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A hearing protection intervention system for agricultural workers

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A HEARING PROTECTION INTERVENTION SYSTEM FOR AGRICULTURAL WORKERS

by

Oliver Stroh

A thesis submitted in partial fulfillment
of the requirements for the Master of Science
degree in Industrial Engineering in the
Graduate College of
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ABSTRACT

Twenty-two million US citizens are exposed to hazardous noise at work each year, putting them at risk for noise induced hearing loss. Noise induced hearing loss is preventable, cumulative, and irreversible with net economic impact estimated at $123 billion. While agencies such as the Occupational Safety and Health Administration have regulations in place to reduce noise induced hearing loss, these regulations are rarely enforced for agricultural workers. These workers have a low rate of hearing protection usage, with several studies finding that almost half of farmers never use hearing protection devices. Additionally, farmers have twice the hearing loss in higher frequencies and three times in mid-range frequencies than non-farmers. Use of hearing protection can reduce noise induced hearing loss, and agricultural workers are interested in increasing their usage. This makes them a promising group to target with a hearing protection intervention.

This paper describes a system that combines a smartphone with a USB based noise dosimeter that can read within +/- 2 A-weighted decibels of a Class 2 sound level meter providing daily noise exposure monitoring. This device is worn by the agricultural worker throughout a work day, collecting location, accelerometer, and audio data. The data is then transferred onto the server and presented to the agricultural worker using a locally hosted website, giving personalized data of loud noise exposures that can be understood without the need for a safety specialist. The dosimeter's data allows the agricultural worker to explore what sound pressure levels they are exposed to and get an estimate of their total noise exposure. The GPS, paired with audio clips of loud noises, allows the agricultural worker to determine what activities put them at risk of noise induced hearing loss, which are good indications of where to place hearing protection devices.

The system was tested on a farm, comparing its output with several reference instruments. A-weighted, 1-second averaged sound pressure levels, GPS, and accelerometer data were collected while performing a variety of tasks indoors and outdoors. The smartphone's external noise dosimeter read within +/- 2 dBA of the Class 2 reference dosimeter 59% of the time. The GPS devices had an average error of sub-4 meters between and the accelerometers had a mean absolute error of less than 0.1 g.

PUBLIC ABSTRACT

Twenty-two million US citizens are exposed to hazardous noise at work each year, putting them at risk for noise induced hearing loss. Noise induced hearing loss is preventable, cumulative, and irreversible with net economic impact estimated at $123 billion. While agencies such as the Occupational Safety and Health Administration have regulations in place to reduce noise induced hearing loss, these regulations rarely make it to agricultural workers. These workers have a low rate of hearing protection usage, with several studies finding that almost half of farmers never use hearing protection devices. Additionally, farmers have twice the hearing loss in higher frequencies and three times in mid-range frequencies than non-farmers.

To improve agricultural workers' usage of hearing protection, this study proposes a device that incorporates personalized exposure measurements, while providing information on when, where, and what activities cause loud noises without the need for a hearing specialist. The system combines a smartphone with a USB based noise dosimeter, which reads within +/- 2 A-weighted decibels of a Class 2 sound level meter providing daily noise exposure monitoring. The device also collects GPS, accelerometer, and audio data related to their loud sound exposures. This data is then presented to the user through a locally hosted website, giving personalized data that can be understood without the need for a safety specialist. The dosimeter's data allows the agricultural worker to explore when loud noises were encountered as well as how loud they were. The GPS, which provides on average sub 4-meter accuracy, paired with audio clips, allows the agricultural worker to determine what activities put them at risk of noise induced hearing loss and helps them figure out good locations to place hearing protection devices.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION AND BACKGROUND

Twenty-two million US citizens are exposed to hazardous noise at work each year (Tak, Davis and Calvert 2009), putting them at risk for noise induced hearing loss. Noise induced hearing loss is preventable, cumulative, and irreversible (National Institute for Occupational Safety and Health, 1998). The World Health Organization estimated healthcare sector costs for hearing-impaired adults in the United States to be more than $13.5 billion (World Health Organization, 2017) with a $123 billion annual net economic cost (Neitzel, et al., 2017).

There are several ways to reduce noise exposure and the risk of noise induced hearing loss. Perhaps the best way would be to engineer and design devices and machines that produce less noise. This can be cost-prohibitive and sometimes infeasible. Reducing the amount of time operating noisy machinery or being in noisy environments also reduces noise exposure, although reducing exposure time can also be difficult. A relatively inexpensive way to reduce noise exposure is to use hearing protection devices. Passive, continuously worn protective devices such as ear plugs and ear muffs are easily obtainable and effectively attenuate noise when worn correctly. Such devices have been shown to significantly reduce the incidence of hearing loss for noise-exposed workers (Hong, Chen and Conrad, 1998 & Pessina and Guerretti, 2000).

The Occupational Safety and Health Administration states in Title 29 of the Code of Federal Regulations, part 1910.95, that general industry employers are required to monitor exposure when employees are exposed to sound pressures equal to or greater than 8-hour time weighted average levels of 85 A-weighted decibels. Additionally, employees are required to wear hearing protection when exposed to noise over the permissible exposure limit, which is 90 A-weighted decibels for an 8-hour time weighted average using a 5-decibel exchange rate (Occupational

Safety and Health Administration 3074, 2002). A-weighting adjusts the measured sound pressure readings based on the human ear's sensitivity to noise by primarily attenuating the low and high frequencies. The exchange rate is the sound pressure increase that one can be exposed to if the time of exposure was cut in half. The National Institute for Occupational Safety and Health has similar recommendations, with a recommended exposure limit set at 85 decibels for 8-hours using a 3-decibel exchange rate (National Institute for Occupational Safety and Health, 1998). These recommendations were put into place to help prevent hearing loss among workers since consistent daily noise exposure exceeding 90 A-weighted decibels has been shown to have deleterious effects on hearing (Clark and Bohne, 1999).

Even with regulations, more than 34 percent of noise-exposed workers report non-use of hearing protection devices such as ear muffs and ear plugs which attenuate noise exposure when worn correctly (Tak, Davis and Calvert 2009). The prevalence of overall hearing loss remains consistently around 20 percent between 1981 and 2010 (Masterson, et al., 2015). Agricultural workers suffer more severe levels of hearing loss, with a study of 49 dairy farmers finding twice the hearing loss in higher frequencies and 3 times the loss in mid-range frequencies as compared to the 49 non-farmers sampled (Marvel, et al., 1991). A study of 93 farmers identified 35 as hearing handicapped (Stewart, Scherer and Lehman, 2003). Another study found almost 98 percent of the 185 screened participants had functionally significant hearing loss with a median loss of 12.1 percent (Beckett, et al., 2000). A convenience sample of 56 farmers and family members found 80.4 percent had hearing loss (Carruth, et al., 2007).

Engineering solutions that control farm noise would be ideal, but many farms do not have the resources to reduce noise to acceptable levels (Gates and Jones, 2007). Decreasing the exposure duration is also often impractical (Solecki, 2000). Consequently, in many cases the best solution is to reduce noise exposure with hearing protection devices (Murphy, Kiernan and Chapman, 1996).

Agricultural workers don't benefit from the systems present in general industry that are designed to protect against noise induced hearing loss (McCullagh, 2016). Even though agricultural workers are regularly exposed to noise levels exceeding the Occupational Safety and Health Administration's permissible exposure limit, the National Institute for Occupational Safety and Health's recommended exposure limit, and the American Conference of Governmental Industrial Hygienists threshold limit value (Milz, et al., 2008), they often don't benefit from noise regulations existing in general industry (Suter, 2009).

Consequentially, agricultural workers suffer from low hearing protection usage. One survey of 532 agricultural workers found hearing protection usage of less than 30 percent when exposed to high noise, defined as noises causing someone to raise their voice to be heard within 3 feet or less. Additionally, only 56.8 percent of agricultural workers had ever used hearing protection at any point in their career. (McCullagh, Ronis and Lusk 2010). A study of 25 farmers found 60 percent of participants never used hearing protection, and only 8 percent often or always used hearing protection (Gates and Jones 2007). A survey of 652 Colorado farmers found only 30.3 percent of participants always or almost always used hearing protection when performing loud operations (Beseler and Stallones 2010). A telephone survey of 1,947 Californian farmers found that of the 1,401 farmers who spent at least 5 percent of their time in noisy conditions, 56.3 percent rarely or never used hearing protection (Schenker, Orenstein and Samuels, 2002).

A study of 532 agricultural workers found that most participants are interested in increasing their use of hearing protection devices (McCullagh, Ronis and Lusk, 2010), but there have been few studies of interventions to promote hearing protection use (Gates and Jones, 2007 & Bernick and McCullagh, 2012). When asked why they didn't use hearing protection, agricultural workers reported responses such as "it is not available," "never thought it was necessary," and "didn't think I needed to use it" (Gates and Jones, 2007). These last two responses suggest that agricultural workers are not aware of the potential hazards of noise exposure, and that increasing awareness would improve hearing protection use. One effective way to increase awareness is to provide workers with reports of their noise exposure (Williams, et al., 2015). This has been shown in manufacturing, with voluntary daily exposure monitoring reducing daily noise exposures by a factor of approximately 2 (McTague, et al., 2013). Subjects from this study did have access to safety specialists, which while common in general industry, are not readily available on farms.

Increasing awareness is just one factor affecting hearing protection device use. One study found that interpersonal influences, barriers, and situational influences are major factors in agricultural workers' usage of hearing protection. Of these, the relatively rare interpersonal influences, such as encouragement from family and other agricultural workers, is the strongest predictor of hearing protection device use (McCullagh, Lusk and Ronis, 2002).

A logical next-step to protecting agricultural workers' hearing would be to integrate the success of daily noise monitoring from manufacturing for use on the farm, increasing knowledge of what tasks are dangerous without the need for a safety specialist, and engaging interpersonal influences. Combining these solutions into one system should result in a large improvement of hearing protection device utilization, which in turn causes a reduction in noise induced hearing loss. A pilot study of adolescent agricultural workers found using a smartphone app for intervention resulted in an improvement of knowledge, attitude, and usage of hearing protection while performing noisy tasks (Khan, et al., 2018) suggesting smartphones could serve as a base for the system. In addition, smartphones are a good option because they are less expensive than commercial noise monitoring solutions, and the lack of need for a specialist makes them a useful noise exposure risk assessment tool (Williams, et al., 2016).

Daily noise monitoring with smartphones has been studied. Some built-in microphones can be effective, with two studies finding that smartphones are capable of reliable measurements within +/- 2 dBA of a Class 2 sound level meter using built in microphones (Kardous and Shaw, 2014 & Murphy, Kiernan and Chapman, 2016). The American National Standards Institute describe in standard 1.4 that Class 2 sound level meters are intended for general field use, such as environmental sounds and has an accuracy of +/- 2 dBA (American National Standard Association, 1983). These meters are the minimum level of precision required by the Occupational Safety and Health Administration for occupational noise measurements (Occupational Safety and Health Administration, 1999). Kardous' study tested both Android™ and Apple™ devices, although only devices running on Apple's iOS were capable of consistently measuring noise within +/- 2 decibels. This inconsistency with Android™ has been found in other studies (Ibekwe, et al., 2016), which is believed to be a result of the many manufacturers and hardware variations between Android™ devices. Continuing studies found an accuracy of +/- 1 dB using external microphones on Apple devices (Kardous and Shaw, 2016) suggesting the use of external microphones is necessary for accuracy (Roberts, Kardous and Neitzel, 2016).

To obtain a +/- 2 decibel of accuracy when compared to Class 2 sound level meters could require calibration to achieve. One study found that only one app, which was used by Kardous, was able to stay within 5 dB of a class 1 sound level meter without calibration (Nast, Speer and Le Prell, 2014). With 5 decibels being the largest commonly used exchange rate, this error could cause data to report a noise exposure with twice the permissible exposure time. An underestimation of noise exposure such as that is significantly more dangerous to users than an overestimation, as wearing hearing protection when not required causes no harm while not wearing hearing protection when required is, indeed, harmful.

The aforementioned tests failed to extend to the maximum recommended impulse noise of 140 dB (National Institute for Occupational Safety and Health, 1998, Occupational Safety and Health Administration, 1999) even though contemporary dosimeters are designed to measure up to this peak (Kardous, Wilson and Murphy, 2005). Although these devices are unlikely to be used for compliance measurements, they can still serve as useful survey tools for noise (Roberts, Kardous and Neitzel, 2016).

Informing farmers of what tasks are dangerous to their hearing is beneficial because inconvenience and unavailability of hearing protection devices is frequently mentioned by agricultural workers as a significant contributor to non-use of hearing protection devices (Darragh, et al., 1998, Meister, Hest and Burnett, 2010, Wadud, Kreuter and Clarkson, 1998, & Gates and Jones, 2007). Additionally, agricultural workers often underestimate sources of loud noise. For example, one study reported that only about half of agricultural workers cited livestock as a source of loud noise and a fifth thought that machinery was the only source of loud noise (Cramer, et al., 2016). Location data such as GPS and accelerometer data can be used to show precisely where loud noise exposures occur with the current minimum GPS accuracy of 4 meters root mean squared (United States Department of Defense, 2008). Smartphone noise dosimeters have been paired with GPS data before for participatory urban noise mapping systems (Rana, et al., 2010 & Kanhere, 2013). This location data can be paired with audio clips to give the user more data to figure out what sources are producing excessively loud noise.

Additionally, the agricultural workers can label this data to enrich the picture of what tasks are not only loud but are commonly done by agricultural workers. By placing hearing protection near these sources of loud noise, convenience and availability are increased, which should improve protection usage.

This paper describes a novel sound monitoring system that addresses three goals: tracking daily noise exposure, communicating the noise exposure to agricultural workers without the need of a safety specialist, and engaging interpersonal influences to help support the agricultural worker in protecting their hearing. To achieve these three broad goals, we have designed our system with the following design features. The system should be able to:

1. Collect sound pressure data within +/- 2 dBA of a Class 2 dosimeter
2. Collect GPS data with an average of 4-meter accuracy
3. Collect accelerometer data with error less than 0.1g
4. Collect audio clips of loud tasks
5. Collect labels of loud tasks
6. Remain powered over an 8-hour period
7. Store at least 8-hours of data
8. Display to the user to where loud noises were measured
9. Allow data to be shared with family and friends
10. Include sensors that are wearable while performing a variety of activities

These requirements provide the agricultural worker with sound pressure data based on the Occupational Health and Safety Administration's minimum requirements for noise dosimetry, and location data with the minimum available accuracy while leveraging factors that have been found to influence agricultural workers' usage of hearing protection, such as daily exposure monitoring and interpersonal influences. Since the device will be worn over the course of a working day, the device should last for at least 8 hours and be wearable during a range of activity.

2. DESIGN

The section discusses the details of designing a system to meet the previously stated specifications. This system monitors an agricultural worker's daily noise exposure and present the collected data in a manner that an agricultural worker can easily interpret and understand. Collecting and storing information about locations and audio clips will help the agricultural worker and his/her family and friends understand which activities involve unsafe noise levels. As the agricultural worker learns more about what tasks are putting them at risk, they will develop a better understanding of how noisy their environment is as well as where to put their hearing protection to best reduce their risk of noise induced hearing loss.

The system contains 3 primary components: a wearable device, the server, and the website. These are shown in figures 1, 2, and 3 respectively. The wearable device collects sound pressure, audio, GPS, and accelerometer data while being comfortable to wear and able to withstand agricultural environments. The server is a laptop computer that stores the collected data and hosts an interactive website to display the data. The website is the education tool, which will inform the user, without a sound expert, as to what tasks are potentially harmful, collect labels of these exposures, and allow users' exposure data to be shared with family and friends. This system will be identified as HearSafe from here on, with the portable sensor being called the wearable device, the server being the HearSafe server, and the website being the HearSafe website.

2.1 Wearable Device

The wearable device, or portable HearSafe sensor, is shown below in figure 1.

Figure 1: The HearSafe sensor which includes a water resistant arm band, custom smartphone application, noise dosimeter, and On-The-Go cable.

To collect sound pressure levels, the noise dosimeter selected for this project is based on a dosimeter previously developed for and successfully used in an earlier project (Zuidema, et al., 2019). The dosimeter is accurate within +/- 2 dBA of a Class 2 sound level meter between 75 and 94 decibels using pink noise (Hallett, et al., 2018) meeting the target requirement for the device. The noise dosimeter uses a microcontroller (Teensy 3.2, PJRC, Sherwood, OR, USA), which reads a microphone signal and converts it to sound pressure level.

The dosimeter works as follows. The microprocessor samples the microphone audio signal at 44.1 kilohertz and applies a Fourier transform every 1024 samples with a 50 percent overlapping hamming window to convert the audio signal to the frequency domain. The sampling rate was chosen so frequencies between 0 and 22.5 kilohertz can be captured based on the Nyquist-Shannon sampling theorem. This encapsulates the range of human hearing which is roughly 20 hertz to 20 kilohertz. At the time of construction, the microprocessor's audio library had a maximum FFT size of 1024 samples and is therefore the maximum level of precision attainable. This FFT size results in bin sizes of approximately 43 hertz. The overlap was included to reduce the effect of windowing, as the hamming window naturally tapers the signal to 0 around the edges of the frame causing potential loss of important information. These measurements result in approximately 86 samples per second. A frequency-specific weighting is applied to calculate the A-weighted noise level, a measure intended to match human sensitivity to noise. These 86 measurements are averaged before converting to decibels, then outputted as serial data to be read by the application. This sensor is inexpensive to manufacture and provides serial communication via USB.

The dosimeter is connected to a Samsung Galaxy S5 Active (Galaxy S5 Active, Samsung, Seoul, South Korea) running the Android™ operating system. The S5 Active was chosen due to its cost (~$84), ease of compatibility with the noise dosimeter, ubiquitous operating system, the ability to freely code applications, and its available sensors and storage. It also has an ingress protection (IP67), meaning it is totally protected from dust ingress and can withstand immersion of up to a 1-meter depth in water. The S5 Active comes with basic smartphone functionality such as wireless communication, GPS positioning, expandable storage, as well as additional sensors such as accelerometers and gyroscopes. The S5 Active can run both the Android™ 6.0 "Marshmallow" and the Android™ 5.0 "Lollipop" operating systems. The application developed for this design used the Lollipop architecture to take advantage of the simplified permission handling.

The application, which was designed specifically for this project and collects and stores the dosimeter and other data, is initiated as soon as HearSafe's noise dosimeter is connected to the device via an On-The-Go cable. Connecting the On-The-Go cable activates Android™ device's host mode, which allows it to receive data from and power the dosimeter. Upon connection, the Android™ device checks the vendor ID of the communicating device to see if it matches the dosimeter's microcontroller. If the vendor ID is a match, the data collection application is opened. The data collection application stops as soon as the dosimeter is unplugged to conserve power.

While the wearable device is running the smartphone application, it reads the external dosimeter's average A-weighted sound pressure levels each second, adds a time stamp, and stores collected values in a text file every minute on an SD card inside the HearSafe's smartphone. Collecting this data over a workday allows estimation of sound exposure and the equivalent 8-hour time weighted average to compare easily to standards set by organizations like the Occupational Safety and Health Administration and the National Institute for Occupational Safety and Health.

Audio and GPS data are collected to help inform farmers what tasks are noisy and where they are occurring. If the device detects a sound level above 80 decibels, the minimum level required by the Occupational Safety and Health Administration to be integrated into noise measurements, the device will record a 15 second audio clip, the current latitude, longitude, time, and accuracy of the GPS reading. Because it communicates with navigational satellites, the GPS will not function properly in certain environments, such as a basement or metal building. When it cannot estimate a position, the wearable device collects the last known location. Using the timestamp of the GPS recording allows HearSafe's server to discern if the reading is old, but readings are still collected since the last known location could still assist the farmer in determining what they were doing. In addition, the smartphone application continuously collects accelerometer data and is sampled at approximately 50 hertz. All data are stored on an external SD card inside HearSafe's smartphone, which permits flexible, non-volatile, copious storage during monitoring.

The wearable device is worn using a runner's armband (Maxboost Armband, Endliss Technology, Hayward, CA, USA) that has a water-resistant design and adjustable strap so the device can be worn with or without a coat on. The external dosimeter and connecting cable are zip-tied tightly to the armband to reduce the risk of snags, potentially damaging the user or the device. The dosimeter is protected by a hard, custom-made plastic case. The case fits tightly around the microcontroller, amplifying circuit, and microphone. The USB connection is hot glued shut to increase the waterproofing of the overall device. The USB connection to the smartphone cannot be hot glued though, since the USB port is used to charge the device with a different cable when the device is not in use.

One unexpected consequence of choosing the Galaxy S5 smartphone is that the screen needs to be on to collect accelerometer readings. Screens consume a great deal of power due to their size and backlighting requirements. This combined with the power draw from the noise dosimeter puts the device at risk of running out of power during a regular work day. To increase the life span of the device, several measures were taken. First, a larger capacity battery was purchased. This increased the battery capacity from 2800 to 6150 mAh, more than doubling the capacity of the battery while not requiring an external case or charger. To minimize the power draw from the screen, the screen is automatically dimmed 30 seconds after the first GPS and sound pressure readings are acquired by the device. The screen brightness is restored when the application is shut down to avoid difficulties when handling the device afterwards and to potentially alert the agricultural worker that the dosimeter has been disconnected. Also, when the application is first opened, it scans for any currently running, non-critical background applications and shuts them down to minimize unnecessary battery usage.

2.2 Server

The HearSafe server, shown in figure 2, stores all data collected by the sensor and hosts a website that allows the agricultural worker, friends, and family to review the wearer's daily exposure.

Figure 2: The server, composed of a laptop and a router.

It consists of a router (TP-Link N300, TP-Link Technologies, Brea, CA, USA) and a laptop (HP Elitebook 8470P, Hewlett Packard, Palo Alto, CA, USA). The router facilitates communications between the wearable device and the laptop. The router defines the IP address of the server to a fixed value of 192.168.1.150, which allows a socket to be created for wireless data transfer between the two devices. When the wearable device is within the proximity of the router, it connects to the router's Wi-Fi network and can then communicate with the server, which is also connected to the router. The user then runs the receiving java program, which is displayed as a clickable executable on the server's desktop, initializing a communication socket between the wearable device and the server. This socket, running on an assigned port, waits for a connection from the wearable device which is begun by the user pressing a button in the application. Once this connection is established, the stored sensor data is transferred to the server. The transferred data is then verified by analyzing randomly selected bytes on the server. If this test passes, the data is deleted from the wearable device's SD card. On the server, the raw data is processed and put into a database (MySQL, Oracle, Redwood Shores, CA, USA) allowing it to be accessed by the website. The raw data is not deleted from the laptop to preserve the data in the event of an unexpected failure. Once the transfer is complete, the user can go to a locally hosted website to review their daily sound exposure.

2.3 Website

The HearSafe website, shown in figure 3, runs locally on the server and displays the loud noise measurements on maps, in graphs, and with audio samples to help the agricultural worker understand which noisy tasks risk loud noise exposures. The website also allows this information to be easily sharable with friends and family. Additionally, it collects labels of these loud tasks, which are provided by the farmer. Because there may be many loud noises on a farm, hundreds of loud noise events could be collected every day. Having the user label each event individually is neither feasible nor desirable.

To organize the data and simplify labeling, a clustering algorithm works to group similar events. The algorithm first compares the time between loud events. If the time between successive loud noise events is less than 2 minutes, the events are grouped into the same cluster, x_i. Iterating through all sound events then creates an array of clusters $x_1, x_2, \ldots, x_m$. Next, the algorithm calculates the average location of all the events in each cluster x_i. Then the algorithm iterates through the array of clusters comparing each cluster x_i to all preceding and proceeding clusters $\{x_1, x_2, \ldots, x_m\}-\{x_i\}$. If the average locations are within 30 feet of each other, x_i and all matching clusters are placed into a final cluster, y_i. The $y_1, y_2, \ldots, y_n$ clusters are displayed to the user, along with their start time, end time, average sound pressure level, and the duration of the interval with loudness above 85 dBA. This allows the number of events and magnitude of noise exposure to be more simply summarized for the agricultural worker. These clusters, which should be a collection of loud noise events from the same task, can be used to help generate a broader understanding of what tasks are loud.

The website also maps where every loud noise event occurred. Each loud noise event is color coded based on its cluster membership. By clicking on an event, the agricultural worker can play the associated audio clip. Below the map, sound pressure data from 15 second events as well as raw sound pressure levels are shown. These data points are also color coded based on their associated cluster. While reviewing this information, the agricultural worker can then provide labels to each presented cluster. This label is then stored in the database for later use. As the agricultural worker reviews their daily noise exposure, they will get a better idea regarding what activities are loud. This data can also be viewed by friends and family, which should bring interpersonal influences to affect the agricultural workers use of hearing protection.

If utilized for an experiment the device could compile data into a summary of noise exposures. This summary could include statistics such as total time exposed to loud noise, where the loudest noise events occurred, and what tasks were most frequently labeled as a loud noise source. This data, paired with average GPS locations of each labeled cluster, should give the agricultural worker a better idea of where to put their hearing protection. Given that agricultural workers have stated “it is not available,” “never thought it was necessary,” and “didn’t think I needed to use it” as reasons for not wearing hearing protection (Gates and Jones, 2007), the data shown by this report should increase agricultural workers awareness of potential hearing damage as well as provide an idea of where to place hearing protection.

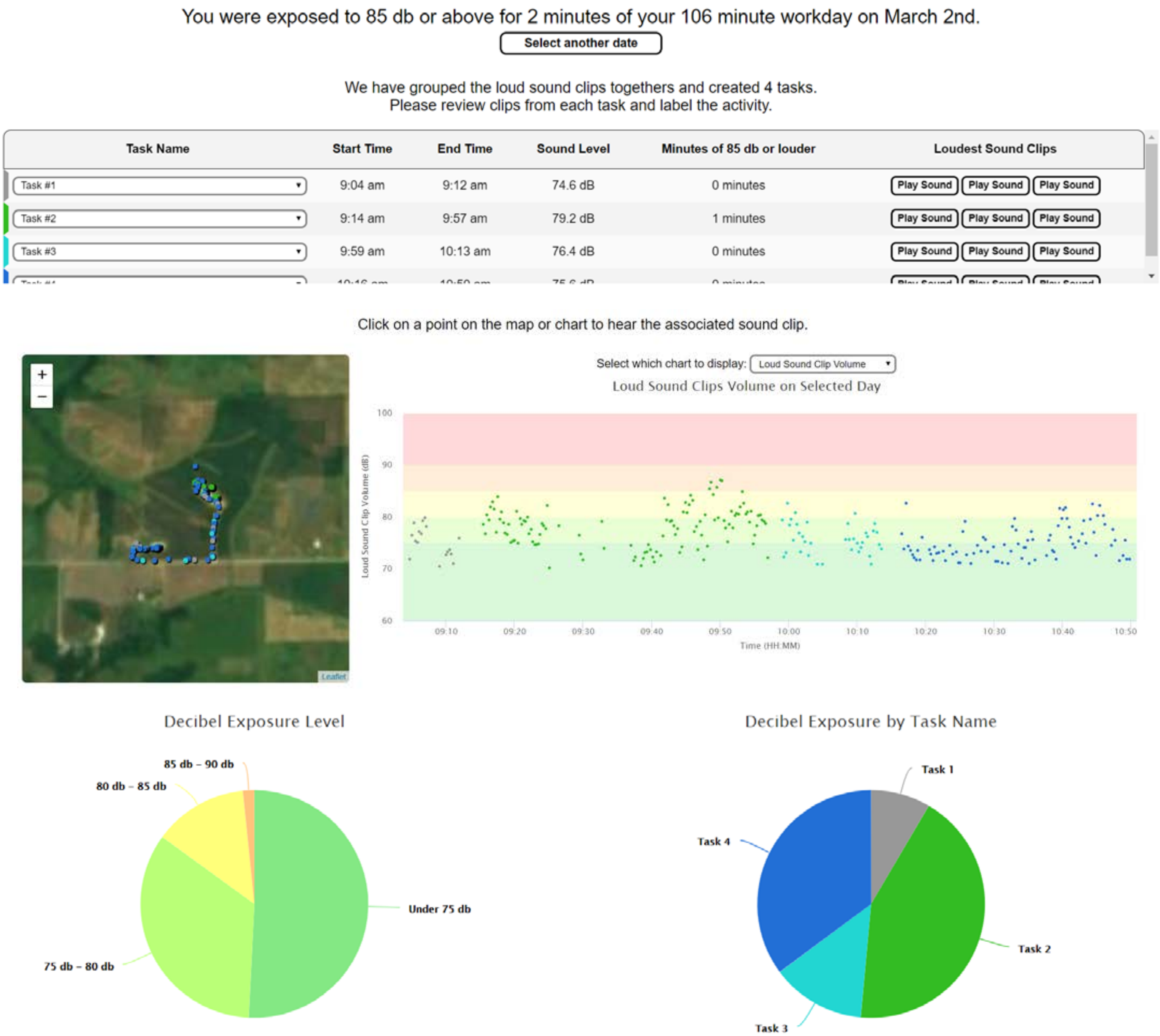

Figure 3: The website, displayed to the user as one static page. It allows the agricultural worker to review exposure rates and determine what activities are likely to cause hearing damage.

The design presented in this chapter is intended to address each of the 10 design features outlined in Chapter 1, which are repeated here for convenience:

1. Collect sound pressure data within +/- 2 dBA of a Class 2 dosimeter
2. Collect GPS data with an average of 4-meter accuracy
3. Collect accelerometer data with error less than 0.1g
4. Collect audio clips of loud tasks
5. Collect labels of loud tasks
6. Remain powered over an 8-hour period
7. Store at least 8 hours of data
8. Display to the user where loud noises were measured
9. Allow data to be shared with family and friends
10. Include sensors that are wearable while performing a variety of activities

Design features 4, 5, 8, 9 and 10 are assumed to be generally satisfied by the presentation above. Runners' armbands are designed to withstand active use, thereby fulfilling this parameter through the mounting choices. The website was designed to display where loud noises occur with their associated audio clips during the agricultural worker's day, which can be seen in the screenshots of the website. This website is open access to anyone, not just the user, which means it can be shared between family and friends. Although feature 1 is met for continuous pink noise, it still needed to be tested in non-continuous noise scenarios. The next chapter will describe tests to confirm features 1, 2, 3, 6, 7, including the accuracy of the sound pressure readings, GPS, and accelerometer data, whether the device can be powered for 8 hours, and whether it can store 8 hours of data.

3. EXPERIMENTS

3.1 General Methods

Three tests were done to check the following design parameters: does the external noise dosimeter read within +/- 2 dBA of a Class 2 instrument; do GPS readings have an average of sub 4-meter accuracy; does accelerometer data on average read within a 0.1g’s; and can the wearable device remain powered for and store data for a minimum of 8 hours. Sensor accuracy tests were done at a farm to best represent their typical use case. Due to limitations of farm access, and the nature of the test, the battery test was done in a lab setting.

To test the accuracy of the three instruments, reference instruments were chosen for comparison. For the external noise dosimeter, the reference instrument was a dBadge 2 Pro (Casella Solutions). The dBadge2 has a larger dB range (54 to 140.3 dB) than the HearSafe’s dosimeter and is a Class 2 instrument. This permits direct comparison between readings, allowing these experiments to show whether the +/- 2 dBA accuracy of a Class 2 dosimeter is met. The dBadge reports a variety of exposure statistics as well as second-averaged, A-weighted data. The GPS readings were compared to an additional smartphone with an externally made Android™ application (GPS Logger, BasicAirData). This application collects GPS readings every second if a new reading is available, allowing for direct comparison to the HearSafe’s GPS, which only collects readings when a loud noise is detected.

The HearSafe’s accelerometer (MPU6500, InvenSense, San Jose, CA, USA) accuracy was determined by comparing its readings to those of a LSM6DS3 (LSM6DS3, STMicroelectronics, Geneva, Switzerland accelerometer. X, Y, and Z accelerations from the LSM6DS3, measured in meters per second squared, were collected by a microcontroller (Teensy

3.2) and stored on an SD card. The LSM6DS3 was set to log data at 50 hertz matching the sampling rate set on the smartphone. Since this instrument isn't connected to any network that would allow it to use a universal clock, all samples were recorded with the local clock time of the Teensy. To convert this to usable time stamps, the epoch time was recorded as the accelerometer began to record. Both the dBadge and the accelerometer logger are shown below in Figure 4.

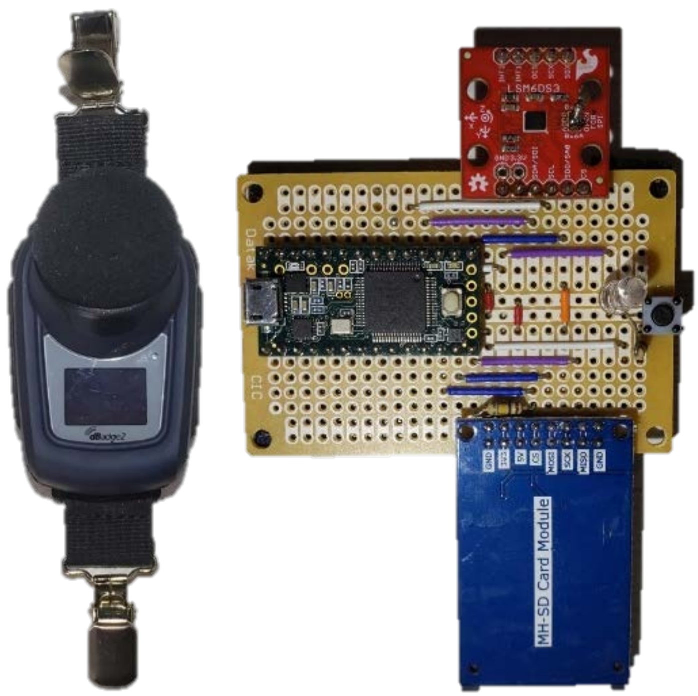

Figure 4: Two of the reference instruments used in the experiments, the dBadge 2 Pro (left) and the accelerometer logger (right).

3.2 Experiment 1: Sound Pressure, GPS, and Accelerometer Test

The first experiment involved two individuals going to a farm and redistributing hogs to ensure a roughly even count of hogs per pen. Each person wore HearSafe's wearable device, as well as a dBadge 2 Pro and the LSM6DS3. One person had a Samsung Galaxy S9 which was running the GPS Logger app. The experiment lasted approximately 1 hour and 15 minutes. The predominant source of noise was the hogs. The dBadge and HearSafe's external noise dosimeter both collected second averaged A-weighted sound pressure levels. The LSM6DS3 and HearSafe's accelerometer collected x,y,z accelerations at approximately 50 hertz. The GPS Logger collected location readings every second when they were available, with HearSafe's GPS collecting data when a sound pressure level of 85 dBA or higher was measured.

The dBadge was mounted on the sleeve of each subject to place it as close as possible to the wearable device. The LSM6DS3 was mounted with Velcro to the armband containing the wearable device's smartphone. The mounting is shown in Figure 5 below. The smartphone with the GPS logger was kept in one test subject's pocket.

Figure 5: The mounting method used in experiment 1.

3.2.1 Experiment 1: Results

During the experiment, one of the LSM6DS3 circuits was shorted, causing a loss of data. This left the following data to be analyzed: 2 pairs of sound pressure readings, one set of accelerometer readings, and one set of GPS readings. The number of readings collected are presented in Table 1 below.

Table 1: Number of readings collected by each sensor in experiment 1.

Data	**Wearable Device Readings**	**Reference Sensor Readings**
Sound Pressure Subject 1	4501	4419
Sound Pressure Subject 2	4861	4375
GPS	33	1170
Accelerometer	203600	243436

The following section reviews the sound pressure data. Table 2 presents the average sound pressure level, 5th and 95th percentile sound pressure levels, readings over 85 dBA, dose, and the 8-hour time weighted average. The average is calculated by anti-logging the data, averaging, then converting back to decibels. The dose and time weighted averages are calculated as per the Occupational Health and Safety Administration's guidelines (OSHA, 1999).

Table 2: Statistics for one-second sound pressure readings from experiment 1.

Sensor	Average (dBA)	5th Percentile (dBA)	95th Percentile (dBA)	Above 85 (dBA)	Dose	8-Hour TWA (dBA)
HearSafe Subject 1	71.54	61.46	76.44	15	1.21%	58.15
dBadge Subject 1	78.12	62.39	82.87	148	2.9%	64.59
HearSafe Subject 2	75.14	58.15	79.93	44	2.15%	62.31
dBadge Subject 2	82.83	63.96	88.71	451	5.62%	69.24

There is no easy way to synchronize the two devices, so a clock offset may be present. Therefore, before the two time series were compared, the data were searched to see if a clock drift was present. To do this, the mean absolute error was calculated while shifting the time stamps of the test data. This error was calculated second by second from 120 seconds before the reported time to 120 seconds after the reading time.

Figure 6 plots the mean absolute error against these clock offsets. It illustrates a significant drop in mean absolute error at 9 seconds, which suggests the dBadge's clock was 9 seconds behind the wearable device's clock. A similar offset of 7 seconds was found for the second subject's devices. These offsets were applied to all subsequent calculations.

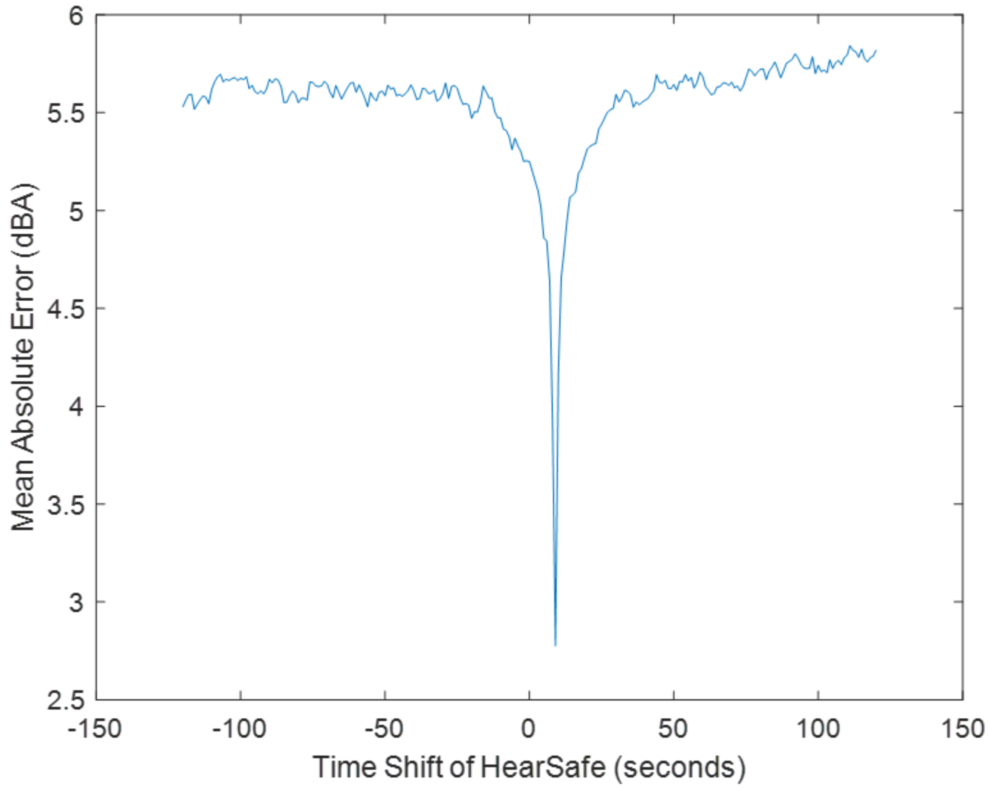

Figure 6: Error versus time shift for subject one's wearable device and the reference dBadge.

The minute averages were calculated from the sound data for analysis, as this data can be used to calculate noise exposure dosage. Since the HearSafe's noise dosimeter has a known floor at 56 dBA, minute averages were calculated using all values whenever the system reported a value 60 or above. This noise floor can be seen in Appendix D. The clock offsets, mean absolute error, and mean error for both minute and second data are tabulated in Table 3. We have also included the percentage of readings within +/- 2dBA (design requirement #1). Figure 7 shows the minute averaged sound pressure levels for subject one's devices.

Table 3: The clock offset, as well as minute averaged statistics for each subject in experiment 1.

Subject	Clock Offset (s)	Mean Absolute Error (dBA)	Mean Error (dBA)	Readings within +/- 2 dBA of dBadge
One	9	5.12	-5.12	5.48%
Two	7	7.08	-7.08	0%

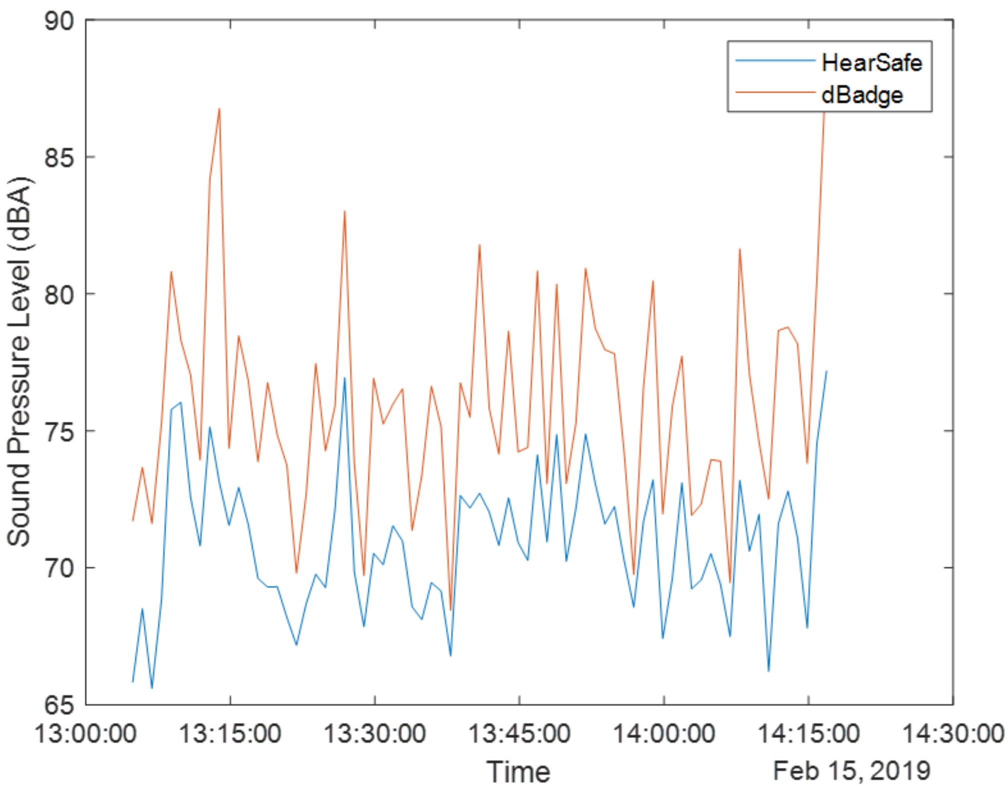

Figure 7: One-minute averaged sound pressure levels for both sensors from experiment 1.

A linear model was fit using the dBadge data as a predictor of the HearSafe data, removing the intercept since the intercept for both devices should be 0, and plotted in Figure 8. The root mean square error was 1.98 dBA, with an R^2 value of 76.9%. The resulting intercept is 0.932 and is significant using an alpha of 0.01. Additionally, a Bland-Altman plot was constructed, shown in figure 9, showing a mean difference of 5.1161 dBA with a standard deviation of 2.18 dBA.

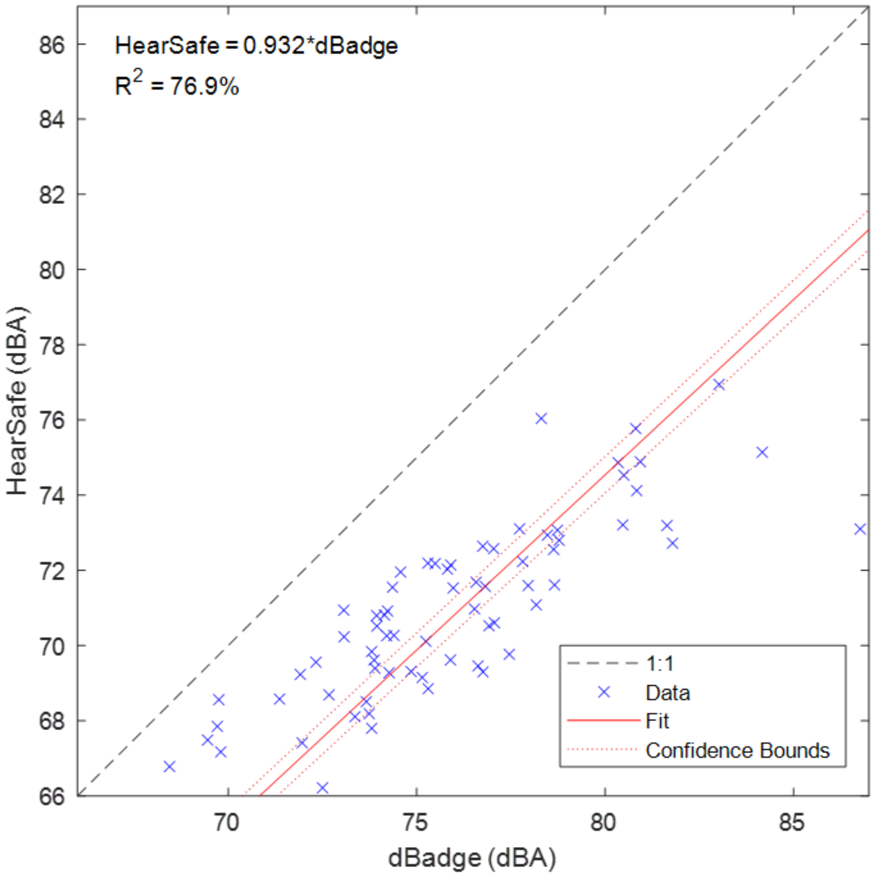

Figure 8: Correlation between the HearSafe and dBadge minute averaged sound pressure levels.

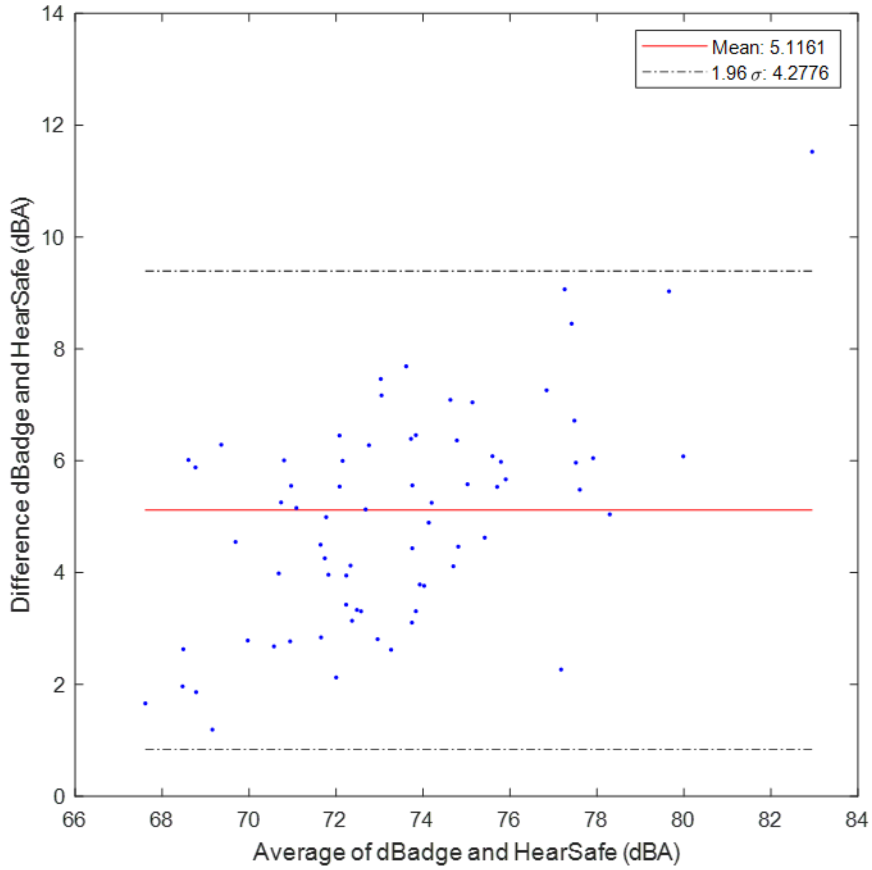

Figure 9: Bland-Altman plot of minute averaged sound pressure levels from experiment 1.

The GPS data were compared by looking for matching timestamps between the GPS Logger and HearSafe's wearable device. The errors between these points were then calculated. Thirty-three GPS measurements were collected by the wearable device, with 22 having timestamps that matched the reference GPS readings. For these 22 measurements, the mean absolute error was 5.8 meters. The minimum error was 0.87 meters, with a maximum of 23.3 meters.

The last sensor in this test is the accelerometer. Table 4 displays the average sampling frequencies, average of x, y, and z, and the norm of all readings for the accelerometer.

Table 4: Accelerometer statistics from experiment 1.

Sensor	**Sampling Frequency (hz)**	**X Average (m/s^2)**	**Y Average (m/s^2)**	**Z Average (m/s^2)**	**Norm Average (m/s^2)**	**Norm Max (m/s^2)**	**Norm Min (m/s^2)**
HearSafe MPU6500	50.12	1.98	-8.79	0.48	10.11	33.97	1.22
LSM6DS3	50	2.41	-8.67	-0.04	10.15	33.97	.039

As mentioned before, the LSM6DS3 clock cannot be synchronized to the wearable device's clock, so the epoch time was recorded at the start of the accelerometer data collection. This time record served as a starting estimate of the actual time when data collection began. To determine the offset from this recorded value, the timestamps of the data set were shifted like the sound pressure data. The reading time was incremented by 1ms, the smallest clock difference for the accelerometer readings. Figure 10 which displays mean absolute error versus time shift, shows shows a minimum error around 1499 ms, which is used in all following calculations

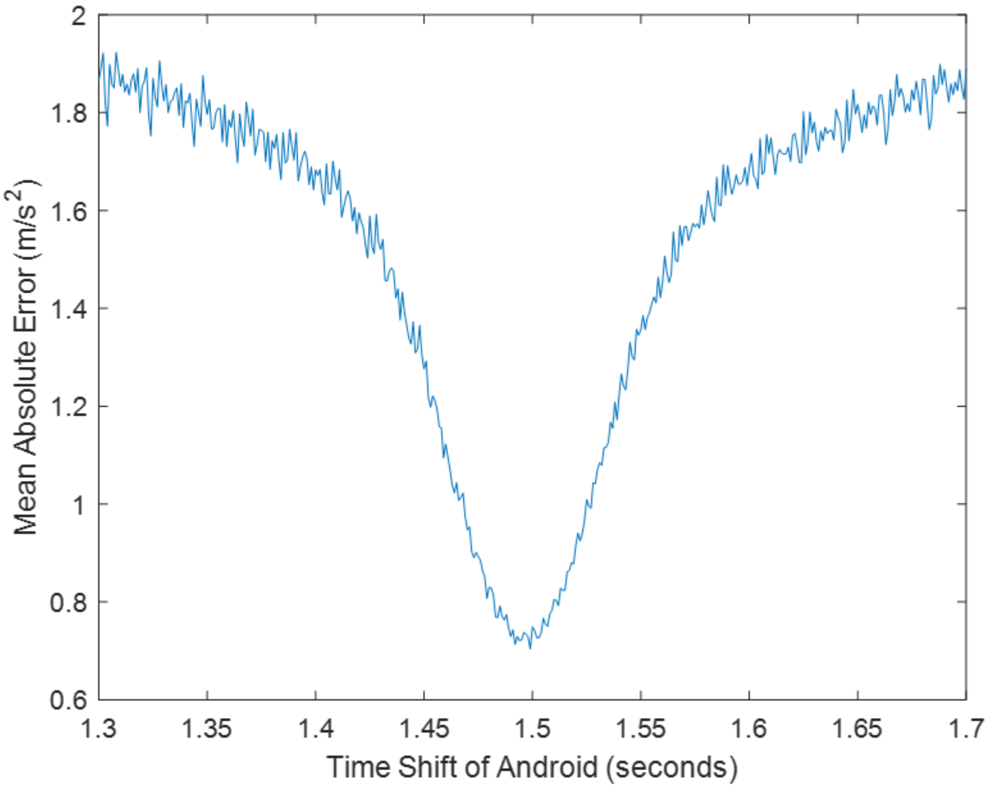

Figure 10: Result of analyzing potential clock differences between the LSM6DS's accelerometer and the wearable device's accelerometer.

For the accelerometer, a relative rotation between the two sensors could potentially cause accelerations in one axis on one sensor to be partially detected in several axes on the other. Therefore, the vector norm of the accelerations was the target for analysis. A linear model was fit between the wearable device and reference sensor, using the reference sensor as a predictor of the wearable device's accelerometer. This model was made with no intercept, since the true intercept for both sensors should be 0. This fit is displayed in Figure 11. The root mean square error was 1.21 m/s^2, with an r-squared value of 71.7 percent. The model estimated a slope of 0.988, significant using an alpha of 0.01. Figure 11 illustrates the average acceleration for both sensors, where each point represents the average of 100 acceleration estimates over a period of 2 seconds. Additionally, a Bland-Altman plot was constructed, shown in figure 12, showing a mean difference of 0.012 m/s^2 with a standard deviation of 1.22 m/s^2.

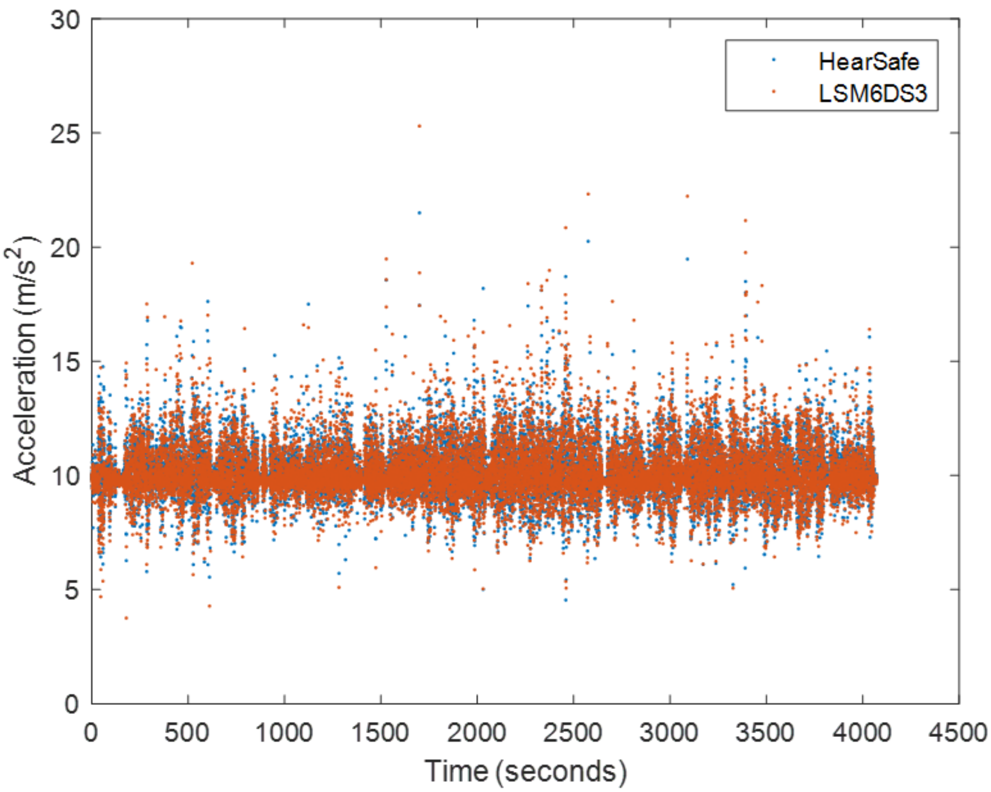

Figure 11: Accelerometer data, over 2 second periods (100 samples per period).

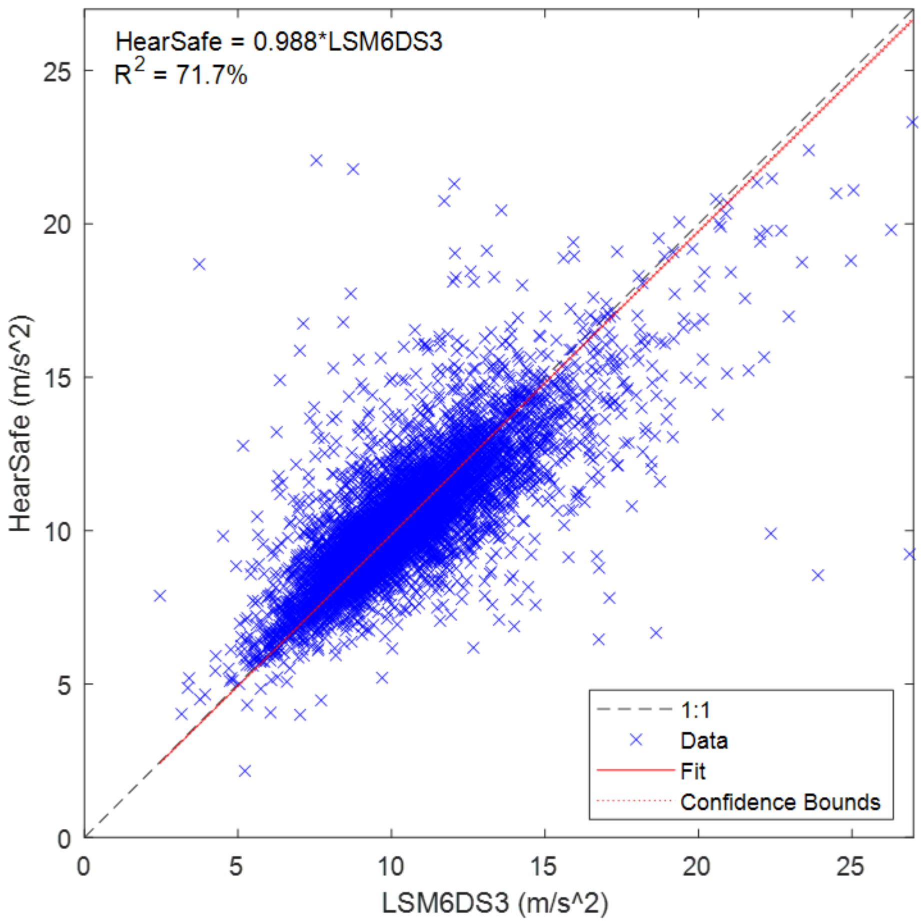

Figure 12: Result of linear regression between the LSM6DS3's accelerometer and the HearSafe's MPU6500 accelerometer.

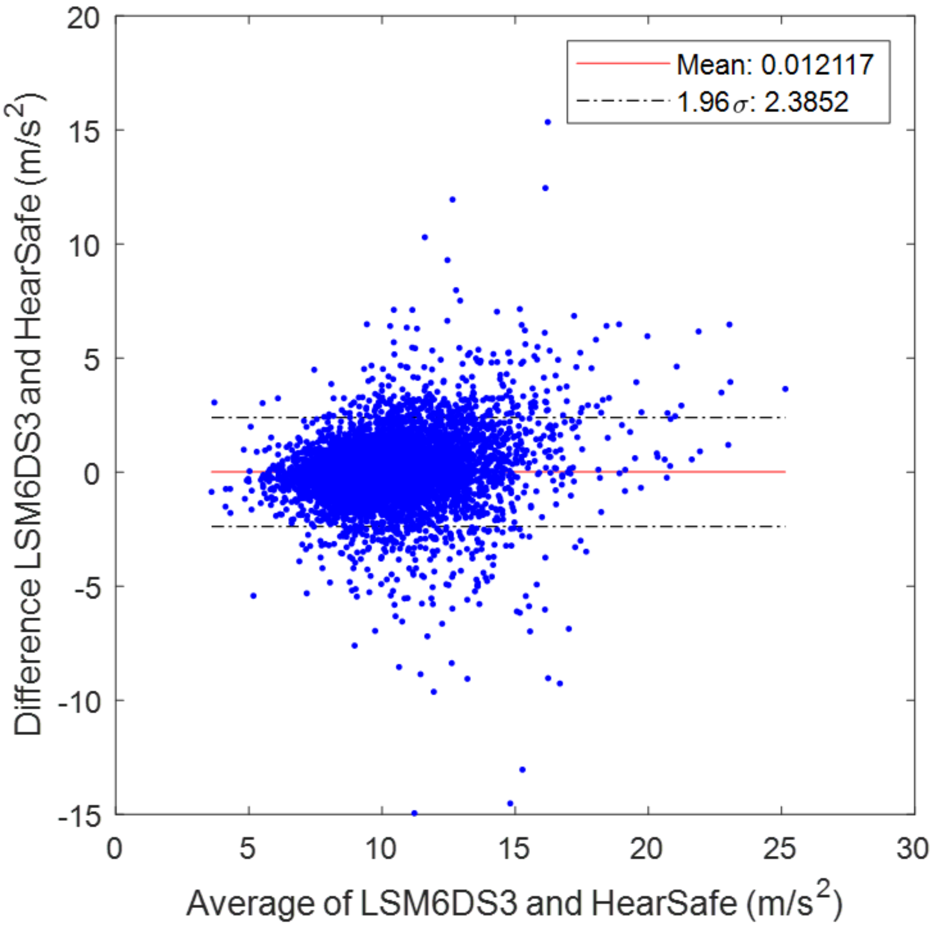

Figure 13: Bland-Altman plot of accelerometer data from experiment 1.

3.2.2 Experiment 1: Discussion and Conclusion

For the sound pressure level, the mean difference of more than 5 dBA shows a notable discrepancy. For one of the devices, none of the minute-averaged data are within +/- 2 dBA, indicating that over a reasonable timespan for the task, the HearSafe noise dosimeter and reference instrument never agreed on the sound levels. Figure 7 illustrates that HearSafe's noise dosimeter is consistently below the dBadge. This error is unacceptable, especially given

Occupational Safety and Health Administration's exchange rate of 5 dBA. Our device would likely predict half the dosage of sound that an agricultural worker would experience.

Reviewing the firmware used for the HearSafe's dosimeter revealed that the algorithm used to calculate the average sound level was incorrect: the sound level readings were being averaged after converting to decibels but should have been averaged before converting to decibels. This error was fixed before conducting a second experiment. We also reconsidered the unconventional mounting location of the dBadge, mounting it closer to the ear in the second experiment, following the manufacturer's recommendations for use.

The GPS had a mean absolute error of 5.8 meters between the 22 matching readings. This is over the goal of sub 4-meter accuracy on average, but the sample size was rather small. This small sample size as well as the location could have contributed to the large error. The location, which was inside a metal hog building, can cause inaccuracies for GPS as it requires non-line of sight communication with the navigational satellites. Therefore, during the second experiment, we were hopeful that GPS data collected outdoors would render more datapoints for comparison. This would also better represent an agricultural worker's daily tasks, since they are not limited to indoor work.

The accelerometers had an average norm of 10.11 and 10.15 m/s^2. This is a difference of less than 1% suggesting good agreement between the devices. Additionally, the linear model explained more than 71% of the variability of the LSM6DS3. The mean absolute error between the two sensors was 0.704, which is below the target of 10% of gravitational acceleration, 0.9806. Therefore, the accelerometer collected data within the target specification.

3.3 Experiment 2: Sound Pressure and GPS Test

This experiment involved one individual going to a farm and performing tasks outdoors as well as working in the same hog bin as the last experiment. The subject drove a truck around a farm while outdoors. Inside the hog building, the subject ensured there was enough feed for the livestock and that no ill or dead pigs were in any pen. The predominant sources of noise for this experiment were the truck's engine and the livestock. The subject wore the wearable device, a dBadge 2, and a Samsung Galaxy S5, which was running the GPS Logger app to continue the investigation of the sound pressure and GPS accuracies. The experiment lasted for approximately 1 hour and 45 minutes.

The dBadge and the wearable device both collected second-averaged, A-weighted sound pressure levels. The GPS Logger collected location readings every second when they were available, with the wearable device collecting GPS data when a sound pressure level of 70 dBA or higher was measured. This threshold value was lowered to trigger more GPS readings for comparison. We also moved the mounting location of the dBadge to be positioned closer to the user's ear. The mounting is shown in Figure 14 below. The smartphone with the GPS logger was kept in the test subject's pocket.

Figure 14: Mounting location of the dBadge, which has been moved closer to the ear compared to Experiment 1.

3.3.1 Experiment 2: Results

The following data was collected during this experiment: a pair of pressure readings, and a pair of accelerometer readings. The number of readings is shown below in Table 5.

Table 5: Number of readings for each device captured in experiment 2.

Source	**Number of HearSafe Sensor Readings**	**Number of Reference Sensor Readings**
Sound Pressure	6,366	6,339
GPS	307	5,061

Table 6 presents the average sound pressure level, 5th and 95th percentile sound pressure levels, readings over 85 dBA, dose, and the 8-hour time weighted average. The average is calculated by anti-logging the data, averaging, then converting back to decibels. Dose and time weighted averages were calculated using the Occupational Health and Safety Administration's guidelines (OSHA, 1999).

Table 6: Statistics for one-second sound pressure levels from experiment 2.

Sensor	**Average (dBA)**	**5th Percentile (dBA)**	**95th Percentile (dBA)**	**Above 85 (dBA)**	**Dose**	**8-Hour TWA (dBA)**
HearSafe	76.5	65.44	81.91	111	3.40%	65.61
dBadge	78.24	63.37	83.26	233	4.31%	67.32

There is no easy way to synchronize the two devices, so a clock offset may be present. Therefore, before the two time series were compared, we searched the data to see if a clock drift was present. To do this, the mean absolute error was calculated while shifting the time stamps of the test data. This error was calculated second by second from 120 seconds before the reported time to 120 seconds after the reading time. Figure 15 below shows a significant drop in mean absolute error at -9 seconds, which suggests the dBadge's clock was 9 seconds ahead of the wearable device's clock. These offsets were applied to all subsequent calculations.

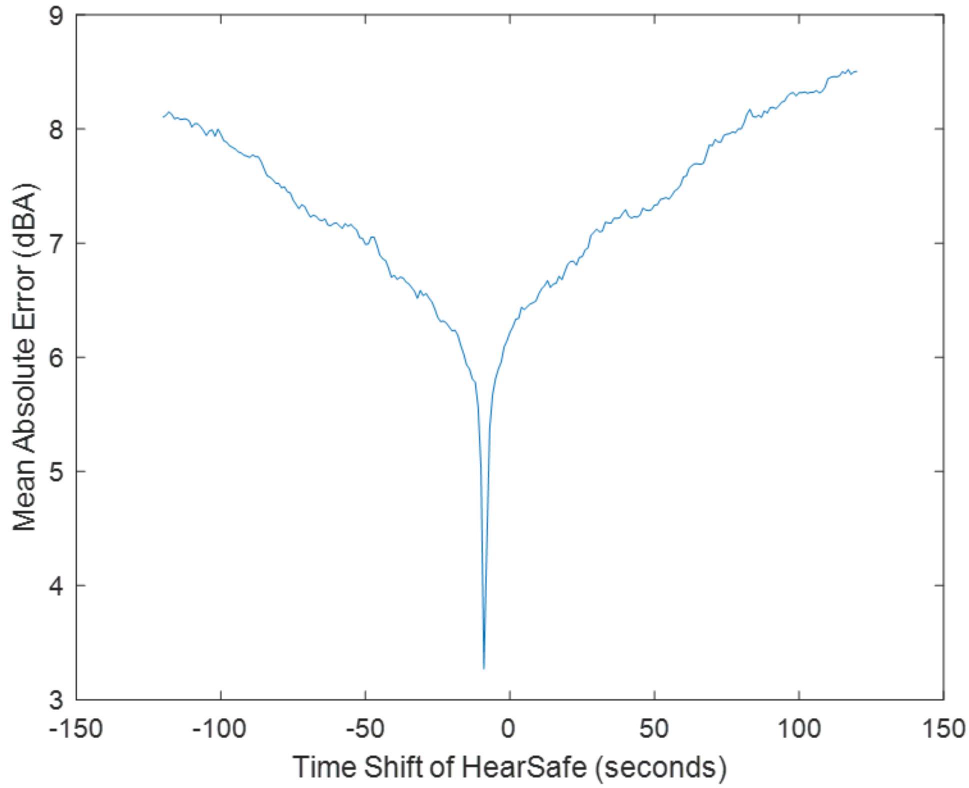

Figure 15: Result of analyzing potential clock differences between the dBadge and the HearSafe.

The minute averages were taken from the sound data for analysis, again excluding values below 60 dBA. The clock offsets, mean absolute error, and mean error for both minute and second data are shown in Table 7 below. Additionally, given that the first design requirement called for a sound dosimeter that measures within +/- 2dBA of a Class 2 dosimeter, the percentage of readings within this threshold are included. Figure 16 shows the minute averaged sound pressure levels for subject one’s devices.

Table 7: The clock offset, as well as minute averaged sound pressure level statistics for experiment 2.

Clock Offset (s)	**Mean Absolute Error (dBA)**	**Mean Error (dBA)**	**Readings within +/- 2 dBA of dBadge**
-9	2.26	-1.02	59.05%

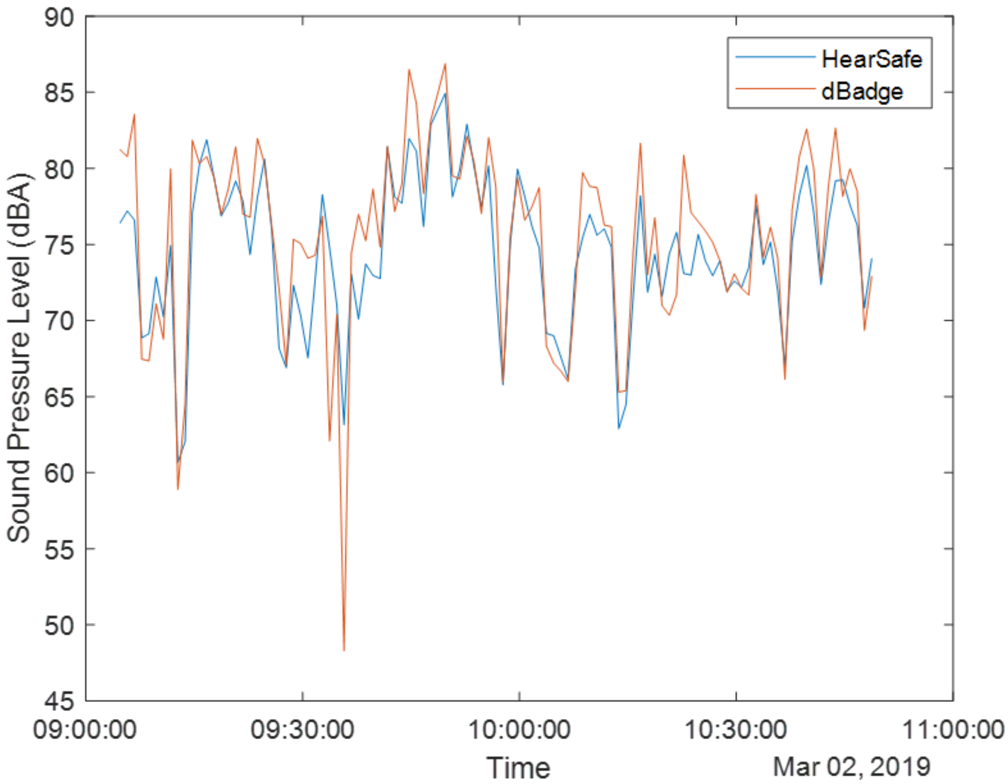

Figure 16: Sound pressure data of both instruments from experiment 2.

A linear model was fit using the dBadge data to predict the wearable device's noise dosimeter data, again with no intercept, which is displayed below in Figure 17. The root mean square error was 3.07, with an R^2 value of 79.5%. The resulting slope was 0.985, significant using an alpha of 0.01. Additionally, a Bland-Altman plot was constructed, shown in figure 18, showing a mean difference of 1.02 dBA with a standard deviation of 3.12 dBA.

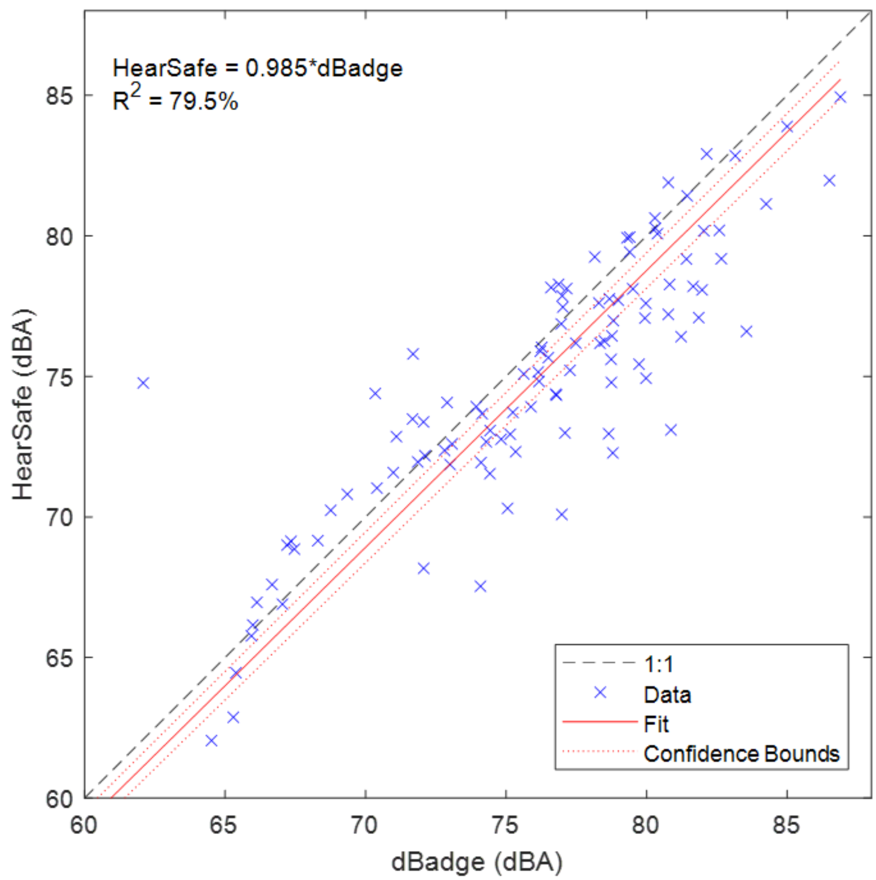

Figure 17: Correlation between the minute averaged sound pressure levels of the HearSafe and dBadge dosimeters with a linear fit.

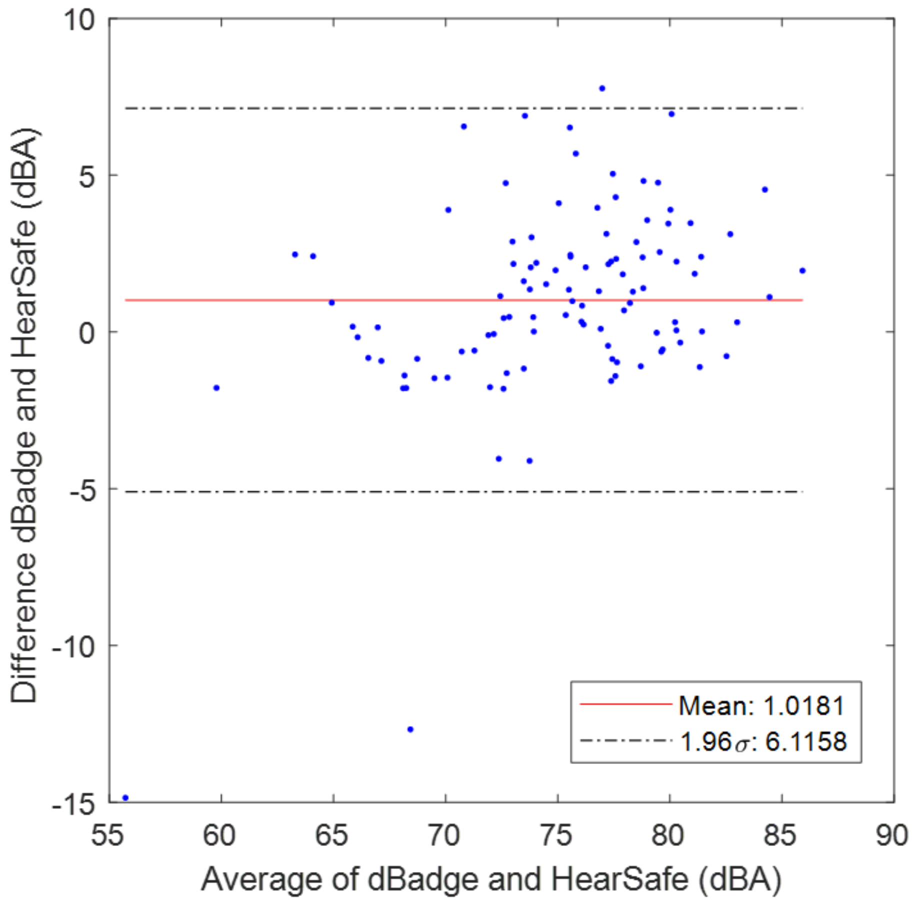

Figure 18: Bland-Altman plot using minute averaged sound pressure levels from experiment 2.

The GPS data was compared by looking for matching timestamps between the GPS Logger and the wearable device. The errors between these points were then calculated, with 307 GPS locations collected by the wearable device, 146 of which had timestamps matching the reference GPS readings. The mean absolute error of these 146 measurements was 3.66 meters. The minimum error was 0.22 meters, with a maximum of 105.3 meters. The datapoints, converted to cartesian coordinates, are plotted in Figure 19.

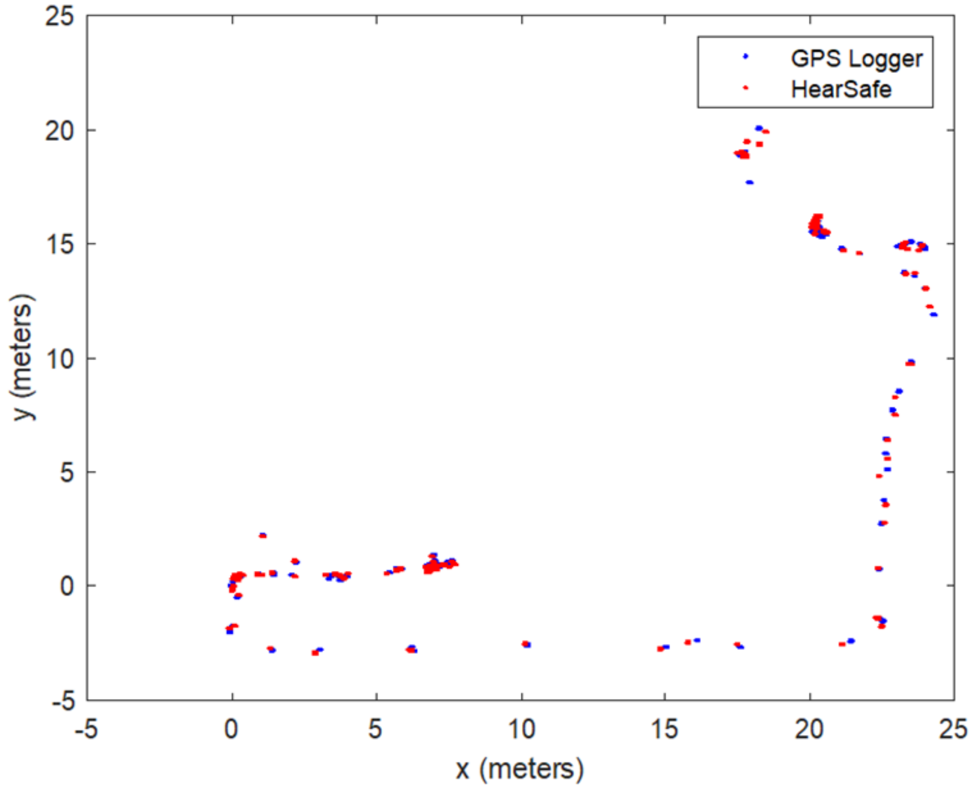

Figure 19: GPS data from experiment 2, converted to a cartesian coordinate system.

3.3.2 Experiment 2: Discussion and Conclusion

For the sound pressure level, the mean absolute error of 2.26 dBA indicates an acceptable tracking between the two devices. An R^2 value of almost 80% suggests the resulting model explains a majority of the variance within the wearable device's noise dosimeter sound pressure levels. Furthermore, looking at the timeseries shown in figure 16, the wearable device's dosimeter tracks well with the dBadge. From this test, 59% of minute averaged data meets the target criteria of being within +/- 2 dBA of a Class 2 dosimeter.

The GPS had a mean absolute error of 3.66 meters with the 146 same readings collected. The sample count is much stronger than the previous 22 samples, and the new average meets the goal of sub 4-meter accuracy on average. Therefore, the GPS module meets the target requirements.

3.4 Experiment 3: Battery and Storage Test

To test the if the battery can last for 8 hours and if the device could store 8 hours' worth of data, the system was run on a fully charged battery until it powered off. A speaker, controlled with an Arduino™ Uno (Arduino Uno, Arduino, Somerville, MA, USA), produced a 5 second tone every minute. Placing the external sound level meter close to the speaker triggered audio events, causing collection GPS data and audio clips. This meant the wearable device logged one GPS point every minute and recorded audio 25% of the time to represent an approximate standard use case. This was done inside to challenge the GPS chip, as searching for a GPS signal is battery intensive. The test should give an estimate of the expected life of the device given standard use.

3.4.1 Results and Discussion

During the battery test, the wearable device ran for approximately 10 hours and 20 minutes, longer than the standard 8-hour workday by a factor of 1.29. The file lengths collected are approximately: 80 bytes for loud sound event data, 103,500 bytes for one-minute accelerometer data, 1300 bytes for one-minute sound pressure data, and the audio clip 290,000 bytes. Assuming each is collected once a minute, around 400,000 bytes are collected per minute. With the SD card having a capacity of 8GB, more than 20,000 events can be stored. Converting this to 8-hour work days results in a capacity to store more than 41 days of data on the device at any given time.

4. CONCLUSIONS

The literature review indicated a need for a novel sound monitoring system that addresses three goals: tracking daily noise exposure, communicating the noise exposure to agricultural workers without the need of a safety specialist, and engaging interpersonal influences to help support the agricultural worker in protecting his or her hearing safety. The system proposed in the paper was designed to meet these goals by achieving the following design features:

1. Collect sound pressure data within +/- 2 dBA of a Class 2 dosimeter
2. Collect GPS data with an average of 4-meter accuracy
3. Collect accelerometer data with error less than 0.1g
4. Collect audio clips of loud tasks
5. Collect labels of loud tasks
6. Remain powered over an 8-hour period
7. Store at least 8-hours of data
8. Display to the user to where loud noises were measured
9. Allow data to be shared with family and friends
10. The sensors should be wearable while performing a variety of activities

Features 4, 5, 8, 9 and 10 were designed into the system, but not specifically tested. The audio clips for loud tasks are played successfully with loud sound events on the website. The website successfully displays where loud sound events occur throughout the farm as shown with screenshots in the design section. This website provides an accessible format that family and friends can use to review a user's exposure data. Finally, the arm band was designed to be used by runners, a highly mobile activity. This allowed the wearer to utilize the device while performing any farm related activity.

The five remaining features were demonstrated in a trio of experiments. The first experiment found that the accelerometer data had a mean error of 0.704 m/s^2, which is below the design goal of 0.9806 m/s^2. This test had over 200,000 data points, suggesting the accelerometer tests within the specified target requirements. The second experiment showed the noise dosimeter partially met the target goal of +/- 2 dBA of a Class 2 dosimeter. With approximately 6300 readings, 59.05% of the minute averaged readings were within the goal range. The GPS data on this test collected 146 matching data points, with an accuracy of 3.66 meters. This is better than the target average accuracy of 4 meters, successfully meeting the design requirement. The last test showed that the device can record audio 25% of the time and last for 10 hours and 20 minutes, longer than the 8-hour target. Finally, with the current 8 GB SD card, the device can store over 41 days' worth of data, well exceeding the one workday requirement.

4.1 Future Work

The system works well within the requirements, yet there are several areas for potential improvement.

4.1.1 Removing the Wire

Although the S5 Active has dust and water ingress protection, the micro USB port is still exposed since it is the communication line between the noise dosimeter and the Galaxy S5. This leaves a weak point in the system if the agricultural worker were to be working outside in dusty or rainy weather, potentially damaging the system. Although the connection can be superglued shut at the dosimeter, this can't be done at the Galaxy S5's USB port since it is still being utilized to charge the device. Additionally, even with the wire being zip-tied tightly to the mounting armband, there is still a risk of the wire getting snagged on a machine or tool, potentially resulting in damage to the device or to the agricultural worker. The wire could be removed by adding a Bluetooth module and external battery to the noise dosimeter. This would also allow it to be clipped closer to the agricultural workers ear while keeping the smartphone in a coat or pant pocket.

4.1.2 Accelerometer Data

Although the accelerometer data is not currently in use, its collection opens the door for multiple applications. First it could be used to improve the clustering algorithm, which will be discussed more later. Secondly, the accelerometer data could also be infused with the GPS data to provide higher resolution position estimation. Additionally, since the accelerometer is mounted on the arm, the data can be used to determine the position of the agricultural workers' arm relative to their body. This information could be useful in ergonomic related work. It could also be utilized to determine non-use, which would be shown through long periods of only capturing gravity. Finally, if the farmer were to get in an accident, such as crashing a vehicle, this could also be captured by the device. In these last two scenarios texts, calls, or e-mails could be sent out regarding these events.

4.1.3 Removing the Smartphone

Because of the smartphone, the system is relatively large in comparison to other noise dosimeters, and the microphone is mounted on the arm instead of the shoulder. Replacing this with an embedded system would reduce the profile of the system and allow it to be mounted closer to the agricultural worker's ear. Additionally, using a smartphone can constrict design capabilities. Certain limitations like the accelerometer turning off when the smartphone screen locks or the inability to set a sample rate can make data more difficult to use. If sensors inside the smartphone fail or are inaccurate, an entirely new device would be needed. Finally, calibration of sensors is nearly impossible, battery size customization is limited, and the large screen consumes a great deal of power.

4.1.4 Improving the Sound Pressure Data

Although previous studies have mentioned that sound data can be a useful surveying tool for noise exposure, even when inaccurate (Roberts, Kardous and Neitzel, 2016 & Williams, et al., 2016), it would still be beneficial to provide better resolution data to give more accurate dosage estimations. The circuit of the microphone has potential places of improvement to affect the sound floor, the ceiling, range, signal to noise ratio, and output of octave band information. Improving this circuit allows improved accuracy and precision of the noise dosimeter without requiring a redesign of rest of the system

4.1.5 Testing Impact on Hearing Protection Usage

Most importantly, the impact of this device on agricultural worker's utilization of hearing protection still needs to be assessed. Research suggests the system should improve usage rates. Agricultural workers themselves have indicated that the main reasons they do not wear hearing protection are "it is not available" and "never thought it was necessary" (Darragh, et al., 1998, Meister, Hest and Burnett, 2010, Wadud, Kreuter and Clarkson, 1998, & Gates and Jones, 2007). Because our system fills the information gap indicated by worker comments, there is a high likelihood that our system would significantly increase hearing protection usage. Additionally, this device fills the gaps from preceding studies (Gates and Jones, 2007, & McCullagh, et al., 2016) by providing daily noise exposure monitoring to agricultural workers while relaying this data without the need for a safety specialist.

4.1.6 Improving Clustering

The clustering algorithm leaves plenty of room for improvement. One way it can be improved would be to calculate the Fourier transform of the acceleration data and make an array of the frequencies with the highest amplitudes. This could be combined with similar frequency data of the audio clips as well as the GPS and other data collected for subsequent clustering. This would remove concerns of misclustering when the agricultural worker is rapidly changing tasks, or if the average GPS location isn't representative of the task. As more data is collected by the system, it could potentially be extended to real-time sound identification and shared between farms.

4.2 In Conclusion

This system has met the proposed design requirements through an Android™ based noise dosimeter paired with a website to provide agricultural workers with a variety of information pertaining to their daily noise exposures. These design requirements were carefully selected after considering studies that analyzed farmers' attitudes toward hearing protection devices and their self-cited reasons for non-use. This leaves the device ready to be tested in a controlled study to analyze its impact on agricultural workers' use of hearing protection.

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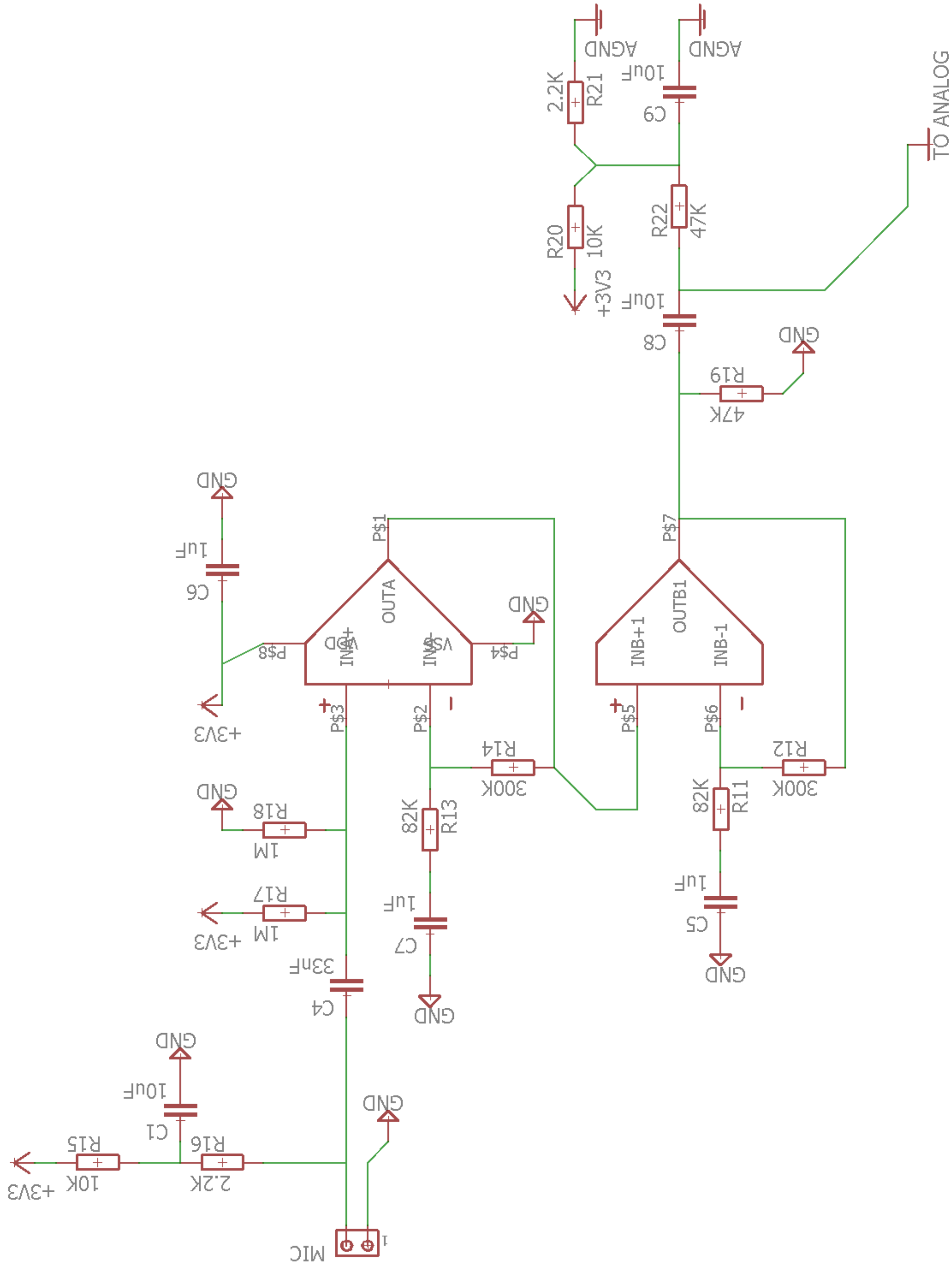
APPENDIX A: Sound Level Meter Code

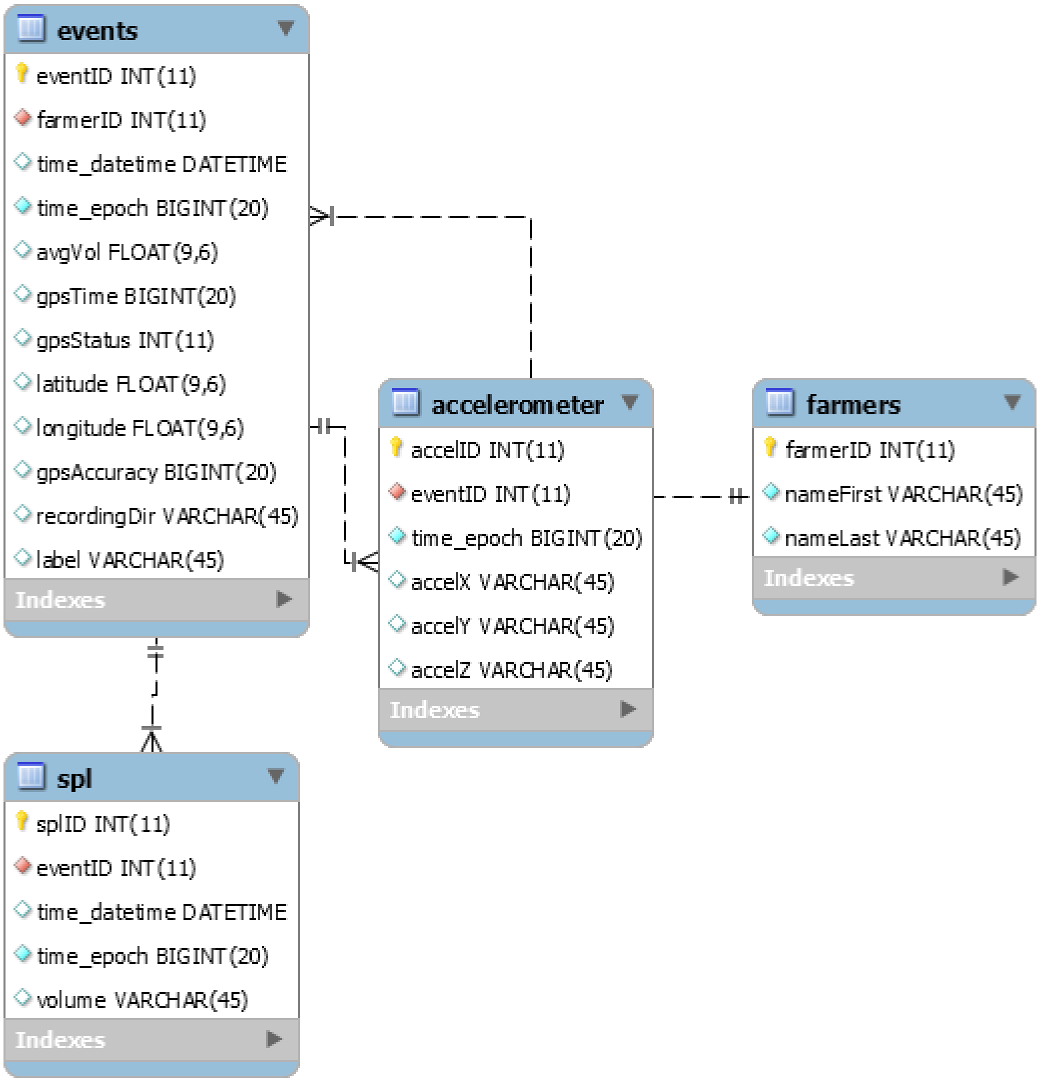
```
#include <Audio.h>
#include <Wire.h>
#include <SPI.h>
#include <SD.h>
#include <SerialFlash.h>

float calibrationConstant = 119.6; // Change this number to calibrate Sound Level Meter

int i;
int fft_samples;
float n;
float v;
float dB_holder;
const int led_pin = 13;

float sampling_rate = 44100;
float samples_fft = 1024;
float freq;
double numerator;
double denominator;

double a_weight[512];
unsigned long sample_time = 1000;
unsigned long start_time;
int l = 0;

float pow_constant;

AudioInputAnalog         adc1;           //xy=155,82
AudioAnalyzeFFT1024      fft1024;      //xy=348,95
AudioConnection          patchCord1(adc1, fft1024);

void setup() {
  // Audio connections require memory to work.
  AudioMemory(12);
  fft1024.windowFunction(AudioWindowHamming1024);

  Serial.begin(9600);
  pinMode(led_pin, OUTPUT);
  digitalWrite(led_pin, HIGH);

  pow_constant = 2/(samples_fft*samples_fft/sampling_rate);

  // Constants from ANSI S1.4
```

```
  double K1K3 = 2.242881*pow(10,16)*1.562339;
  double f1 = 20.598997;
  double f2 = 107.65265;
  double f3 = 737.86223;
  double f4 = 12194.22;

  a_weight[0] = 0;
  for(i=1; i < 512; i++){
    freq = ((float) i *sampling_rate)/samples_fft;

    numerator = K1K3*pow(freq,8);
    denominator = pow((pow(f1,2) + pow(freq,2)),2);
    denominator = denominator * (pow(f2, 2) + pow(freq, 2));
    denominator = denominator * (pow(f3, 2) + pow(freq, 2));
    denominator = denominator * pow( (pow(f4, 2) + pow(freq, 2)), 2);
    a_weight[i] = numerator / denominator;
  }
}

void loop()
{
  dB_holder = 0;
  fft_samples = 0;
  start_time = millis();

  while((millis() - start_time) < sample_time){
    if (fft1024.available()) {
      for(i=0; i<511; i++) {
        n = fft1024.read(i);
        n = n * a_weight[i];
        v = pow_constant * pow(n,2);
        dB_holder = dB_holder + v;
      }
      fft_samples++;
    }
  }

  dB_holder = dB_holder/fft_samples;
  dB_holder = db(dB_holder);
  Serial.println(dB_holder);
}
float db(float n) {
   return log10f(n) * 10.0f + calibrationConstant;
}
```

APPENDIX B: Sound Level Meter Circuit



APPENDIX C: Database Entity Relationship Diagram



APPENDIX D: Raw Sound Pressure Data