THE EFFECTS OF DESIGN ON PERFORMANCE FOR DATA-BASED AND TASK-BASED SONIFICATION DESIGNS: EVALUATION OF A TASK-BASED APPROACH TO SONIFICATION DESIGN FOR SURFACE ELECTROMYOGRAPHY

A Thesis

by

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ABSTRACT

The goal of this work was to evaluate a task-analysis-based approach to sonification design for surface electromyography (sEMG) data. A sonification is a type of auditory display that uses sound to convey information about data to a listener. Sonifications work by mapping changes in a parameter of sound (e.g., pitch) to changes in data values and they have been shown to be useful in biofeedback and movement analysis applications. However, research that investigates and evaluates sonifications has been difficult due to the highly interdisciplinary nature of the field. Progress has been made but to date, many sonification designs have not been empirically evaluated and have been described as annoying, confusing, or fatiguing. Sonification design decisions have also often been based on characteristics of the data being sonified, and not on the listener's data analysis task.

The hypothesis for this thesis was that focusing on the listener's task when designing sonifications could result in sonifications that were more readily understood and less annoying to listen to. Task analysis methods have been developed in fields like Human Factors and Human Computer Interaction, and their purpose is to break tasks down into their most basic elements so that products and software can be developed to meet user needs. Applying this approach to sonification design, a type of task analysis focused on Goals, Operators, Methods, and Selection rules (GOMS) was used to analyze two sEMG data evaluation tasks, identify design criteria that a sonification would need to meet in

order to allow a listener to perform these two tasks, and two sonification designs were created to facilitate accomplishment of these tasks. These two Task-based sonification designs were then empirically compared to two Data-based sonification designs. The Task-based designs resulted in better listener performance for both sEMG data evaluation tasks, demonstrating the effectiveness of the Task-based approach and suggesting that sonification designers may benefit from adopting a task-based approach to sonification design.

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NOMENCLATURE

AD	Auditory Display
ADSR	Attack, Decay, Sustain, Release
CTA	Cognitive Task Analysis
GOMS	Goals, Operators, Methods, Selection Rules
HCI	Human Computer Interaction
HF	Human Factors
HRTF	Head Related Transfer Function
HTA	Hierarchical Task Analysis
ICAD	International Conference on Auditory Display
ILD	Interaural Level Difference
ITD	Interaural Time Difference
LCR	Left-Center-Right
MBS	Model-Based Sonification
PMSon	Parameter-Mapping Sonification
sEMG	Surface Electromyography
TaDa	Task Analysis/Data Characterization
TMP	The Mapping Problem

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1. INTRODUCTION

1.1 What is an Auditory Display?

An auditory display is a display that uses sound to present information to a listener. Auditory displays are analogous to visual displays, which present visual representations of data to a viewer. Auditory displays can be used in both technical and artistic applications. A technical auditory display might be created in order to allow a listener to monitor data over time (e.g. heart rate, oxygen saturation, or muscle exertion level) or explore a large, multi-dimensional data set for trends and patterns. These kinds of auditory displays typically focus on faithfully representing the data that they present to the listener. An artistic auditory display might be created in order to allow a listener to hear and experience a sonic interpretation of a given data set (e.g. a dancer's movements). For the purpose of this thesis – which will focus on sonification of sEMG (surface electromyography) data – discussion of auditory displays will be limited to those that are created for technical purposes.

1.2 Brief History and Classification of Auditory Displays

An early example of an auditory display is the Geiger counter, a device invented in 1908 that displays radiation levels using clicks (Neuhoff, Wayand, & Kramer, 2002). The first scientific study regarding the use of audio to represent data was published in 1954 (Pollack & Ficks, 1954), and work on auditory graphing was done at Bell Laboratories in the 1970s (Chambers, Matthews, & Moore, 1974). Despite these initial efforts, relatively little progress was made in the field of auditory displays until the 1980s and early 1990s (Frysinger, 2005). This was due, at least in part, to the fact that digital sound generation technology did not become widely available until the mid 1980s.

The field of Auditory Display as it is known today was formalized in 1992 when Gregory Kramer organized the first International Conference on Auditory Display (ICAD) in Santa Fe, New Mexico. Since the field's inception, various methods for representing data using audio have been developed. These methods include audification, a technique by which data samples are isomorphically mapped to the amplitude of consecutive audio samples, creating a direct data-to-audio conversion (Alexander, Roberts, Gilbert, & Zurbuchen, 2014), and sonification, which uses non-speech audio to convey information (Kramer et al., 1999). Sonification can be further classified into two sub-categories: parameter-mapping sonification and model-based sonification (Hermann, 2008). Parameter-mapping sonification (PMSon) is a technique in which values in a data set are mapped to various acoustic parameters of sound such as pitch, loudness, or harmonic content (among many others). These parameter mappings can vary in the auditory parameter used (e.g. pitch, loudness, tempo, etc.), the range over which the auditory parameter is used (e.g. data values could be mapped to pitch over a one octave range or a several octave range) and polarity (e.g. an increase in data values could be mapped to an increase or a decrease in pitch, depending on the nature of the sonification and the expectation of the listener). In model-based sonifications (MBS), the user must interact with a model of a data set (in which sonic structures are pre-defined) before any sound is heard. For the purpose of this thesis, discussion of sonification and sonification design will be limited to parameter-mapping sonification, as it is more widely used than model-based sonification.

1.3 Why Auditory Display?

Traditionally, data sets have been displayed visually through graphs, charts, and the like. There is good reason for this, as visual displays are often informative and compelling. However, there are certain drawbacks to visual displays that have motivated the development and exploration of auditory displays.

First, visual displays usually require that users focus their visual attention on the display, which is often in a fixed location. This can limit the mobility of the user while using the display (Henkelmann, 2007). Sonification is, by definition, eyes-free, and thus allows the user to focus his or her visual attention elsewhere while using the display (Kramer et al., 1999).

Second, there is a growing body of work suggesting that auditory displays could be useful in various medical applications such as EMG sonification, movement sonification (measured with a Microsoft Kinect), and sonification for data monitoring in the operating room. Electromyography (EMG) sonifications have shown potential for identifying osteoarthritis (Pauletto & Hunt, 2006), helping people perform biceps curls more consistently, (Yang & Hunt, 2015), and for helping visually impaired people perform certain tasks (Iguchi, Matsubara, Kadone, Terasawa, & Suzuki, 2013).

Sonification of movement data has shown potential for use in stroke rehabilitation and athletic training. One study showed that stroke patients whose movements were sonified while re-learning gross-motor control showed increased performance and felt less impaired by their stroke as compared to patients whose movements were not sonified during motor re-learning (Scholz, Rhode, GroBbach, Rollnik, & Altenmuller, 2015). Another study discovered that sonification of elite athletes’ movements revealed information about their movements that was not apparent on a video of the movements (Schaffert, Mattes, & Effenberg, 2009). For data monitoring purposes, sonifying a simulation of anesthesia was shown to be an effective means of identifying potential adverse events during anesthesia (Watson & Sanderson, 2004). In these kinds of critical care situations, sonification of patient data can be useful due to the communal characteristic of sound – everyone present in the room can have simultaneous access to the display regardless of their orientation within the rrom, a feature not common to visual displays.

Third, and finally, visual displays do not take into account certain capacities of the human auditory system. Human hearing has roughly twice the temporal resolution of human vision (hearing: 20-30 ms, vision: 50-60 ms), and when sounds are spatialized (played to sound as though they are coming from different points in space), the human ear can resolve time differences on the order of 1 ms (Warren, 1993). Additionally, humans can hear over a wide range of loudness and pitch, allowing for a high resolution of data presentation (Henkelmann, 2007). Finally, the human hearing system, via a well-designed sonification, can also afford listeners the ability to distinguish changes in states with minimal disruption of attentional focus (Watson & Sanderson, 2004).

To conclude, the human ear is fine-tuned to recognize minute changes in sound, and if researchers can properly leverage the capacities of the human ear, current research has shown that auditory displays have the potential to provide a meaningful and intuitive form of data display.

2. DEFINITIONS

This section will elaborate on different definitions of sonification that have been given over the years, and provide definitions of some common parameters of sound used in parameter-mapping sonification as well as provide definitions for common synthesizer terminology.

2.1 Definitions of Sonification

One of the first definitions of auditory display was formulated by Stuart Smith in 1990:

> *"...sound is used as a medium for representing data. Here, the values of various sound parameters – pitch, loudness, duration, and so on – represent the values of multidimensional data (Reuter, Tukey, Maloney, Pani, & Smith, 1990)."*

Smith stated further that using sound for data representation is the auditory counterpart of data visualization, and he credited Bill Buxton (HCI specialist and Principal Researcher at Microsoft Research) for first proposing that this activity be called "sonification." Researchers who attended the first ICAD conference in 1992 recognized the need for the auditory display community to begin using a shared vocabulary, and in 1994, Gregory Kramer published a foundational book presenting the results of the first ICAD conference (Kramer, 1994) Several definitions of sonification were offered in this book, and among these, Dubus and Bresin (2013) identified Carla Scaletti's definition as the most elaborate. Scaletti's definition of sonification was:

"A mapping of numerically represented relations in some domain under study to relations in an acoustic domain for the purposes of interpreting, understanding, or communicating relations in the domain under study (Scaletti, 1994)."

Three years after this, Stephen Barrass looked closely at Scaletti's definition in his doctoral dissertation in order to reconsider her definition from a design perspective (Barrass, 1997). Through some substitutions of words and phrases, he arrived at the following definition of auditory information design:

"The design of sounds to support an information processing activity."

According to Barras and Vickers (Barrass & Vickers, 2011), Barrass's reconsideration of Scaletti's definition "…embraces both functionality and aesthetics, while sidestepping the thorny issues of veridical interpretation and objective communication." Barrass and Vickers explained further that this reconsideration focused on usefulness rather than interpretation, providing a basis for display evaluation, iterative development, and theory building. Barrass's definition and Scaletti's definition were reworded and combined in the NSF Sonification Report of 1999 to provide a generally accepted definition of sonification:

"Sonification is the use of non-speech audio to convey information. More specifically, sonification is the transformation of data relations into perceived relations in an acoustic signal for the purposes of facilitating communication or interpretation (Kramer et al., 1999)*."*

This definition stood for the next nine years until it was reconsidered by Thomas Hermann when it became apparent that these previous definitions of sonification were too narrow to include new sonification techniques such as model-based sonification (Hermann, 2008). Seeing this limitation, Hermann proposed four conditions that must be met in order for a technique that uses data as input and generates sound to be called sonification:

- *The sound reflects objective properties or relations in the input data.*
- *The transformation is systematic. This means that there is a precise definition provided of how the data (and optional interactions) cause the sound to change.*
- *The sonification is reproducible: given the same data and identical interactions (or triggers) the resulting sound has to be structurally identical.*
- *The system can intentionally be used with different data, and also be used in repetition with the same data.*

Hermann argued that this definition emphasizes important prerequisites for the scientific utility of sonification.

While these various definitions are similar in nature, they do have subtle differences and nuances. Understanding the variety of viewpoints on how to define sonification could help to provide sonification designers with some flexibility as they approach different sonification design spaces.

2.2 Definitions of Sound Parameters

There are five parameters of sound that are referred to in this thesis – pitch, loudness, timbre, attack time, and spatial location (also referred to as spatialization).

Pitch is the human perception of a sound's fundamental frequency, measured in Hz or cycles per second (CPS) (Hass, 2003). Pitch is the quality of sound that allows listeners to determine the "highness" or "lowness" of a given sound. The higher a sound's fundamental frequency, the higher the perceived pitch, and vice versa. As a general rule, young and healthy people can perceive pitches in the frequency range of 20 – 20,000 Hz.

Loudness has multiple components, but most generally it is the human perception of sound intensity (Nave, 2016b). Sound intensity is defined as the sound power per unit area and is generally measured in Watts/m^2. Loudness is closely related to sound intensity, but the two are not the same, since perception of loudness is dependent on the amplitude of a sound wave, the specific frequencies contained within the sound wave, as well as the duration of the sound wave. Information regarding the amplitude and frequency dependence of loudness perception is contained within the equal loudness curves, and sounds of equal sound pressure level (SPL) will be perceived to increase in loudness as their duration increases over the range of 20, 50, 100, 200 ms. Loudness perception then stabilizes for sounds longer than 1 sec (Bard & Negreira, 2017). While sound intensity can also be measured on the logarithmic decibel scale, loudness is often measured using a unit called phons.

Timbre, in addition to pitch and loudness, is another way that sounds can be characterized, and timbre has to do with the "tone" or "quality" of the sound (Nave, 2016c). Timbre is the human perception of at least three different components of sound:

- the harmonic/spectral content of the sound
- the vibrato/tremolo of the sound
- changes in loudness over the duration of the sound (commonly referred to as the "amplitude envelope" of the sound)

Timbre is the quality of sound that allows a listener to distinguish between the sound of a trumpet and the sound of a guitar if both instruments were used to play the same pitch at the same loudness for the same duration.

Attack time refers to the amount of time required for a sound to reach full volume and it is the first component of the amplitude envelope mentioned above (Nave, 2016a). The shorter the attack time of a sound, the sharper or more percussive it will sound. The longer the attack time of a sound, the more the sound will seem to "fade in."

Spatial location refers to the human perception of a sound's location in space. Human beings can determine the location of an external sound in space by calculating the interaural time difference (ITD) which is the time difference between the sound hitting one hear and then hitting the other ear, by calculating the interaural level difference (ILD) which the amplitude difference between the sound when it hits one hear and the sound when it hits the other ear, and through the way in which the pinna (outer ear) and head affect the intensity of certain frequencies (this affect is described by head-related transfer functions, or HRTF's) (Heeger, 2006) When audio is recorded or synthesized and listened to on a 2-channel stereo system (i.e. headphones), the easiest way to adjust the sound's spatial location is to adjust the left/right panning control. This alters the balance of loudness between the left and right audio channels, causing one channel (e.g. the left channel) to become louder than the other, which changes the sound's perceived spatial location (in this example, the sound would be perceived as panning to the left).

2.3 Synthesizer Terminology

Sonifications are generally created using some kind of audio synthesizer. There are three basic components of a synthesizer that are useful to understand when discussing sonification: the oscillator, filter, and envelope.

An oscillator is usually the first step in the signal chain of a synthesizer (Sievers, n.d.-b). Its function is to generate periodic oscillations anywhere in the audio frequency range (between 20 – 20,000 Hz) over a range of different amplitudes. Oscillators can generate different kinds of periodic waveforms, from sine waves to triangle, square, or sawtooth waves. Each of these waves has a different harmonic content, and thus has different timbres when they are played back on a speaker.

A filter amplifies or reduces selected frequencies in the signal created by the oscillator for the purpose of controlling the timbre of the sound. Most synthesizers come equipped with a low pass filter, and some have high pass, band pass, and notch options as well.

Envelopes are more abstract conceptually than oscillators and filters but are powerful when designing or shaping the timbre of a sound. They are used to control various parameters (such as frequency, amplitude, filter cutoff, etc.) of a synthesizer over time whenever a note or tone is played. One of the most common envelope types is the ADSR envelope, which consists of **A**ttack time, **D**ecay time, **S**ustain level, and **R**elease time (shown below in Figure 1). When applied to amplitude, Attack time is the amount of time required for the signal created by the oscillator to reach its maximum amplitude whenever a note is played. Decay time and Sustain level can be considered together, where the Decay time is the amount of time required for the signal to decay from its maximum amplitude to its Sustain amplitude (or level). Release time is the amount of time required for the signal to decay from its Sustain amplitude down to zero once a note is released.

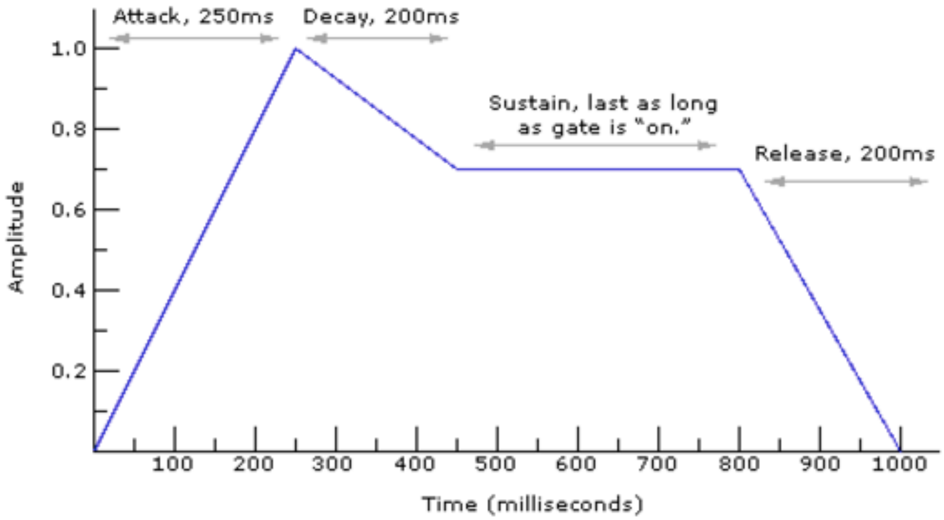

Figure 1: An ADSR envelope (Reprinted from Sievers, n.d.-a)

3. SONIFICATION LITERATURE REVIEW

In this literature review, four topics will be addressed relating to the sonification literature: general approaches to, and principles of, sonification design, sonification design frameworks, EMG sonification, and obstacles to sonification design. The purpose of this section is twofold: to present relevant information regarding sonification research that has already been done, and to identify research needs that have not yet been fully addressed. The prior research will form the foundation for the work performed in this thesis, while the research needs will motivate, inform and provide constraints for the research methodology.

3.1 General Approaches and Principles of Sonification Design

Towards the beginning of the auditory display community's development in the early 1990s, it seemed clear that sound could be an excellent medium for communicating information to a listener. However, at that time it was unclear how to go about developing and evaluating auditory displays, as there were no established, systematic methods for doing so (Walker & Kramer, 2005).

Many different concepts to consider when approaching sonification design were proposed early on in (Kramer, 1994) and three of these concepts are presented here. These concepts demonstrate some of the complexity regarding sonification design – complexity that made early design and evaluation of auditory displays difficult. The first concept was the idea that different sonification designs would be needed for different tasks (this concept is discussed further in the section on EMG sonification). The second concept was the notion of an analogic vs. symbolic spectrum for sonification design; where an “analogic” design refers to a direct one-to-one conversion from points in the data space to points in the representation space and a “symbolic” design refers to a more categorical representation where relations in the representation (i.e. the sound that is heard) are not necessarily reflective of relations in the data. Third was the concept that auditory parameters (such as pitch, loudness, etc.) can interact unexpectedly. For example, changes in attack time can be perceived as changes in the “brightness” of a sound (Kramer, 1994). These kinds of unexpected interactions between auditory parameters can make the listener’s perception of an auditory display difficult to predict. Taking concepts like these into consideration, it became clear that beginning research into the design and evaluation of auditory displays would not be easy, particularly when considering the inherently interdisciplinary nature of the field – musical, technical, and programming skill would all be required just to begin (Walker & Kramer, 2005).

One of the early empirical evaluations of sonification designs was performed by Walker and Kramer in a study that sought to begin moving beyond conceptual, non-standardized ideas about sonification (Walker & Kramer, 1996). To do this, Walker and Kramer decided to investigate the mapping of data onto sound by creating sonifications of temperature, pressure, size, and rate of production for a fictitious crystal factory using four different “ensembles” of sonification designs: those ensembles they felt would be “intuitive,” those they felt would be “okay,” those they felt would be “bad” or counterintuitive, and those that were “random.” They found that the “bad” and “random” sonification ensembles actually resulted in better listener performance than the “intuitive” and “okay” sonification ensembles. These results revealed two important aspects of sonification design research: the need for empirical assessments of sonification designs and the importance of mapping polarity - whether or not an increase or a decrease in a particular parameter of sound (i.e. pitch) should be used to represent a change in data values.

In 1999, Barrass and Kramer identified parameter-mapping sonification as the “usual approach” to representing data with sound (Barrass & Kramer, 1999). They stated that while this design approach has the benefit of ease of use and the ability to display multiple variables simultaneously, it can result in sounds that are unpleasant, and unexpected interactions between auditory dimensions can be difficult to predict and can obscure data relations (this phenomenon came to be known as The Mapping Problem).

In 2000, three specific questions relating to sonification design were asked by Walker, Kramer, and Lane (Walker, Kramer, & Lane, 2000). These were:

1. What auditory dimension best represents a given data dimension?
2. What is the listener’s preference regarding the polarity of the data-to-display mapping?

3. Once a mapping and a polarity are established, how much change in a given parameter of sound must be used to represent a given change in data values? What is the scaling factor for the data and display pair?

This work investigated different experimental paradigms for determining a listener's preference regarding mapping and polarity. Magnitude estimation, a psychophysical scaling paradigm, was determined to be effective for identifying listener preferences regarding mapping and polarity. This paradigm also provided transfer functions that could be used to effectively scale changes in a data dimension (e.g. temperature or pressure) to the appropriate changes in the display dimension (e.g. pitch or tempo). These kinds of transfer functions were needed because up until that point, sonification designers had often had little theory upon which to base their sonification designs, and what sounded good to one – or even several – sonification/sound designers may not have matched the expectations or conceptions of the intended listeners (Walker, 2002).

Multiple auditory dimensions can be mapped to the same data variable in order to create what is called a *redundant* mapping. In 2005, Peres and Lane presented work done on creating auditory graphs using three auditory dimensions: pitch, loudness, and time (Peres & Lane, 2005). The integral auditory dimensions of pitch and loudness were combined to create one redundant mapping while the non-integral dimensions of pitch and time were combined to create a second redundant mapping. Listener performance was compared between single parameter mappings (pitch, loudness, and time individually) and the redundant parameter mappings. Results indicated that listeners performed better with the redundant mapping of integral sound parameters (pitch and loudness) than they did with the individual parameter mappings, indicating that redundant mappings can be beneficial in certain cases.

While the work done on mapping, polarity, psychophysical scaling, transfer functions, and redundant mappings was needed to begin establishing a theoretical basis for sonification design, it has not, to date, effectively taken the listener's task into account. Very little has been said about the listener's task and how the specifics of that task could inform the design of the sonification. One notable exception to this is Barrass's doctoral dissertation, which is discussed in the next section on sonification design frameworks (Barrass, 1997). This work considered the listener's task as a means for establishing sonification design criteria, but no empirical evaluations of task-based sonification designs were performed. Recall from Kramer's book (discussed above) that different sonification designs will be needed for different tasks – thus the listener's task is likely an important consideration when designing a sonification. Additionally, recall from Walker and Kramer's work that sonification designs need empirical evaluation. In a systematic review of sonification publications, Dubus and Bresin reported that as work on sonification design expanded, researchers began using many different parameters of sound for mapping, including pitch, loudness, timbre, polyphonic content, brightness, spatialization, tempo, filter cutoff, Doppler effect, and decay time (Dubus & Bresin, 2013). However, they stated that many of these sonification designs were not assessed and they argued that there is a problematic lack of empirical evaluation of sonification designs. Couple this finding with the general lack of task-based approaches to sonification design as well as the lack of empirical evaluation of certain task-based approaches and there is a need for empirical evaluations of task-based approaches to sonification design.

3.2 Sonification Design Frameworks

In 1997, at the request of the NSF, auditory display researchers prepared a report overviewing sonification research and discussing the status of the field and its research agenda (Kramer et al., 1999). The report identified sonification design and application as one of the three major components of auditory display, and further specified that research into sonification design should focus on the formulation of a method for sonification design.

To this end, Barrass published his doctoral dissertation in 1997 in which he introduced the TaDa method for auditory information design (Barrass, 1997). In this method, “Ta” refers to task analysis and “Da” refers to data characterization. Task analysis methods are a way of breaking down a given task into its most basic elements for the purpose of identifying the user’s needs as well as finding potential problems/hazards that could prevent the user from successfully completing the task. Task analysis methods are discussed further in Section 4 below. Data characterization refers to identifying characteristics of the data set to be sonified: how many data points there are, how many data dimensions there are, which data dimensions are relevant, which data relations are relevant, etc. In the TaDa framework, task analysis and data characterization are combined with information requirements, perceptual factors, and device characterization in order to form a multifaceted framework of methods that allows sonification designers flexibility in approaching a range of complex sonification design problems.

Barrass also described another method for sonification design using what are called Design Patterns – ways of describing good solutions to common problems in context (Barrass, 2003). Design Patterns were originally used in architecture but have been extended to other fields such as computer programming and HCI. Barrass argued that the use of Design Patterns – which are written templates containing complex "IF-THEN" statements – could be extended to sonification design as well.

In 2005, Janet Anderson proposed a framework for sonification design that included seven facets to consider (Anderson, 2005). First, designers must understand the work domain. Second and third, respectively, designers must represent the higher order relationships in the data (those relationships that convey meaningful patterns) and determine which data variables should be displayed aurally. Designers must then scale the auditory dimensions and data variables appropriately and map the data to the sound parameters; these are the fourth and fifth aspects, respectively. Sixth, the designer must determine the number of auditory streams needed in the sonification. An auditory stream is a sound or group of sounds perceived as coming from the same source (Williams, 1994). For example, when one is walking along a busy street and hears the sounds of multiple cars passing by as well as the sounds of multiple birds chirping, it is easy to perceive the traffic sounds as a single stream and the bird sounds as a separate stream. The final step in Anderson's framework is mapping the auditory dimensions to the auditory streams identified previously.

In 2007, Alberto de Campo proposed a data sonification design space map (de Campo, 2007). This map addresses a similar, though slightly different, problem than what Barrass's TaDa framework addressed. Barrass's framework focused on finding ways to represent data relations that are already known in an intuitive manner. De Campo's framework focused on providing a map for creating sonifications of data whose structures/relations are not previously known so that these structures can emerge as perceptual entities or audible "sound objects" in the acoustic domain.

Despite these proposed methods and frameworks for sonification design, during the 2016 ICAD Student Think Tank, students and leading auditory display researchers discussed the status of the field regarding an agreed-upon design framework and concluded that thus far, there is no agreed-upon sonification design framework (S. Barrass, D. Brock, M. Gröhn, B. Walker, D. Worrall, personal communication, July 3, 2016). Thus, there is still a need within the auditory display community to develop a sonification design framework.

3.3 Electromyography Sonification

The work conducted here began as research specifically on surface electromyography (sEMG) sonification. sEMG is a technique for measuring muscle activation onset and duration, as well as muscle exertion level. It is used by physical therapists (Kang, Kim, & Kim, 2014), ergonomists (Mabrouk & Kandil, 2012), and scientists (De Luca, 1997) as a biofeedback tool (Steele & Bennett, 2012) and as an index of muscle fatigue (De Luca, 1997). EMG sonification has shown potential for identifying musculoskeletal disorders (Pauletto & Hunt, 2006), helping people perform biceps curls consistently (Yang & Hunt, 2015), and for helping visually impaired people perform certain tasks (Iguchi et al., 2013). In addition to this work, Matsubara et al. explored whether or not participants could listen to an EMG sonification of two different muscles and identify certain data characteristics such as whether only one muscle contracted or if both muscles contracted (Matsubara, Terasawa, Kadone, Suzuki, & Makino, 2012). They tested three different sonification designs (a pitch mapping, polyphonic timbre/loudness mapping, and timbre mapping) and found that the polyphonic timbre/loudness mapping resulted in the best listener performance (with 85.2% accuracy), but that listeners showed a slight subjective preference for the pitch mapping.

Given this information, coupled with the facts that sonification designs need empirical evaluation (Walker & Kramer, 2005) and that there have been relatively few empirical comparisons between sonification designs to date (Dubus, 2012), one study sought to explore the effects of sonification design on listener performance by empirically comparing six different sonification designs for sEMG data (Peres, Verona, Nisar, & Ritchey, 2017). Six different redundant sonification designs using the following auditory dimensions: pitch, loudness, attack time, and spatial location. Prerecorded sEMG data were used to create the sonifications. In each sonification, listeners heard sEMG data from two different muscles played simultaneously (referred to as Muscle A and Muscle B). Each sonification was 10 seconds long and in each sonification, both Muscle A and Muscle B began at rest, contracted at close to the same time, and then returned to rest. The six redundant mapping designs are shown below:

1. Loudness, Attack, Non-Spatialized
2. Loudness, Attack, Spatialized
3. Pitch, Loudness, Attack, Non-Spatialized
4. Pitch, Loudness, Attack, Spatialized
5. Pitch, Loudness, Non-Spatialized
6. Pitch, Loudness, Spatialized

For the spatialized conditions (Designs 2, 4, and 6), data from Muscle A were played in the left ear while data from Muscle B were played in the right ear. For the non-spatialized conditions (Designs 1, 3, and 5), data from both muscles were played equally in the left and right audio channels. Participants were given two tasks to perform after listening to each sonification: identify which muscle (A or B) activated first (TIME task), and which muscle (A or B) exhibited a higher exertion level (LEVEL task). Participants listened to 10 sonifications of each design, and their accuracy in answering the questions for both tasks was calculated as a percentage (for example, if a participant answered 6 out of 10 questions correctly for the LEVEL task for Design #2, then their score for that task/design pair was 0.6). Results indicated that Design #6 (Pitch, Loudness, Spatialized) yielded the best listener performance for the TIME task, but Design #4 (Pitch, Loudness, Attack, Spatialized) yielded the best performance for the LEVEL task. These results indicated that sonification design can impact listener performance and that effective sonification designs for sEMG data will need to be different based on the task that the listener is performing—indicating that the design of the sonification should be based on an *analysis* of the specific tasks. These results motivated the use of task analysis methods (discussed below in Section 4) as a tool for informing sonification design.

3.4 Obstacles to Sonification Design: Aesthetics and The Mapping Problem

As discussed in Section 3.1, there is a general lack of empirical evaluation of different sonification designs. Section 3.2 showed that there is still a need for the development of an agreed-upon framework or method for sonification design. Section 3.3 showed that the listener's task is important in the design of a sonification.

There are also problems specifically related to sEMG sonification design. Despite the potential that sEMG sonification has shown, researchers have identified aspects of the sonification designs that needed improvement. Pauletto and Hunt found that 60% of the participants in their study did not want to listen to any more of the same type of sonifications after only 20 minutes of listening (Pauletto & Hunt, 2006). They suggested that their display seemed to cause fatigue and that this signaled a need for improvement in the aesthetic of the sonifications they used. Furthermore, Yang and Hunt found that while EMG sonifications helped participants perform biceps curls more consistently, there was still room for aesthetic improvement in the sound (Yang & Hunt, 2015). Matsubara et al. found that one of their mappings did not contain enough timbre variation to be effective and ultimately they suggested that sonifications must sound both friendly and clear while also taking the familiarity of a sound into consideration (Matsubara et al., 2012). Each of these problems is, on some level, related to the problem of sonification aesthetics.

Sonification aesthetics has become a prominent topic within the field of auditory display (Barrass & Vickers, 2011; Grond & Hermann, 2012; Roddy & Furlong, 2014; Walker & Nees, 2011). The precise definition of what "sonification aesthetics" really is, however, is still in a state of flux because views on sonification aesthetics have been developing over time.

Initially, Kramer suggested that improving sonification aesthetics would likely reduce display fatigue (Kramer, 1994). Roddy and Furlong argue that, historically, sonification aesthetics are treated as a means of reducing annoyance and guaranteeing listener engagement (Roddy & Furlong, 2014). Walker and Nees considered it advisable to design aesthetically pleasing (i.e., musical) sonifications to the extent possible while still conveying the intended message (Walker & Nees, 2011). Barrass and Vickers stated that while aesthetics is sometimes considered to be an exclusively artistic pursuit – and therefore excluding a scientific field like sonification – this view is predicated on the false dichotomy that art and science are incompatible (Barrass & Vickers, 2011). They further stated that aesthetics, at its core, is about sensuous perception, not just art. Going beyond these ideas, Leplatre and McGregor argued that the aesthetic of a sonification and the function of a sonification are not two different things and that function and aesthetics cannot be dealt with independently in auditory display (Leplatre & McGregor, 2004). Furthermore, Johnson noted that aesthetics are the substrate of meaning, and that embodied schemata are the syntax by which that meaning unfolds (Johnson, 1990). Roddy and Furlong looked to Johnson's idea in order to propose an understanding of sonification aesthetics that looks to embodied cognition and embodied meaning-making in order to form an aesthetic framework for sonification design (Roddy & Furlong, 2014).

Despite this ongoing debate regarding the proper definition of sonification aesthetics, perhaps an even larger problem currently facing sonification research is known as The Mapping Problem (Worrall, 2011). The Mapping Problem (TMP) is specific to parameter mapping sonification, and is thought to arise from the non-orthogonality or co-dependence of psychophysical parameters: linear changes in one domain can produce non-linear auditory effects in another (Worrall, 2014). Worrall suggests that a new and evolving paradigm of perception – involving the way in which perception is influenced by the physical body – may allow for a new mapping model for data sonification to emerge, which may allow for the creation of sonifications that are more perceptually coherent and stable (Worrall, 2011).

To conclude this section on sonification literature review: sonification design research is currently in need of empirical evaluations of different sonification designs, movement towards an agreed-upon sonification design framework, improvements in sonification aesthetics, and a way to address The Mapping Problem.

4. TASK ANALYSIS METHODS

4.1 Task Analysis

Since the effectiveness of a given sonification design has been shown to be dependent on the data analysis task that the listener is performing, it follows that having a framework for analyzing the listener's task would be beneficial for understanding the specifics of a given task and predicting which features in a data set would need to be displayed audibly in order for a listener to perform that task. To that end, this section explains what task analysis methods are, what they are used for, how they are often categorized, and presents the reasoning for my choice of which task analysis technique to use in this thesis.

Task analysis methods are commonly used by researchers and designers in the fields of Human Factors (HF) and Human Computer Interaction (HCI) in order to break down a task into its most basic elements (Phipps, Meakin, Beatty, Nsoedo, & Parker, 2008; van der Veer, Lenting, & Bergevoet, 1996). Furthermore, task analysis methods can be used in several different ways; as the entire front-end predesign process, as one element of the front end process, or as a range of techniques that come into play at different times during design and development (Redish & Wixon, 2002). Despite this variety in how task analysis methods can be used, there is a common thread to each approach: a task analysis is meant to provide designers and researchers with knowledge about the users, their goals in accomplishing the task, their environment, the manual elements of the task, the cognitive elements of the task, the tools used to perform the task, the duration, order, and complexity of the task, as well as any other unique factors pertaining to the task (Kirwan & Ainsworth, 1992). Task analysis methods were developed primarily as a means for assessing and reducing human error, though the use of these methods has expanded over time (Berecuartia, 2011).

There are many different types of task analysis methods available and one simple way to categorize them is to divide them into action oriented methods and cognitive methods (Embrey, 2000). Action oriented methods (such as the commonly used hierarchical task analysis, or HTA) focus on observable actions, or identifying, in top down fashion, the goal of the task, as well as the various subtasks and conditions under which those subtasks must be performed in order to achieve the goal. Cognitive methods, on the other hand, focus on analyzing and outlining the unseen mental processes – diagnosis, decision making, problem solving, etc. – that can give rise to human error (Embrey, 2000).

As discussed in Section 3, the field of auditory display is still in need of methods for improving sonification design. Prior research investigating sEMG sonification has shown that different sonification designs will be needed for different tasks, and that task analysis methods such as those mentioned above may prove useful for informing, improving, and selecting a sonification design for a given task. But the question then becomes, and indeed Anderson asks: out of the multiple types of task analysis methods available, which analysis methods are appropriate and could be used to inform and improve sonification design (Anderson, 2005)?

To propose an answer to this question, as well as lay out the task analysis method chosen for use in this thesis, two different definitions of design that have been offered in the sonification literature are presented, aspects of both are combined, and the problem of sonification aesthetics discussed in Section 3.4 is incorporated into the proposition.

Barrass and Vickers offer the first definition of design: "*an iterative practice-based discipline involving cycles of hypothesis testing and critical evaluation that aims for solutions to specific problems in context*" (Barrass & Vickers, 2011). The idea of finding solutions to "specific problems in context" is key, and one significant element of a sonification design problem's context is the listener's task. This suggests that task analysis methods might be useful as a tool for addressing the context of a sonification design problem.

The second definition, which is specifically related to sonification design, is Barrass's definition, which was discussed in Section 2: "*the design of sounds to support an information processing activity*." Information processing activities are cognitive activities, where cognition is understood to be the acquisition of knowledge and understanding through thought, experience, or the senses. Thus, according to these two definitions, an effective sonification design must accomplish at least two things:

1. It must address the context of the design problem (which is, in part, related to the listener's task), and
2. It must support the cognitive needs of the listener while performing that task

To satisfy these two criteria, it seems appropriate to choose a task analysis method that identifies the cognitive aspects of interpreting a sonification for use in aiding the sonification design process.

4.2 Identification of GOMS as Desired Task Analysis Method

Given these two criteria, the first appropriate step was to use cognitive task analysis (CTA) methods to identify the cognitive needs of the listener for a specific listening task, as CTA methods are well established and have been widely used. However, upon further investigation, it became obvious that using CTA methods would be problematic because they usually involve observation of expert performance, interviews with subject matter experts (SMEs), and capturing an expert's performance with a think aloud protocol or subsequent recall (Clark, Feldon, Merrienboer, Yates, & Early, 2008). In short, observing experts' behavior while interpreting a sonification would be largely fruitless since cognitive tasks cannot be visually observed and using a think aloud process would be remarkably difficult because it would not be possible to "think aloud" without interfering with the act of listening to the sonified sEMG data.

To account for the cognitive aspects inherent to sonification interpretation, and to avoid the complications involved with using CTA methods for decomposing sonification interpretation tasks, the task analysis method known as GOMS was chosen to analyze the cognitive requirements of a sonification interpretation task. GOMS is a form of hierarchical task analysis (Gray & Broehm-Davis, 2000) developed by Card, Moran, and Newell (Card, Moran, & Newell, 1983) and stands for Goals, Operators, Methods, and Selection rules. The four components of a GOMS analysis can be described as follows (John & Kieras, 1996):

- **Goals:** what the user is trying to accomplish. Goals can be, and often are, decomposed into Goal/Subgoal hierarchies.
- **Operators:** actions performed in service of a goal. Operators can be perceptual, cognitive, or motor acts, or some combination of these.
- **Methods:** sequences of operators and sub-goal invocations that accomplish a goal.
- **Selection rules:** when there is more than one method for accomplishing a goal, selection rules are the rules that the user employs to determine which method to use to accomplish the goal.

GOMS analyses can tackle the cognitive elements of a task without the need for conducting interviews or observing expert performance. GOMS has been widely used and validated as a means of modeling human performance of various tasks (Card et al., 1983), and as such, it was deemed an ideal type of task analysis for aiding and informing sonification design. The specifics of the tasks that were analyzed using GOMS and the actual GOMS analyses are presented in Sections 6.1 and 6.2 below.

5. EXPERIMENTAL QUESTION AND SPECIFIC AIMS

There are currently many needs in sonification research. Of these needs, this thesis addresses the following:

1. the lack of empirical evaluation of sonification designs. This will be addressed by performing an empirical evaluation of four sonification designs
2. the need for addressing the context – of which the task is a significant part – of sonification design problems. This will be addressed by performing task analyses for two sEMG data evaluation tasks and identifying sonification design criteria based on the results of these task analyses
3. the need for sonification designs to support cognitive aspects of the task that the listener is performing. This will be addressed by performing GOMS task analyses, as opposed to task analyses which focus on observable actions

To date, many sonification designs have been based on the characteristics of the data to be sonified (i.e.,What type of data is it? How many data dimensions are there? How many data points are there?) (de Campo, 2007). Thus far, there has been little work done describing sonifications that were both based on the results of a task analysis and were empirically evaluated.

Based on the results of previous sEMG sonification research, it is clear that approaching sonification design from the perspective of the task to be accomplished and the cognitive requirements of that task – rather than the characteristics of the data – is an area needing investigating as a potential means to improving sonification design.

5.1 Experimental Question

The experimental question for this research is based on the fundamental assumption that sEMG sonification designs based on a task analysis that focuses on the cognitive requirements of the task will yield better performance than a sEMG sonification design based on characteristics of the sEMG data. The question is thus: to what extent can task-analysis-based sEMG sonification designs, as compared to data-based designs, aid listeners in accomplishing their sEMG data evaluation tasks and improve their performance on these tasks?

5.2 Specific Aim #1:

Perform an empirical comparison between task-analysis-based sonification designs (Task-based designs) and sonification designs based on data characteristics (Data-based designs). Participants completed multiple trials with two different Task-based designs and two different Data-based designs in order to determine whether or not certain Task-based designs can result in improved listener performance for specific tasks as compared to Data-based designs.

5.3 Significance of Aim #1:

If a Task-based approach to sonification design is found to be beneficial, this could mean that in certain cases, Task-based designs would outperform Data-based designs. If this is the case, an empirical argument could be made for including task analysis methods in a general sonification design framework. This could also mean that the two Data-based designs were simply not the best Data-based designs that could have been used, though efforts were made to ensure that the Data-based sonification designs used in this work were effective, so as not to make for a straw-man comparison between the Task-based and Data-based designs (this is described further in Section 6.4 below).

If the Task-based approach is not found to be beneficial, this could mean that either there was a problem with the specific task analysis method used or that there was a problem with the specific way in which the sonification design was based on the results of the task analysis. It could also mean that certain Data-based designs are sufficient or intuitive for performing certain sEMG data analysis tasks.

5.4 Specific Aim #2:

Compare listener performance for the difficulty level of the task. Participants were asked to perform two sEMG data evaluation tasks after listening to each sEMG sonification, and these tasks were to identify which of two muscles contracted first and which of two muscles had a higher exertion level. Data from previous research showed that when identifying which of two muscles contracted first, listeners were better able to do so when the two muscles contracted 0.4 sec apart than they were when the muscles contracted 0.1 sec apart (Peres et al., 2017). However, measurements between these difficulty levels were not done systematically and thus statistical comparisons could not be made. Thus, in this work, to more accurately measure listener performance for different task difficulty levels, four difficulty levels were defined for each task, resulting in a 4x4 matrix that determined how the difficulty level of sonification was determined (see Table 2, Section 6.6).

5.5 Significance of Aim #2:

If listener performance decreases as the difficulty of the task increases, this could reveal flaws in particular sonification designs and would allow comparisons to be made between designs that could not otherwise be made. For example, testing across difficulty levels allows listener performance for both Data-based and Task-based designs to be compared at low difficulty levels and high difficulty levels in order to determine if the Task-based designs performed more consistently across all difficulty levels. If this is the case, it would allow the designer to see where the limitations of each design begin to manifest themselves, and would also reduce the likelihood of encountering a ceiling effect in which all designs show similarly high performance due to the tasks being too easy. In short, testing across difficulty levels allows for more sophisticated conclusions to be drawn regarding the efficacy of each sonification design.

6. METHODS*

Each sonification design created for this study was coded in the SuperCollider audio synthesis environment. All sEMG data processing (rectifying and filtering) was performed using MATLAB.

6.1 sEMG Evaluation Tasks

For this thesis, the sEMG data evaluation tasks that the participants were asked to complete were the same TIME and LEVEL tasks originally mentioned in Section 3.3, and used in a prior sEMG sonification study (Peres et al., 2017). The two tasks are outlined below for clarity:

- TIME Task: determine which of two muscles (Muscle A or Muscle B) activates first
- LEVEL Task: determine which of two muscles (Muscle A or Muscle B) has a higher exertion level during muscle contraction

6.2 GOMS Analyses of TIME and LEVEL Tasks

In this thesis research, participants were asked to listen to sonifications of two channels of sEMG data, referred to as Muscle A and Muscle B, respectively. In the sonifications, both Muscle A and Muscle B began at rest, contracted at close to the same time,

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remained contracted for a few seconds, and then returned to rest. After listening to each sonification, participants were asked to perform the TIME and LEVEL tasks. GOMS analyses of these tasks are shown below in Figures 2 and 3.

Figure 2: GOMS Analysis for the TIME Task (from Verona & Peres, 2017)

Goal: DETERMINE IF A OR B CONTRACTS FIRST, OR IF THEY CONTRACTED SIMULTANEOUSLY
Method for TIME Goal: SG 1. Start Task SG 2. Identify 1st Muscle Activation SG 3. Determine if 1st Activation was Muscle A or Muscle B SG 4. Determine if other Muscle Activated also SG 5. If Unsure regarding Subgoal 3, Identify 2nd Muscle Activation SG 6. Determine if 2nd Activation was A or B SG 7. Determine if A or B Contracted First SG 8. Report if A or B Activated First
Method for Subgoal 1: *Start Task* Op 1. Grasp computer mouse Op 2. Point with mouse to PLAY button Op 3. Left-click PLAY button
Method for Subgoal 2: *Identify 1st Muscle Activation* Op 1. Perceive sonic event indicating muscle activation Op 2. Place sonic event in auditory store Op 3. Shift attention to auditory store
Method for Subgoal 3: *Determine if 1st Activation was A or B* Op 1. Perceive unique sonic identifier for A or B Op 2. Equate sonic identifier with A or B Op 3. Place identification of A or B into working memory
Method for Subgoal 4: *Determine if other Muscle Activated also* Op 1. Sonic event indicating other muscle activating simultaneously perceived? Op 2. If yes, store this knowledge in working memory Op 3. If no, then keep identification of A or B (from Subgoal 3) in working memory

Figure 2 Continued

Method for Subgoal 5: *If Unsure regarding Subgoal 3, Identify 2nd Muscle Activation* Same as Method for Subgoal 2, but for second muscle activation
Method for Subgoal 6: *Determine if 2nd Activation was A or B* Same as Method for Subgoal 3, but for the second muscle activation
Method for Subgoal 7: *Determine if A or B Contracted First* Op 1. Retrieve identification of first activation as Muscle A or B from working memory (Subgoal 3) Op 2. If second muscle activation was perceived simultaneously, retrieve this knowledge from working memory (Subgoal 4)
Method for Subgoal 8: *Report if A or B Contracted First* Op 1. Grasp computer mouse Op 2. Point with mouse to radio button indicating correct answer Op 3. Left-click radio button

Figure 3: GOMS Analysis for the LEVEL Task (from Verona & Peres, 2017)

Goal: DETERMINE IF A OR B HAS A HIGHER EXERTION LEVEL, OR IF THEY HAD THE SAME EXERTION LEVEL
Method for LEVEL Goal: SG 1. Start Task SG 2. Identify Muscle A's Activation SG 3. Identify Muscle B's Activation SG 4. Monitor A's Exertion Relative to B's Exertion during muscle contraction SG 5. Identify when A Returns to Rest SG 6. Identify when B Returns to Rest SG 7. Determine if A or B had Higher Exertion Level SG 8. Report if A or B had Higher Exertion Level
Method for Subgoal 1: *Start Task* Op 1. Grasp computer mouse Op 2. Point with mouse to PLAY button Op 3. Left-click PLAY button

Figure 3 Continued

Method for Subgoal 2: *Identify Muscle A's Activation* Op 1. Perceive sonic event Op 2. Perceive unique sonic identifier for Muscle A Op 3. Place sonic event in auditory store Op 4. Shift attention to auditory store Op 5. Equate identifier with Muscle A
Method for Subgoal 3: *Identify Muscle B's Activation* Same as Method for Subgoal 2, but for Muscle B
Method for Subgoal 4: *Monitor A's Exertion Relative to B's Exertion* Op 1. Use echoic memory to continuously update A's max exertion Op 2. Use echoic memory to continuously update B's max exertion Op 3. Place max exertion in working memory
Method for Subgoal 5: *Identify when A Returns to Rest* Op 1. Perceive sonic event indicating Muscle A returning to rest Op 2. Place sonic event in auditory store Op 3. Shift attention to auditory store Op 4. Stop continuously updating max exertion for Muscle A
Method for Subgoal 6: *Identify when B Returns to Rest* Same as Method for Subgoal 5, but for Muscle B
Method for Subgoal 7: *Determine if A or B had a Higher Exertion Level* Op 1. Retrieve max exertion level from working memory Op 2. Equate max exertion level with Muscle A or Muscle B
Method for Subgoal 8: *Report if A or B had a Higher Exertion Level* Op 1. Grasp computer mouse Op 2. Point with mouse to radio button indicating correct answer Op 3. Left-click radio button

6.3 Study Design

This study compared the efficacy of two Task-based sonification designs to two Data-based sonification designs taken from the EMG sonification literature, for two different tasks – muscle activation time and muscle exertion level. There were thus three main independent variables (IVs: Design (4: 2 Data and 2 Task), Task (2), and Difficulty Level (4)). For the two Data-based designs, the first level was a pitch mapping and the second level was a loudness/timbre mapping (loudness). These designs were taken from a 2012 study investigating sonification of EMG data for use in analyzing human movements (Matsubara et al., 2012). The details of these designs are explained below in Section 6.4. For the two Task-based designs, the first level was the "Task-Panning" design that used short beeps to indicate the onset of muscle activation and a panning tone to indicate exertion level difference. The second level was the "Task-Filter" design that also used short beeps to indicate the onset of muscle activation, but used a panned filter cutoff mapping to indicate muscle exertion difference. The two tasks were the judgment of muscle activation time (TIME task) and judgment of muscle exertion level (LEVEL task). The IV's and Levels are described in Table 1 below.

Table 1: Independent Variables and Level for the four sonification designs and two tasks (from Verona & Peres, 2017)

IV 1: Data-based	IV 2: Task-based	IV 3: Task	IV 4: Task Difficulty
Data-Pitch	Task-Panning	Muscle activation time difference	Four difficulty levels for TIME task
Data-Loudness	Task-Filter	Muscle exertion Level difference	Four difficulty levels for LEVEL task

This study was a within-subjects repeated measures factorial design. Participants listened to 16 sonifications with each of the four designs for a total of 64 sonifications.

The presentation order of the four sonification designs was counterbalanced to account for order effects.

6.4 Data-Based Designs

As previously mentioned, the two Data-based designs used in this study were taken from a 2012 paper (Matsubara et al., 2012). These were because participants in Matsubara's study were asked to perform sEMG data evaluation tasks that were similar to the sEMG data evaluation tasks participants perform in the current study. There were three design methods used in Matsubara's study: Method A: Pitch, Method B: Loudness/Polyphonic Timbre, and Method C: Timbre. Methods A and B were chosen as the Data-based designs for this study because they resulted in the best listener performance.

The Data-Pitch design was created according to the specifications laid out in Matsubara (Matsubara et al., 2012) for Method A, with the first channel of sEMG data (Muscle A) sonified using a sine wave tone over a frequency range of 300-525 Hz, and the second channel of sEMG data (Muscle B) sonified using a sine wave tone over a lower frequency range of 165-345 Hz. Additionally, we decided to spatialize this design by panning the first channel of sEMG data (A) hard left and panning the second channel of sEMG data (B) hard right. We made this decision based on our previous findings that spatialization helps listeners distinguish between sEMG channels (Peres et al., 2017).

The Data-Loudness design was also created according to the specifications laid out in Matsubara's paper for Method B. Again, we spatialized the design in an attempt to enhance listener performance in keeping with our previous findings.

6.5 Task-Based Designs

To design sonifications specifically for the TIME and LEVEL tasks, GOMS analyses were performed for both tasks, and the results are shown above in Figures 2 and 3. These GOMS analyses only show Goals, Subgoals, and Operators. The Method is to follow the Subgoals in numerical order, and for each Subgoal to follow the Operators in numerical order. The assumption is that there are not additional Methods that would allow for the accomplishment of each Goal, and thus there are no Selection Rules shown for selecting between competing Methods. Identification of the various Subgoals involved for each task served as the primary factor in establishing sonification design criteria for the Task-Based Designs.

For the TIME task, the analysis shown in Figure 2 indicates that a listener must be able to understand that the task has started (Subgoal 1), identify when the first muscle changes state from rest to contraction (Subgoal 2), then determine if that muscle was Muscle A or Muscle B (Subgoal 3). If the sonification does not give the listener the ability to accomplish even one of these Subgoals, the listener will not be able to complete the task. Thus, the design criteria for the sonifications based on the GOMS model for the TIME task are:

1. The start of the listening task must be evident
2. The sound of the first muscle changing state from rest to contraction must be evident
3. The listener must have a way of distinguishing between the sound of Muscle A activating and the sound of Muscle B activating

For the task of identifying which muscle has a higher exertion level, the analysis shown in the right column of Figure 1 indicates that the listener must be able to understand that the task has started (Subgoal 1), determine when both muscles change state from rest to contraction (Subgoals 2 and 3), monitor the exertion level difference between Muscle A and B for the duration of their contractions (Subgoal 4), identify when both muscles revert back to rest (Subgoals 5 and 6), then determine if Muscle A or B had a higher exertion level (Subgoal 7). Once again, failure to accomplish any of these Subgoals will prevent the listener from completing the task. Thus, the design criteria for the sonifications based on the GOMS model for the LEVEL task are:

1. The start of the listening task must be evident
2. The sound of both muscles changing state from rest to contraction must be evident
3. The exertion level difference between the two muscles must be evident
4. The sound of both muscles changing state from contraction back to rest must be evident

As previously mentioned, two sonification designs were created based on these design criteria: the Task-Panning design and the Task-Filter design. The Task-Panning design was also based on an interview conducted with a sound designer, in which he recommended exploring metaphoric sounds for use in sonification such as those heard in film and TV. To this end, a soft, low-pass-filtered (cutoff frequency: 1000 Hz) white noise was played while the muscles were at rest. This decision was made because white noise is generally associated with inactivity and would also serve to let the listener know that the sonification was indeed playing.

To indicate when each muscle activated, short beep tones were played at the moment of muscle activation. This decision was made to ensure a sonic contrast between the sound of the muscle at rest (white noise) and the sound of the muscle activating. The beeps were quite short so that the sound of the first beep would not bleed into the sound of the second beep. To indicate the activation of Muscle A, a short beep (0.07 sec duration) using a triangle wave at a frequency of 440 Hz was played in the left ear. To indicate the activation of Muscle B, a short beep of equal duration using a triangle wave at a frequency of 330 Hz was played in the right ear. Once both muscles had begun to contract, the LPF white noise was turned off and a tone indicating exertion level difference began to play.

To indicate the exertion level difference between Muscle A and B, the sonification code calculated the difference in amplitude between A and B (Amp_A - Amp_B), and then mapped this difference to the pan position of a tone that played during muscle contraction. If the difference was positive, this meant that Muscle A had a higher exertion level and the tone panned left, and vice versa. When the difference in exertion was small (~0.05 V), the tone panned slightly left or right (to a value of +/– 0.7 on SuperCollider's Pan2 function). When the difference in exertion was larger (> 0.1 V), the tone panned hard left or right.

After muscle contraction, the tone became silent and the white noise returned to indicate that the muscles had returned to rest.

The Task-Filter design was also based on the design criteria for the TIME and LEVEL tasks from the task analyses, as well as on another interview conducted with a different sound designer. This sound designer recommended using a filter cutoff mapping to indicate muscle exertion level, since changes in filter cutoff can lead to easily recognizable changes in timbre. Thus, for this design, when the muscles were at rest, a soft, low-pass-filtered sawtooth wave was played, one in the left channel to represent Muscle A and one in the right channel to represent Muscle B. The frequency of the waves was 100 Hz, and the cutoff frequency of the LPF was set to 300 Hz when the muscles were at rest. The two waves were played at equal amplitude so as to be perceived in the center of the stereo field.

To indicate when each muscle activated, short beep tones were played right when each muscle began to contract. To indicate the activation of Muscle A, a short beep (0.09 sec duration) using an additive synthesis tone with a fundamental frequency of 300 Hz was played in the left ear. To indicate the activation of Muscle B, the same short beep was played in the right ear. The fundamental frequency of 300 Hz was chosen so that these beeps would "sit on top of" the sawtooth wave tones (which were LPF'd at 300 Hz) and not interfere with them.

To indicate the exertion level difference between Muscle A and B, the sonification code calculated the amplitude difference in the same manner as in the Task-Panning design. If the difference was positive, this meant that Muscle A (in the left channel) had a higher exertion level and the difference was mapped to the cutoff frequency of the LPF in the left channel, such that the cutoff increased to allow more high frequency content to be heard in the left channel during muscle contraction. The opposite occurred when the amplitude difference was negative, with the cutoff of the right channel's LPF increasing to indicate that Muscle B had a higher exertion level. For small exertion differences (0.05 V), the cutoff would increase from 300 Hz to 1200 Hz, and for larger exertion differences (0.15 V), the cutoff increased from 300 Hz to 3600 Hz.

After muscle contraction, the cutoff of both LPF's was set back to 300 Hz to indicate that the muscles had returned to rest.

6.6 Activation Time/Exertion Level Differences

For each of the four sonification designs, participants listened to 16 sonifications. Of these 16, 4 displayed both muscles activating at the same time, and 4 each displayed both muscles activating 0.13 sec apart, 0.26 sec apart, and 0.39 sec apart.

Additionally, out of the 16, 4 sonifications displayed both muscles exhibiting the same exertion level, and 4 each displayed both muscles exhibiting a 0.05 V, 0.10 V, and 0.15 V amplitude difference during muscle contraction. The 16 sonifications for each design were numbered according to Table 2 below.

As an example, Sonification #1 for any given design displayed both muscles contracting at the same time (0 sec activation time difference) and exhibiting the same exertion level (0 V amplitude difference during contraction). Similarly, Sonification #11 in any given design displayed a 0.26 sec difference between the activation of Muscle A and the activation of Muscle B, and a 0.1 V difference in amplitude between Muscle A and Muscle B. The order in which each sonification within a given design was presented was randomized for each counterbalance.

Table 2: Listing of structure for the 16 sonifications for each design (from Verona and Peres, 2017)

		Activation time difference			
		0 sec	0.13 sec	0.26 sec	0.39 sec
Exertion level difference	0 V	*1*	*2*	*3*	*4*
	0.05 V	*5*	*6*	*7*	*8*
	0.10 V	*9*	*10*	*11*	*12*
	0.15 V	*13*	*14*	*15*	*16*

6.7 Participants

Forty students and faculty from Texas A&M university participated in this study (27 male, 16 female, ages 19-59). They all self-reported as not having any hearing impairment that would interfere with their ability to participate. At the beginning of each session, participants signed a consent form, completed a demographic survey, and were asked about their knowledge of and experience with sEMG data. After this, they were briefly trained on what sEMG data is, what sonification is, and how sEMG data can be sonified.

6.8 Computer/Audio Setup

The study was run locally through Google Chrome using the XAMPP environment in conjunction with a MySQL database for recording participant responses. Participants listened to the sonifications through a pair of Beyerdynamic DT 770 Pro headphones.

6.9 Measures

After listening to each sonification, participants were asked two multiple choice questions, one each for the TIME and LEVEL tasks. The choices were:

1. Muscle A activated first (or had a higher exertion)
2. Muscle B activated first (or had a higher exertion)
3. A and B had the same activation time (or exertion level)
4. Unsure

Listener accuracy was measured as a proportion of correct responses for both tasks. For example, if a listener correctly identified if Muscle A or B contracted first for 8 out of the 16 Data-Pitch sonifications, their score was 8/16 = 0.5 for that Design/Task pair.

6.10 Analyses

To identify the effects of Design (4), Task (2), and Level (4) on participants' performance, a 4 X 2 X 4 Repeated Measure factorial Analysis of Variance (RMANOVA) was conducted and Greenhouse-Geisser correction was used for any violation of sphericity. All post hoc comparisons were done using Bonferroni corrections with the family-wise error rate set at 0.05 using SPSS v.22 ®.

7 RESULTS*

7.1 Overall Performance

There was no effect of counterbalance on listener performance (p = 0.448), thus all subsequent analyses were done collapsed across counterbalance. As seen in Figure 4, there was no effect of Task, $F(1, 42) = 1.78$, $p = 0.19$. However, there was a main effect of design, $F(2.08, 87.29) = 91.23$, $p < 0.001$, $\eta^2 = 0.69$, and an interaction between Task and Design $F(2.55, 107.23) = 32.83$, $p < 0.001$, $\eta^2 = 0.44$.

Pairwise comparisons indicated that performance was different based on design with the Data-Pitch design having the worst performance and Task-Filter having the best ($p <$ 0.001). Data-Loudness and Task-Panning had performance levels in between those two and Bonferroni pairwise comparisons show that performance on all designs were significantly different from each other (all p's < 0.001). As shown in Figure 4, there was an interaction between Design and Task with the Data-Pitch design having better performance for the TIME task ($p < 0.034$), and the Task-Filter design having better performance for the LEVEL task ($p < 0.028$).

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7.2 Performance by Difficulty Level

Figure 5 shows the results by difficulty level for the activation time task. This figure shows that performance differed by Design with the Task-based designs resulting in better performance than the Data-based designs (all p's < 0.01). The Task-based designs and Data-based designs were not different from each other (p's > 0.29), $F(2.25, 94.32) = 19.60$, $p < 0.001$, $\eta^2 = 0.318$. Figure 5 also shows that there were overall differences in performance based on the Activation Time Differences (ATD) with better performance when the differences were larger (0.26 sec and 0.39 sec) (all p's < 0.001), $F(1.54, 64.65) = 12.27$, $p < 0.001$, $\eta^2 = 0.23$. The differences by Level differed by Design for the TIME task with Bonferroni comparisons indicating that Data-Pitch (0.13 sec) was different than all others and Data-Pitch (0 sec) was different than Data-Pitch (0.39 sec); Data-Loudness (0.13 sec) was different than all others; Task-Panning showed no performance differences by level; and Task-Filter (0.13 sec) was different than Task-Filter (0.26 sec), $F(5.43, 228.11) = 7.68$, $p < 0.001$, $\eta^2 = 0.12$.

Figure 6 shows that overall performance for the LEVEL task differed by Design with the Task-Filter Design (all p's < 0.01) resulting in the best performance and Data-Pitch design resulting in the worst. Bonferroni comparisons showed that all designs were different from each other with performance on the Task-Panning being lower than Task-Filter and greater than Data-Loudness, $F(2.37, 99.55) = 154.54$, $p < 0.001$, $\eta^2 = 0.79$. Figure 6 also shows that there were differences in performance based on the Exertion Level Differences with performance generally increasing as exertion level differences increased (all p's < 0.038). The exception to this was the decrease in performance from 0 V difference to 0.05 V difference, $F(1.95, 81.91) = 38.12$, $p < 0.001$, $\eta^2 = 0.476$. The differences by Level differed by Design with Bonferroni comparisons indicating that Data-Pitch (0.05 V) was different than Data-Pitch(0.15 V), Data-Loudness (0.15 V) was different than Data-Loudness (0, 0.05, 0.1 V), Data-Loudness (0, 0.05 V) was different than Data-Loudness (0.1, 0.15 V), Task-Panning (0.05 V) was different than Task-Panning (0, 0.1, 0.15 V), and Task-Filter showed no differences between levels, $F(5.56, 233.65) = 15.53$, $p < 0.001$, $\eta^2 = 0.27$.

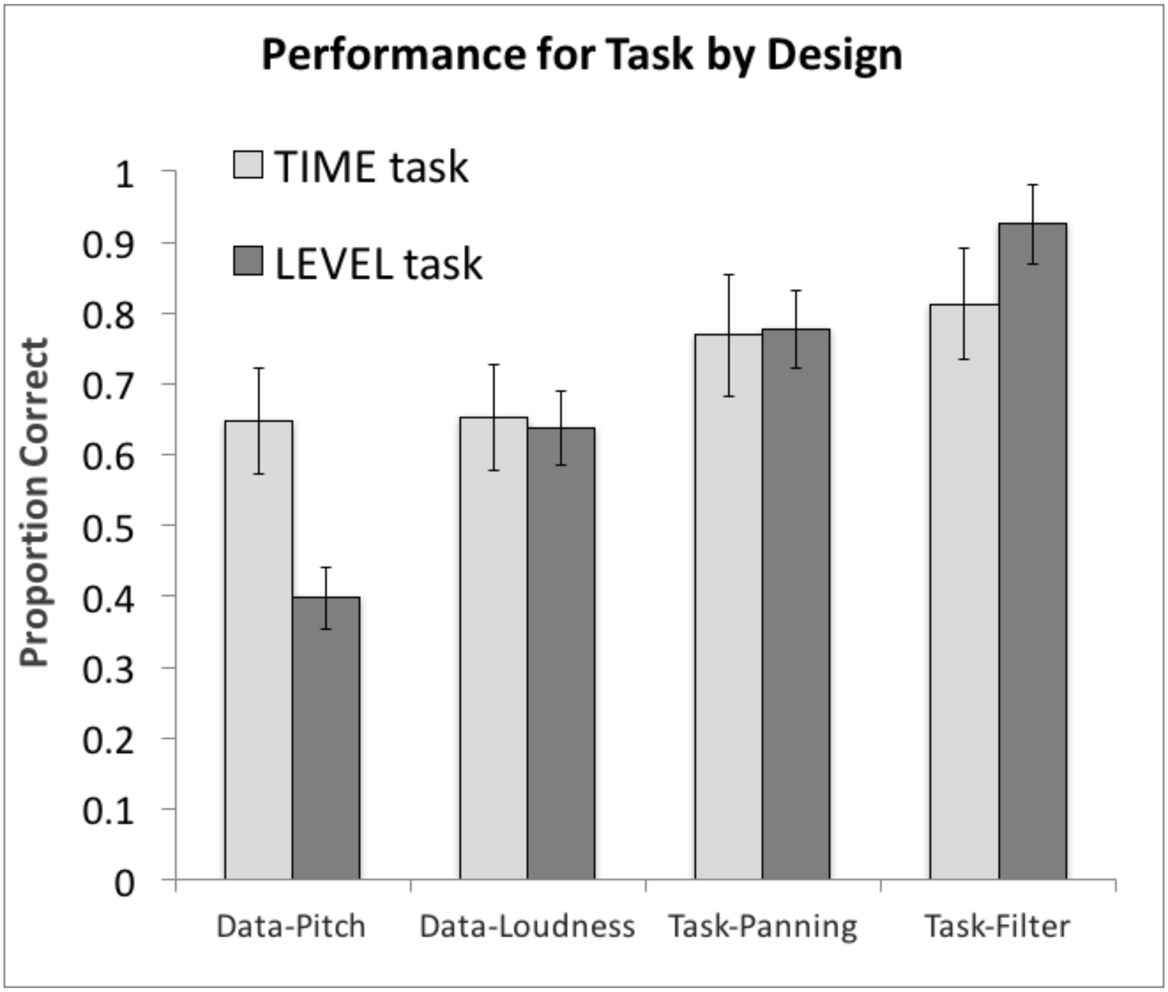

Figure 4: Overall listener performance for each Design and for both Tasks (from Verona & Peres, 2017)

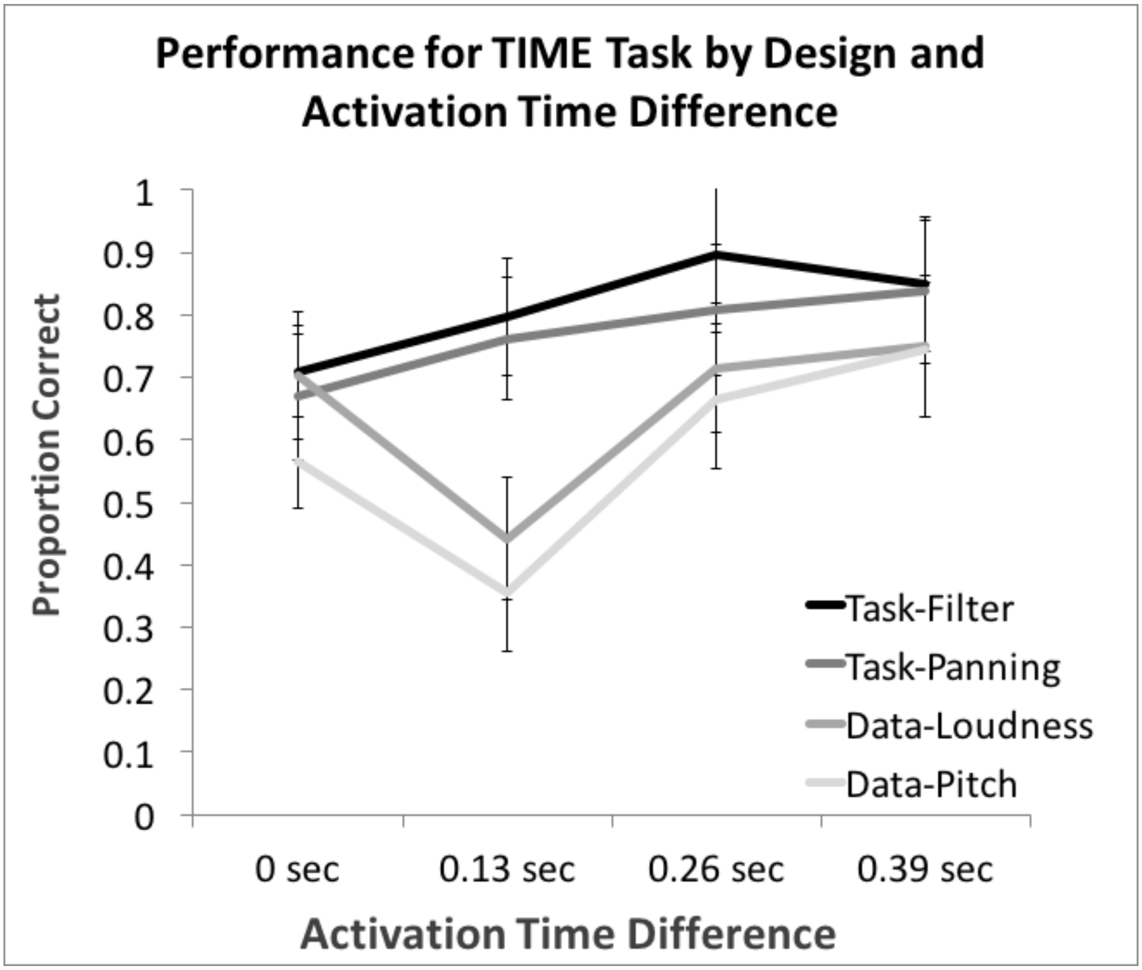

Figure 5: Listener performance for the TIME Task for each Design and Activation Time Difference (ATD). ATD = time difference between activation of Muscle A and Muscle B (from Verona & Peres, 2017)

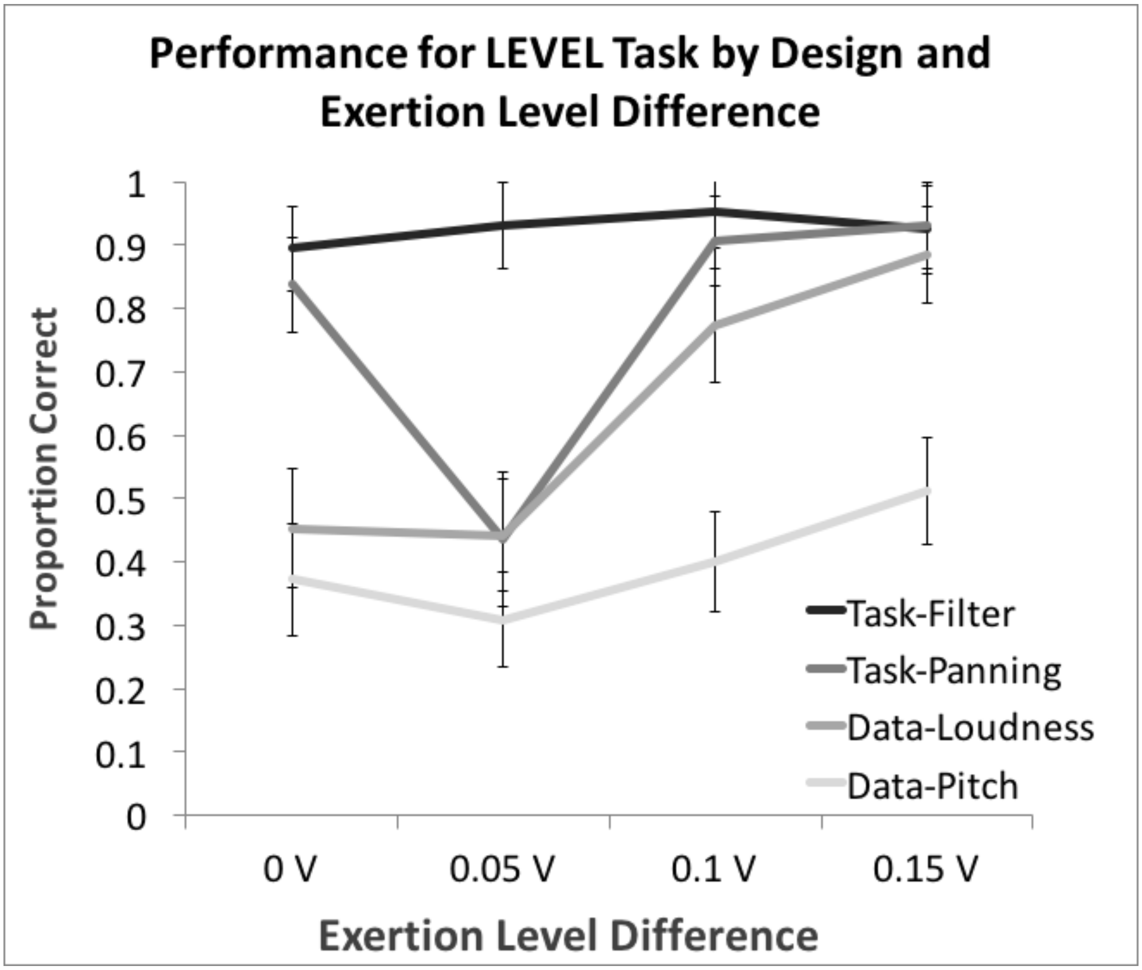

Figure 6: Listener performance for the LEVEL task for each Design and Exertion Level Difference (ELD). ELD = amplitude difference during contraction between Muscle A and Muscle B (from Verona & Peres, 2017)

8 DISCUSSION

The results of this study clearly indicate that for interpreting sEMG sonifications for these two tasks (TIME and LEVEL), using sonification designs based on a task analysis resulted in superior performance, particularly for the TIME task.

Further, there was an interaction between Design and Task with better listener performance for the TIME Task than for the LEVEL Task for the Data-Pitch design, reverse performance for the Task-Filter design, and no difference in performance for the TIME and LEVEL for the other two designs.

Decreased performance for the LEVEL task with the Data-Pitch design was likely due to the fact that this design used different pitch ranges for the two muscles. Thus, when listening to the Data-Pitch design, the listener would hear the sound of Muscle A in the left ear at the pitch range of 300-525 Hz, and would hear Muscle B in the right ear at a lower pitch range of 165-345 Hz. This could lead to at least two different phenomena that may have confused the listeners.

The first phenomenon is that listeners would have heard different pitches when both muscles actually had the same exertion level. If the sEMG data values from both muscles were to rise to an average value of 0.25 V during muscle contraction (i.e. no exertion level difference between Muscle A and B), the listener would hear two different pitches (Muscle A: 525 Hz/left ear, and Muscle B: 345 Hz/right ear) and would thus not be able to perform a direct exertion level comparison between the two muscles. This could result in the listener reporting that the muscles had different exertion levels since the listener would have heard different pitches for both muscles. It could also result in the listeners realizing that they cannot perform a direct exertion level comparison, which could lead to confusion.

The second phenomenon is that listeners could have heard the same pitch for both muscles during contraction when the two muscles actually had large exertion level differences. If Muscle A (sonified over a higher pitch range) had a low exertion level during contraction, and Muscle B (sonified over a lower pitch range) had a high exertion level during contraction, it would be possible for the pitch of Muscle A to rise from 300 to 345 Hz during contraction, and for the pitch of Muscle B to rise from 165 to 345 Hz during contraction. If this were to happen, the listener would hear the same pitch for both muscles during contraction that could result in the listener falsely reporting that the two muscles exhibited the same exertion level. It seems likely that these two phenomena could account for the poor performance that the Data-Pitch design showed for the LEVEL task.

Although the Task-Filter design resulted in overall high performance, there was a difference in performance between the two tasks (LEVEL and TIME) for this design. One possible explanation for this phenomenon needs to start with a recognition that the listener was asked to perform two tasks sequentially – to identify if Muscle A or B contracted first, and then to immediately shift attention to the second task of identifying which muscle had a higher exertion level. The temporal proximity of these two tasks could have made it somewhat difficult to accomplish both of them when accomplishing either one required interpreting a spatialized sonic event. However, given that both task-based designs resulted in superior performance than the data-based designed, this appears to not result in performance as low as that of the Data-based designs.

To reduce the difference between the two tasks for Data-Filter design, although spatialization is highly effective for identifying separate sEMG channels, it may be that hearing and interpreting two spatialized events in such close temporal proximity is not ideal. In this case, un-spatializing the beeps would create a stereo separation between the first sonic event indicating muscle activation and the second sonic event indicating exertion difference. This approach would require the use of different-sounding beeps to distinguish between A and B (as was done in the Task-Panning design but not in the Task-Filter design). But this way, identifying which muscle activated first could be done by listening to sounds in the center of the stereo field, and identifying which muscle had a higher exertion level could be done by subsequently paying attention to the left and right sides of the stereo field. Designing the sonification in this way could also help to avoid the disorientation that may have resulted when hearing too many sounds bounce back and forth between left and right too quickly. This possible effect of perceptual interference between multiple spatialized designs in close temporal proximity would be worthy of further investigation, due to the fact that Left/Right panning seems to be highly effective for individual tasks, but, as shown here, might not be as effective if multiple sequential tasks all require interpretation of spatialized designs.

Another issue that may have made the TIME task slightly more difficult than the LEVEL task for the Task-based designs was the condition where both muscles activated at the same time. In this condition, listeners would hear a short beep indicating muscle activation, but they would hear two beeps at the same time, one in either ear. This would effectively eliminate the spatialized effect if the beeps sounded the same (as in the Task-Filter design), and could potentially mask of one of the beeps if the beeps sounded different (as in the Task-Panning design). In the case of the Task-Filter design, hearing two identical beeps at the same time, one in either ear, may have been confusing because it would have been perceived as a non-spatialized event and the listener may have been anticipating a spatialized event. In the case of the Task-Panning design, when two beeps that were identical except for their pitch were heard at the same time, it may have been that one of the beeps (e.g., the one lower in pitch representing Muscle B's activation) was masked by the presence of the other, which may have lead to the listener only perceiving the higher-pitch beep and false reporting that Muscle A had activated first when in fact they had both activated at the same time.

For the LEVEL task, when comparing the performance of the Task-panning (using graduated panning) and the Task-filter (using hard panning) designs, it appears that hard-panning is a more effective way to display muscle exertion level difference. To explain this, it is important to note how the Task-Filter design made use of panning. In the Task-Filter design, any difference in muscle exertion level between Muscle A and B resulted in a hard-panned filter cutoff mapping. Thus, if Muscle A had just a slightly higher exertion level than Muscle B, the listener would hear a filter cutoff change in only the left ear, and vice versa. This was also true when the exertion difference between A and B was larger. For the Task-Panning design, however, this was not the case. For the Task-Panning design, differences in muscle exertion level between A and B were mapped to the pan position *based on the size of the exertion difference.* Thus, if A had only a slightly higher exertion level difference than B (0.05 V difference), the tone representing exertion level difference would only pan 70% left and not 100% left (hard-panned). For exertion level differences of 0.1 V or more, however, the tone representing exertion difference would pan 100% left or right. It is quite clear from Figure 6 that this 70% panning at low exertion level differences for the Task-Panning design significantly inhibited listeners' ability to determine which muscle had a higher exertion level. In fact, further post hoc analysis of the data revealed that whenever listeners heard a 70% left/right panning, 45.9% of the time they perceived no panning and responded saying that the two muscles had the same exertion level.

However, at greater exertion differences (0.1 V and 0.15 V), when the tone panned 100% left or right, listeners were much better able to identify which muscle had a higher exertion level and performance was comparable to the Task-Filter design (again clearly visible in Figure 6). It thus seems reasonable to conclude that had the Task-Panning design been designed such that small exertion level differences between Muscle A and B resulted in a hard-panned tone, rather than a 70% panned tone, overall average listener performance for the Task-Panning design would have been similar to that of the Task-Filter design for the LEVEL task.

This finding that a 70% left/right panning was difficult for listeners to interpret is very interesting, and suggests that an LCR (Left-Center-Right) approach to panning may be more useful in sonification design than attempting to use any finer resolution of panning. This is another area that is ripe for further investigation in auditory displays, namely, to what degree can listeners distinguish between different amounts of panning? Should sonification designers stick to LCR panning, or can they find ways to increase the granularity of spatial location that listeners can readily detect? It also seems that sonification designers who use spatial location would also need to take the frequency of the spatialized sound into account, given that the human ability to spatialize sound is somewhat frequency dependent, with low frequency sounds being more difficult to spatialize. This may mean that higher frequency sounds could be mapped to spatial location with a higher degree of granularity than lower frequency sounds. If this is the case, then perhaps if I had used a higher-pitch tone, or more higher harmonics in the tone, to display exertion level difference in the Task-Panning design, the 70% left-right panning at small exertion differences may have been sufficient.

Regarding performance for the TIME task at each Activation Time Difference (Figure

5), it is clear that the Task-based designs performed better than both of the Data-based designs, and that there was a general trend of improved performance as activation time difference increased. This trend is not particularly surprising, except for what happened in both Data-based designs as activation time difference increased from 0 sec to 0.13 sec. It is clearly visible in Figure 5 that performance *decreased* as the time difference went from 0 sec to 0.13 sec, but then *increased* again as the time difference increased from 0.13 sec to 0.26 sec. This phenomenon is indicative of a limitation of the Data-based designs, suggesting that the moment of transition from rest to muscle activation could not be precisely pinpointed to less than 0.26 sec accuracy using the Data-based designs. The reason for this may be that sounds heard in the Data-based designs changed in roughly direct proportion to the data, rather than changing significantly when the data indicated a transition from rest to activation. In this way, the Data-based designs performed more *analogically* as opposed to the Task-based designs which performed more *symbolically*. In other words, the Data-based designs faithfully represented the data using a more-or-less 1:1 conversion from (rectified and filtered) data to sound. Looking at the rectified, filtered sEMG data (shown below in Figure 7), it is clear *approximately* when the data transitions from rest to activation, but it is not clear at what precise instant this transition takes place.

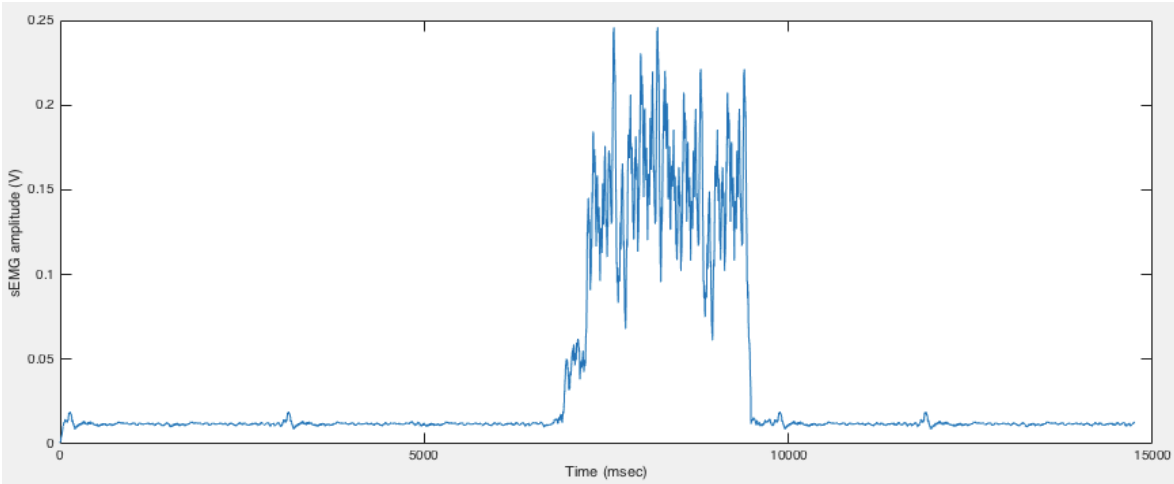

Figure 7: A sample of the rectified, filtered sEMG data sonified in this thesis work

Thus, when a sonification design (in this case, the Data-based designs) performs a more-or-less direct conversion of the data into sound, it makes sense that the listener would be able to hear *approximately* when the transition from rest to activation happens, but would not be able to identify the precise instant at which the transition occurred because they would hear the sound change somewhat gradually just as the data changes somewhat gradually. It seems clear that for this particular task, an analogic sonification design is not ideal, since comparing muscle activation times, particularly when they occur in close temporal proximity, requires being able to identify the precise instant of activation. The Task-based designs, on the other hand, were designed symbolically, and for both Tasks, the symbolic designs resulted in improved listener performance. The Task-based designs were symbolic in the sense that they did not attempt to perform a faithful translation of data to audio, but instead looked for the data properties relevant to each task, attempted to make those properties evident to the listener, and ignored all other data properties. In addition to being symbolic, the Task-Panning design made use of a potential sonic metaphor in that it used soft white noise to convey to the listener when the muscle was at rest. White noise is what is heard when flipping to a TV channel that is currently inactive or tuning in to a radio station that is currently off-air. Thus, in our collective cultural consciousness, white noise is associated with inactivity, and using white noise in the Task-Panning design may have been particularly effective at conveying that the muscles were inactive.

For the TIME task, The Data-Pitch and Data-Loudness designs showed poor performance when the activation time difference was 0.13 sec. By contrast, the Task-Panning and Task-Filter designs showed performance that essentially increased as the TIME difference increased (Figure 5). This was likely due to the fact that the Task-based designs were designed specifically to create a large, temporally precise contrast between the sound of a muscle at rest and the sound of a muscle beginning to contract. The Data-based designs did not provide the same level of perceivable contrast between the sound of a muscle changing state from rest to activation.

For the LEVEL task, there were interesting interactions based on the difficulty level of task with the more difficult stimuli (.05 V) reducing performance remarkably more with the Task-Panning design than any of other of the designs. Further, there were differences in performance between the Data-Pitch and Data-Loudness designs for the LEVEL task. This is likely due to two things: the Data-Pitch design used different pitch ranges for Muscles A and B which made a direct comparison between the two difficult, and the Data-Loudness design essentially made use of a panning effect by mapping muscle exertion level to loudness. Since the designs were spatialized into left and right audio channels, at larger exertion level differences (0.1 and 0.15 V), the Data-Loudness design acted like a panning mapping, and indeed, the Data-Loudness design showed similar performance for the LEVEL task as both of the Task-based designs, which both made explicit use of panning (Figure 6).

9 CONCLUSION

These findings that Task-based designs can result in better listener performance than Data-based designs strongly suggest the broader integration of task-based approaches into the sonification design problem space. Additionally, they indicate that the inclusion of task analyses within a theoretical framework for sonification design may facilitate the development of this illusive framework.

Task-based approaches to sonification design are not well represented in the auditory display literature. It is not uncommon in the EMG sonification literature, for example, to see an explanation for *how* a sonification was designed but to not see an explanation for *why* it was designed that way. Justifications for design decisions are sometimes given, but they rarely seem to go beyond appeals to sonic cosmetics or "traditional" mappings like pitch and loudness.

A task-based approach to sonification design could allow sonification designers to use Human Factors and HCI design methodology to identify sonification design criteria. In so doing, this approach could afford sonification designers stronger justification for design decisions, as well as facilitate easier communication between sonification designers and HF/HCI researchers – which could broaden interest in auditory displays and stimulate wider interest in the field.

Roddy and Furlong have discussed sonification aesthetics and the problem of a disembodied approach to sonification design, and they have argued that leveraging knowledge of embodied cognition and embodied schemata may help sonification designers to circumvent the Mapping Problem by mapping sonifications along embodied dimensions (Roddy & Furlong, 2014). Task-based approaches to sonification design may not be *embodied* in and of themselves, but since task analyses can provide in-depth knowledge of a user's task, and since mapping sonifications along embodied dimensions requires a deep understanding of the user's task, it seems that task-based approaches to sonification design may aid in identifying useful embodied schemata along which to map sonifications for specific tasks.

In conclusion, task analysis techniques are well established in fields such as Human Factors and HCI, where design decisions are critical. In this work, implementing task analysis techniques into the design of auditory displays was shown to be an effective approach for creating interpretable sonifications. Further use of task analysis techniques in auditory display is thus recommended. This work has served as a "proof-of-concept," and further use of task-based approaches in sonification research may help to ultimately ground sonifications in a more accessible – and perhaps embodied – aesthetic framework, thus leading to the development of more easily interpretable sonifications.

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