for saving data

            for i=1:(length(xcols));
                col=xcols(i);
                ind1=isnan(DataIN(:,col)); %Find blank
            rows in x data array
                D1 = DataIN(:,[1 col]); D1(ind1,:)=[]; %New x data
            matrix without zeros
                D1(:,1)=transpose((1/1200):(1/1200):(length(D1(:,1))/1200)); %Time
            counting from zero (minutes)
                ind2=isnan(DataIN(:,col+1)); %Find blank
            rows in y data array
                D2 = DataIN(:,[1 col+1]); D2(ind2,:)=[]; %New y data
            matrix without zeros
                D2(:,1)=transpose((1/1200):(1/1200):(length(D2(:,1))/1200)); %Time
            counting from zero (minutes)
                ind3=isnan(DataIN(:,col+2)); %Find blank
            rows in z data array
                D3 = DataIN(:,[1 col+2]); D3(ind3,:)=[]; %New z data
            matrix without zeros
                D3(:,1)=transpose((1/1200):(1/1200):(length(D3(:,1))/1200)); %Time
            counting from zero (minutes)
        end
    end
end
```

```

        node1=words(11,col); axis1=words(19,col);           %Finding body location
and axis for data column
        node2=words(11,col+1); axis2=words(19,col+1);
        node3=words(11,col+2); axis3=words(19,col+2);

        fprintf('Processing %s Data \n',node1{1});         %Notify which
limb/chest is being processed
        Resp2=input('Do you wish to FFT this sensors data? Please input y or n:
','s');

        if(Resp2=='y');
            if ~strcmp(node1,'Chest');
                N=1200; M=1200;                             %Set values for FFT, 1
min with 0% overlap
                P=12000;                                     %Variable to track
block start point, start 10 mins in
                h1=length(D1(:,1)); h2=length(D2(:,1)); h3=length(D3(:,1));
%Determine lengths of data sets

                FFTrmat=zeros(N,floor(h3/N)); b=1;          %Initializing variables
                Pwrr = zeros(floor(h3/N),18); Fs = 20;

                while P+N<h1 && P+N<h2 && P+N<h3           %Loop to separate
columns into blocks
                    x=D1(P:P+N-1,2);                       %Extract block of data
                    y=D2(P:P+N-1,2);                       %Extract block of data
                    z=D3(P:P+N-1,2);                       %Extract block of data

                    r = sqrt(x.^2 + y.^2 + z.^2);          %Form resultant
                    r=r-mean(r);                            %Zero mean block of
time data

                    FFTr=(2/N)*fft(r); FFTrmat(:,b)= FFTr; %FFT block of data in Z
column and build matrix

                    for ab=2:1:19;                         %Find signal power in
half Hz increments
                        Pwrr(b,(ab-1))= bandpower(r,Fs,[(ab/2) (ab/2)+.5]);
                    end
                    P=P+M; b=b+1;
                end
                FFTrmat(1:60,:) = 0;                       %Removes data up to 1
Hz

                if strcmp(node1,'Left Arm');               %Set plot location
                    spot = 1;
                else if strcmp(node1,'Right Arm');
                    spot = 2;
                else if strcmp(node1,'Left Leg');
                    spot = 3;
                else if strcmp(node1,'Right Leg');
                    spot = 4;
                end;
            end;
        end;

        %Plot, Power Ratio
        subplot(2,2,spot); xaxis = linspace(1,9.5,18);

```

```

a=(sort(Pwrr,'descend')); maxish = mean(a(1:24,:)); %Avg
of top 5% of values

Pwrrdist=[(mean(Pwrr))/sum(mean(Pwrr)); (maxish)/sum(maxish)];
Pwrrdist=transpose(100.*Pwrrdist); bar(xaxis, Pwrrdist); %Bar
plot of power distribution
title(node1); xlabel('Frequency (Hz)'); ylabel('Percentage of
Total Power (%)');
xlim([0 10]); legend('Full Avg.','Top 5% Avg. '); ylim([0 30]);

%Storing plotted data, organized by limb
Pwrdata(:,(spot*2 - 1):spot*2) = Pwrrdist; %Data order(Avg,5%):
LA, RA, LL, RL

Ready=input('Press enter when ready to continue','s');
end
end
end

%Save File
cd('D:\1 NAS Data\CSV Data\Output Figures'); %Switch to location where files
will be saved
figname = strcat(filenamees(d).name(1:end-4),'_ResPwrDist');
savefig(h(1),figname); %Saves the current figure to a FIG-file named
filename.fig.

%Save data file for pwr dist results
resfile = strcat(filenamees(d).name(1:end-4),'_ResPwrDataFile.mat');
save(resfile,'Pwrdata'); %Saves resultant power dist data to file

cd('C:\Users\Dexter\Documents\2014-2016 PMDI\NAS\Data Notes'); %Return to
folder of main code
end
d=d+1; toc;
end

%%
close all; clear; clc;
%Used for comparison of files separated into SetA and SetB folders
%Separate .mat files into different folders based on comparison groups
%Output plots must be manually saved

%SetA - Folder of selected data files
patha='D:\1 NAS Data\CSV Data\Output Figures\SetA'; addpath(patha); %Adds path to
what matlab can see
filenameesa=dir([patha '*mat']); filecounta = length(filenameesa(:,1)); %Find and
count chosen file type

LAa=[]; RAa=[]; LLa=[]; RLa=[];
for a=1:1:filecounta %Loop through each file in folder and gather values
filea=filenameesa(a).name; load(filea);
LAacomb= [Pwrdata(:,1);Pwrdata(:,2)]; LAa=[LAa LAacomb]; %Rows: Avg 1-
18, 5% 19-36
RAacomb= [Pwrdata(:,3);Pwrdata(:,4)]; RAa=[RAa RAacomb]; %Rows: Avg 1-
18, 5% 19-36
LLacomb= [Pwrdata(:,5);Pwrdata(:,6)]; LLa=[LLa LLacomb]; %Rows: Avg 1-
18, 5% 19-36
RLacomb= [Pwrdata(:,7);Pwrdata(:,8)]; RLa=[RLa RLacomb]; %Rows: Avg 1-
18, 5% 19-36

```

```

end
%Averaging values for the included data files
LAaAvg = mean(LAa,2); RAaAvg = mean(RAa,2); LLaAvg = mean(LLa,2); RLaAvg =
mean(RLa,2);
armAvga = mean([LAaAvg RAaAvg],2); legAvga = mean([LLaAvg RLaAvg],2); allAvga =
mean([armAvga legAvga],2);

%SetB - Folder of selected data files
pathb='D:\1 NAS Data\CSV Data\Output Figures\SetB'; addpath(pathb); %Adds path to
what matlab can see
filenamesb=dir([pathb '\*.mat']); filecountb = length(filenamesb(:,1)); %Find and
count chosen file type

LAB=[]; RAB=[]; LLb=[]; RLb=[];
for b=1:1:filecountb %Loop through each file in folder and gather values
    fileb=filenamesb(b).name; load(fileb);
    LABcomb= [Pwrdata(:,1);Pwrdata(:,2)]; LAB=[LAB LABcomb]; %Rows: Avg 1-
18, 5% 19-36
    RABcomb= [Pwrdata(:,3);Pwrdata(:,4)]; RAB=[RAB RABcomb]; %Rows: Avg 1-
18, 5% 19-36
    LLbcomb= [Pwrdata(:,5);Pwrdata(:,6)]; LLb=[LLb LLbcomb]; %Rows: Avg 1-
18, 5% 19-36
    RLbcomb= [Pwrdata(:,7);Pwrdata(:,8)]; RLb=[RLb RLbcomb]; %Rows: Avg 1-
18, 5% 19-36
end
%Averaging values for the included data files
LABAvg = mean(LAB,2); RABAvg = mean(RAB,2); LLbAvg = mean(LLb,2); RLbAvg =
mean(RLb,2);
armAvgb = mean([LABAvg RABAvg],2); legAvgb = mean([LLbAvg RLbAvg],2); allAvgb =
mean([armAvgb legAvgb],2);

%Comparison - Graphical comparisons of combined results

%Results from averaging data

h(1)=figure('units','normalized','outerposition',[0 .05 1 .95]); xaxis =
linspace(1,9.5,18);
suptitle('Resultant Avg Power Distribution Comparison');

subplot(2,2,1);
PwrdistLA=[LAaAvg(1:18) LABAvg(1:18)]; bar(xaxis, PwrdistLA); %Bar plot of power
distribution
title('Left Arm'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([LAaAvg(1:18); LABAvg(1:18)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(LAaAvg(1:18)-
dcoeff)),(transpose(xaxis).*(LABAvg(1:18)-dcoeff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')'],['Non NAS - 83 (N=' num2str(b) ')'],['P-Value
= ' num2str(aap)']);
clear aah aap aaci aastats dcoeff

subplot(2,2,2);
PwrdistRA=[RAaAvg(1:18) RABAvg(1:18)]; bar(xaxis, PwrdistRA); %Bar plot of power
distribution
title('Right Arm'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([RAaAvg(1:18); RABAvg(1:18)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;

```

```

%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(RAaAvg(1:18)-
dcoff)),(transpose(xaxis).*(RAbAvg(1:18)-dcoff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')],['Non NAS - 83 (N=' num2str(b) ')],['P-Value
= ' num2str(aap)]);
clear aah aap aaci aastats dcoff

subplot(2,2,3);
PwrdistLL=[LLaAvg(1:18) LLbAvg(1:18)]; bar(xaxis, PwrdistLL); %Bar plot of power
distribution
title('Left Leg'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoff=min([LLaAvg(1:18); LLbAvg(1:18)])-.25;
xlim([0 10]); ylim([dcoff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(LLaAvg(1:18)-
dcoff)),(transpose(xaxis).*(LLbAvg(1:18)-dcoff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')],['Non NAS - 83 (N=' num2str(b) ')],['P-Value
= ' num2str(aap)]);
clear aah aap aaci aastats dcoff

subplot(2,2,4);
PwrdistRL=[RLaAvg(1:18) RLbAvg(1:18)]; bar(xaxis, PwrdistRL); %Bar plot of power
distribution
title('Right Leg'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoff=min([RLaAvg(1:18); RLbAvg(1:18)])-.25;
xlim([0 10]); ylim([dcoff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(RLaAvg(1:18)-
dcoff)),(transpose(xaxis).*(RLbAvg(1:18)-dcoff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')],['Non NAS - 83 (N=' num2str(b) ')],['P-Value
= ' num2str(aap)]);
clear aah aap aaci aastats dcoff

% %Combination of Limbs
% h(2)=figure(); xaxis = linspace(1,9.5,18);
%
% subplot(2,1,1); %Avg Combination of Arms
% Pwrdistarm=[armAvga(1:18) armAvgb(1:18)]; bar(xaxis, Pwrdistarm); %Bar plot of power
distribution
% title('Arms'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
% %xlim([0 10]); legend('SetA','SetB'); ylim([0 30]);
% xlim([0 10]); ylim([0 10]); grid on;
% legend(['NAS - Tremor (N=' num2str(a) ')],['NAS - No Tremor (N=' num2str(b) ')]);
%
% subplot(2,1,2); %Avg Combination of Legs
% Pwrdistleg=[legAvga(1:18) legAvgb(1:18)]; bar(xaxis, Pwrdistleg); %Bar plot of power
distribution
% title('Legs'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
% %xlim([0 10]); legend('SetA','SetB'); ylim([0 30]);
% xlim([0 10]); ylim([0 10]); grid on;
% legend(['NAS - Tremor (N=' num2str(a) ')],['NAS - No Tremor (N=' num2str(b) ')]);
% suptitle('Resultant Avg Power Distribution Comparison');
%
% figure(); %Avg Combination of all limbs
% Pwrdistall=[allAvga(1:18) allAvgb(1:18)]; bar(xaxis, Pwrdistall); %Bar plot of power
distribution
% title('Resultant Avg Power Distribution - All Limbs'); xlabel('Frequency (Hz)');
ylabel('Percentage of Total Power (%)');

```

```

% %xlim([0 10]); legend('SetA','SetB'); ylim([0 30]);
% xlim([0 10]); ylim([0 10]); grid on;
% legend(['NAS - Tremor (N=' num2str(a) ')'],['NAS - No Tremor (N=' num2str(b) ')']);

%Results from avg of top 5% of data

h(3)=figure('units','normalized','outerposition',[0 .05 1 .95]); xaxis =
linspace(1,9.5,18);
suptitle('Resultant Top 5% Power Distribution Comparison');

subplot(2,2,1);
PwrdistLA=[LAAvg(19:36) LAbAvg(19:36)]; bar(xaxis, PwrdistLA); %Bar plot of power
distribution
title('Left Arm'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([LAAvg(19:36); LAbAvg(19:36)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(LAAvg(19:36)-
dcoeff)),(transpose(xaxis).*(LAbAvg(19:36)-dcoeff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')'],['Non NAS - 83 (N=' num2str(b) ')'],['P-Value
= ' num2str(aap)']);
clear aah aap aaci aastats dcoeff

subplot(2,2,2);
PwrdistRA=[RAAvg(19:36) RABAvg(19:36)]; bar(xaxis, PwrdistRA); %Bar plot of power
distribution
title('Right Arm'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([RAAvg(19:36); RABAvg(19:36)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(RAAvg(19:36)-
dcoeff)),(transpose(xaxis).*(RABAvg(19:36)-dcoeff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')'],['Non NAS - 83 (N=' num2str(b) ')'],['P-Value
= ' num2str(aap)']);
clear aah aap aaci aastats dcoeff

subplot(2,2,3);
PwrdistLL=[LLAvg(19:36) LLbAvg(19:36)]; bar(xaxis, PwrdistLL); %Bar plot of power
distribution
title('Left Leg'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([LLAvg(19:36); LLbAvg(19:36)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;
%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(LLAvg(19:36)-
dcoeff)),(transpose(xaxis).*(LLbAvg(19:36)-dcoeff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ')'],['Non NAS - 83 (N=' num2str(b) ')'],['P-Value
= ' num2str(aap)']);
clear aah aap aaci aastats dcoeff

subplot(2,2,4);
PwrdistRL=[RLAvg(19:36) RLbAvg(19:36)]; bar(xaxis, PwrdistRL); %Bar plot of power
distribution
title('Right Leg'); xlabel('Frequency (Hz)'); ylabel('Percentage of Total Power (%)');
dcoeff=min([RLAvg(19:36); RLbAvg(19:36)])-.25;
xlim([0 10]); ylim([dcoeff 11]); grid on; hold on;

```

```

%2 sample t-test for statistical analysis
[aah,aap,aaci,aastats] = ttest2((transpose(xaxis).*(RLaAvg(19:36)-
dcoff)),(transpose(xaxis).*(RLbAvg(19:36)-dcoff)));
h = zeros(3, 1); h(1) = plot(NaN,'b'); h(2) = plot(NaN,'y'); h(3) = plot(NaN,'w');
legend(h,['All NAS (N=' num2str(a) ' )'],['Non NAS - 83 (N=' num2str(b) ' )'],['P-Value
= ' num2str(aap)]);
clear aah aap aaci aastats dcoff

```

Appendix B – MATLAB Program: Audio

```

%Selection of programs used to process audio data
close all; clc; clear;

d=input ('input number of file to start at: ');
path='D:\1 NAS Data\Audio Data'; addpath(path);
fnames=dir([path '*.mp3']); filenum = length(fnames(:,1)); %Find and count
chosen file type
mins=15; bsize=60*48000*mins; %Set minutes of
data to be read in

while d < (filenum+1)
    %close all
    FFTM1mat=[]; M1mat=[]; spot=[]; %Initializing
    matrices
    file=fnames(d).name; fprintf(file); %fprintf('\n'); %Display file
    name for user
    info = audioinfo(file); pts=info.TotalSamples; %Finding number
    of data points in file
    Resp=input(' - Do you wish to analyze this data file? Please input y or
n: ','s');
    if(Resp=='y');
        tic; start=0; snips=floor(pts/bsize); %Start point
        (mins) and number of audio snippets

        for i=1:1:snips
            startpt=1+start*60*48000;
            [y,SampFreq] = audioread(file,[startpt,startpt+bsize]); %Reading
            data from mp3 file
            NyqFreq=SampFreq/2;
            %Calculate Nyquist Frequency

            N=48000; M=48000; %Values for FFT,
            1 second with 0% overlap
            P=1; h=length(y(:,1)); %Variable to
            track block; check data length
            while P+N<=h %Loop to
            separate columns into blocks
                M1=y(P:P+N-1,1); M1=M1-mean(M1); %Extract and
            zero-mean block of data, pick column
                FFTM1=(2/N)*fft(M1); %FFT block of
            data
                if (abs(max(FFTM1(6500:24000))) > 0.0005) %Filter
            magnitude within frequency range
                    FFTM1mat= [FFTM1mat FFTM1]; %Store FFT data
            block in matrix
                    M1mat= [M1mat M1]; %Store time data
            block in matrix
                    spot = [spot ((P+(i-1)*bsize)/(48000*60))]; %Save
            indexed value in mins
                end; P=P+M;
            end
        end
    end
end

```

```

        fprintf('Block #%.0f/%.0f processed \n',i,snips); %Display
progression to user
        clearvars -except FFTM1mat M1mat start file N d mins bsize i
filename fnames snips FFTM1 spot
        start=start+mins;
    end
    cd('D:\1 NAS Data\Audio Data\Matlab Folder'); %Switch to
location where files will be saved
    s1 = 'FFT_Result_'; ss1 = strcat(s1,file(1:end-4));
save(ss1,'FFTM1mat'); %Save FFT results
    s2 = 'Time_Result_'; ss2 = strcat(s2,file(1:end-4));
save(ss2,'M1mat'); %Save raw time data
    s3 = 'Marker_Result_'; ss3 = strcat(s3,file(1:end-4));
save(ss3,'spot'); %Save raw time data
    cd('C:\Users\Dexter\Documents\2014-2016 PMDI\NAS\Data Notes');
%Return to main folder

    %3-D plot of fft results for microphone
    figure(); mesh(abs(FFTM1mat(1:(N/2),:))); set(gca,'Ydir','reverse');
axis([1 length(FFTM1mat(1,:)) 0 24000]); %zlim([0 .0005]);
    title([file ' - M1 Results']); xlabel('Event'); ylabel('Spectral
Line'); zlabel('Amplitude');

    figure(); histogram(spot,'BinWidth',N/(48000*60)); %Plot markers of
cry occurence
    title('Cry Occurence'); xlabel('Time (Min)');

    Ready=input('Press enter to continue or Ctl+C to access audio','s');
%Access results for plotting or manual filtering
    end
    clearvars -except file N d mins bsize filename fnames ss1 ss2 ss3 FFTM1
d=d+1;
end

%%
%Manual Audio Filtering: Use to open file and manually process audio, then
plot and resave filtered info
%Begin manual filter section
cd('D:\1 NAS Data\Audio Data\Matlab Folder');
%Switch to location where files will be saved
ss1file = strcat(ss1,'.mat'); ss1data=open(ss1file); FFTdata=
ss1data.FFTM1mat; %Retrieve data
ss2file = strcat(ss2,'.mat'); ss2data=open(ss2file); Timedata= ss2data.M1mat;
%Retrieve data
ss3file = strcat(ss3,'.mat'); ss3data=open(ss3file); Spotdata= ss3data.spot;
%Retrieve data

filtM1mat=[]; filtFFTM1mat=[]; filtspot=[]; len=length(Timedata(1,:));
for aa=1:1:len
%Cycle through data
    %for aa=1:1:15
    sound(Timedata(:,aa),48000); pause(1);
%Play sound for user
    fprintf('(#%.0f/%.0f) ',aa,len);
    Resp=input('If this is not a cry, input n: ','s');

```

```

    if(Resp=='n');
%User input filter
    %filtMlmat = filtMlmat;
%If not a cry, skip
    else
        filtFFTMlmat = [filtFFTMlmat FFTdata(:,aa)];
%Keep FFT result for cry
        filtMlmat = [filtMlmat Timedata(:,aa)];
%Keep time data for cry
        filtpspot = [filtpspot Spotdata(:,aa)];
%Keep marker for cry
    end
end

%cd('D:\1 NAS Data\Audio Data\Matlab Folder');
%Switch to location where files will be saved
s4 = 'FFT_Result_Filtered_'; ss4 = strcat(s4,file(1:end-4));
save(ss4,'filtFFTMlmat'); %Save filtered FFT results
s5 = 'Time_Result_Filtered_'; ss5 = strcat(s5,file(1:end-4));
save(ss5,'filtMlmat'); %Save filtered raw time data
s6 = 'Marker_Result_Filtered_'; ss6 = strcat(s6,file(1:end-4));
save(ss6,'filtpspot'); %Save filtered marker data

cd('C:\Users\Dexter\Documents\2014-2016 PMDI\NAS\Data Notes');
%Return to main folder

%Plotting filtered FFT results
figure(); mesh(abs(filtFFTMlmat(1:(N/2),:))); set(gca,'Ydir','reverse');
axis([1 length(filtFFTMlmat(1,:)) 0 24000]);
title([file ' - Filtered FFT Results']); xlabel('Event'); ylabel('Frequency
(Hz)'); zlabel('Amplitude');

figure();
filtavg=median(filtFFTMlmat,2); plot(abs(filtavg(1:(N/2),1))); hold on;
%Plot single combined FFT result
filtavg2=max(filtFFTMlmat,[],2); plot(abs(filtavg2(1:(N/2),1)));
%Plot max values of each spectral line
title([file ' - Filtered FFT Result']); xlabel('Frequency (Hz)');
ylabel('Amplitude'); zlabel('Amplitude');
legend('Median','Max Values');

figure();
histogram(filtpspot,'BinWidth',N/(48000*60));
title('Cry Occurrence - Manually Checked'); xlabel('Time (Min)');
%Convert to seconds and plot
%End manual filter section

%%
%Duration and count program, use marker result filtered, units of minutes
%Output to be manually saved in excel file
%Directions: Open "Marker Result Filtered", run, copy/paste results to excel
file

clc;

```

```

data = ceil(filtspot.*60); num=0; trans=[]; dur=[]; %Read in data and
initialize variables
loc = zeros(1,data(end)); loc(data)=1; %Loc array used to mark
locations of cry with 1's

for v=1:1:(length(data)-1) %Loop to assign 1's to
loc array
    if data(v+1) - data(v) <= 5 %5 seconds for minimum
cry spacing
        loc(data(v):data(v+1)) = 1;
    end
end
loc=[loc 0]; %Append zero to allow
counting method to work properly
figure(); bar(loc); xlim([0,data(end)+20]); title('Cry Locations'); %Plotting
locations of cry over time

for vv=1:1:(length(loc)-1) %Loop to count number of cries and
determine beginning/end times
    if loc(vv)~= loc(vv+1)
        num = num+1;
        trans = [trans vv];
    end
end
count = ceil(num/2); %num contains rising and falling
edges, divide by two for correct count

for vvv=1:2:(length(trans)-1) %Loop to calculate length
of cries in seconds
    diff = trans(vvv+1)-trans(vvv); dur = [dur;diff];
end
dur
fprintf('Number of cries: %2.0f \n',count); %Output results to be
recorded
clear

```