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Towards a systematic approach to real-time sonification design for surface electromyography ☆

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ABSTRACT

Surface electromyography (sEMG) is a technique for measuring the electrical activity of muscles and is often used as a biofeedback tool. However, challenges associated with the typically visual display of sEMG data have motivated researchers to find non-visual ways of displaying sEMG data, and parameter-mapping sonification has been explored in order to present sEMG data acoustically. Parameter-mapping sonification is a technique that involves mapping values in a data set to acoustic properties of sound. Sonification of EMG data has shown potential for identifying musculoskeletal disease and improving athletic and exercise performance. However, many sonification designs to date have not been systematically evaluated and there have been few quantitative approaches to objective comparisons of sonification paradigms. In this study, we performed a quantitative comparison of different sonification designs in order to test our hypothesis that different sonification designs may be better suited to different tasks. Thirty-six participants (ages 18–31, 14 male) who volunteered to listen to the sEMG sonifications created for this study were asked to identify two different features of the data: muscle activation time and muscle exertion level. Their responses were analyzed in order to determine the effect of sonification design on listener performance. Results indicated that having the sonifications spatialized resulted in the best performance for both tasks. However, different sonification designs resulted in the best performance for the muscle activation time estimation task (Pitch and Loudness mapped redundantly) and the muscle exertion level estimation task (Pitch, Loudness, and Attack mapped redundantly). Further, for the time estimation task, the use of the Attack mapping appeared to reliably inhibit performance. These findings strongly suggest that sonification designs for sEMG need to be designed differently based on the task the user is performing.

1. Introduction

Surface electromyography (sEMG) is a technique for measuring muscle activation onset, muscle activation duration, and muscle exertion level. Physical therapists [1], ergonomists [2], and scientists [3] use sEMG as an index of muscle fatigue [3] and as a biofeedback tool [4]. sEMG biofeedback has been shown to be an effective tool for increasing muscle strength [5] as well as for various motor learning and rehabilitation therapies [6] and many of these applications require the monitoring of sEMG data in real time or "live".

sEMG data are typically presented to a user visually on a computer monitor. While this can be effective, problems with this method have arisen from both a data monitoring standpoint as well as a motor learning standpoint. When recording and monitoring sEMG data, often times data from multiple muscles are being recorded and displayed simultaneously. Monitoring data from multiple muscle groups on a screen creates a high visual load for the therapist or researcher collecting the data. This can be overwhelming and can also prevent the data collector from focusing on the movements of the subject. For motor learning in sports applications, most movements are mastered in response to real-time visual feedback of the sEMG data, and thus providing visual biofeedback to an athlete can overload the capacities of the athlete's visual perception system [7]. To make use of biofeedback while also avoiding visual overload, researchers have looked for non-visual ways to present sEMG data and doing so acoustically by means of sonification has shown potential for improving athletic and exercise performance [7,8] and identifying

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musculoskeletal problems [9]. Additionally, sonification of stroke patients' movements in a 3-D space has resulted in improved motor function as compared to patients whose movements were not sonified [10].

Sonification put simply is "the use of non-speech audio to convey information" [11]. However, as distinct techniques for sonification have been developed, further classification of sonification techniques has become necessary. According to Hermann [12], the type of sonification used in a particular application should be defined as either audification, parameter-mapping sonification (PMSon), or model-based sonification. Audification is a technique by which data samples are isomorphically mapped to the amplitude of consecutive audio samples, creating a direct form of sonification [13]. In parameter-mapping sonification, data values are mapped to acoustic attributes or parameters of sound [12], and in model-based sonification, the user must interact with a model of a data set (in which sonic structures are pre-defined) before any sound is heard [14].

The study presented in this paper used PMSon to present sEMG data to a listener. PMSon is a common form of sonification [15–17], and many parameters of sound have been explored for use in PMSon, including pitch, loudness, harmonics, speed, tremolo, attack time, and spatial location [18–20]. However, there has been little objective evaluation of these sonification parameters for sEMG data [20].

There have been evaluations done to evaluate the effects on performance for these sonification parameters with other auditory display types. For instance, researchers found that mapping more than one sound parameter redundantly (such as pitch and loudness) resulted in better performance than mapping just one parameter at a time for auditory box plots [21]. However, this benefit in performance was only found when certain dimensions of sound were used, specifically pitch and loudness. When scatterplots of temperature data were sonified and spatialization (panning) was used to redundantly represent time (x-axis), performance improved compared to a temporal mapping only [22]. Octave ranges were also varied for the same scatterplots and it was found that participants performed better with wider octave ranges than they did with just a one-octave range [22].

These findings suggest that the design of a sonification influences the listener's ability to derive the intended meaning from the sonification. This has implications for sonification designers who are creating sonifications for data display (as opposed to artistic sonifications) and who are concerned with sonification aesthetics. Sonification designs to date have often not been systematically evaluated [7], and few quantitative approaches to objective comparison of sonification paradigms have been used [23]. This may lead to arbitrary sonification designs that, when applied to the domain of sEMG sonification, could actually constrain motor learning by being distracting, demotivating, or uninterpretable [7].

For the study presented in this paper, we hypothesized that optimizing listeners' accuracy in identifying different features of sEMG data (e.g., muscle activation order, muscle exertion level) using sonifications of sEMG data will require different sonification designs depending on the specific feature being identified. In other words, the best sonification design (i.e., resulting in the highest level of performance) will be dependent on the user's task.

Six different sonifications were created for this study in order to present sEMG data to a listener. The sonifications were created using three redundant combinations of pitch, loudness, and attack time. Spatial location was used to place data from two different muscles into different regions within the stereo field. Study participants listened to a series of sEMG sonifications, and after listening to each were given two tasks: (1) identify muscle activation order and (2) identify relative muscle exertion level. The purpose of this study was to perform a quantitative evaluation of various sonification designs in order to investigate the effects of sonification design on listener performance for these two tasks.

2. Methods

Given that the focus of this study is on the *design* of the sonifications for real-time sEMG sonification use, for expediency and experimental control, the experimental protocol used recorded sEMG readings from a previous study that used sEMG data to identify potential musculoskeletal issues with touch screens [24].

2.1. Participants

Participants for this study were recruited from Texas A&M University, all self-reported no hearing impairment, and completed the informed consent process before participating in the study. There were 36 participants total (14 male, 22 female), ranging in age from 18 to 31 years old.

2.2. Sonification designs

Mapping pitch and loudness redundantly has been shown to improve user performance [21]. However, it may be the case that only certain redundant mappings result in such redundancy gains [21]. With this in mind, the four parameters of sound mentioned above were combined in the following ways to create six unique sonification mapping schemes:

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.

2.3. Audio synthesis

The sEMG data used for this study were sampled at 1000 Hz, and then rectified and bandpass filtered (from 20 Hz to 450 Hz) using MATLAB. SuperCollider (a free, open source software for real-time audio synthesis and algorithmic composition) was used as the synthesis engine to create the sonifications for this study. The filtered, rectified sEMG data were imported into SuperCollider, and SuperCollider then calculated the average value of each block of one hundred data points. These averaged values were outputted to a new array, and this new array was scaled individually for each parameter (pitch, loudness, and attack time) using separate mapping equations for each parameter. This created three new scaled arrays (one for each parameter) and these new scaled arrays were sonified using SuperCollider's Pbind function along with a triangle waveform oscillator. The Pbind function sequentially steps through each value of an array at a user defined rate, and plays a tone for each value. The parameters of each tone (pitch, loudness, etc.) are controlled by the values in the arrays. Each tone (henceforth referred to as an "Event" to use SuperCollider's terminology) of the Pbind function was assigned a duration of 0.1 s with no space between each Event. This resulted in a sonification that played 10 Events per second (in order to preserve the time scale of the original sEMG signal – i.e. a 10 s segment of sEMG data resulted in a 10 s sonification). To ensure that the Events did not "bleed" together sonically and that each Event could be heard individually, the decay time for each event was set very low (<0.1 s). The pitch, loudness, and attack time of each Event were then controlled by the sEMG data.

The sEMG data used in this study, once rectified and filtered, contained values between 0 and 0.4 V. Pitch was mapped from this voltage range to a frequency range of 200–768 Hz (roughly G3 to G5), such that an increase in sEMG data amplitude resulted in an increase in pitch, and vice versa. Loudness was mapped to a range of 50–68 dB(Z) as measured by the SoundMeter iOS app from Faber Acoustical. Loudness was mapped such that an increase in sEMG data amplitude resulted in an increase in loudness, and vice versa. Attack time was mapped to a range of 0–39 ms, but was mapped with an inverse polarity as compared to pitch and loudness. Specifically, at the lowest sEMG data amplitudes (near 0 V), the attack time for each Event was near its maximum of 39 ms. As the sEMG data amplitude increased to its maximum of 0.4 V, the attack time for each Event decreased down to its minimum of 0 ms. The mappings including attack time thus sounded smoother and more connected when a muscle was relaxed, and sharper and more percussive when a muscle was contracted.

For each trial, participants were presented two sonified channels of sEMG data simultaneously, and the first and second channels were referred to as Muscle A and Muscle B, respectively. To spatialize the channels, data from Muscle A were panned hard left (i.e., played only in the left audio channel) and data from Muscle B were panned hard right. When the channels were non-spatialized, the data from both Muscle A and Muscle B played directly in the center of the stereo field (i.e., both muscles were heard equally in the left and right audio channels).

Each sonification created for this study was 10 s long and consisted of both Muscle A and Muscle B starting at rest, contracting at close to the same time, and then returning to rest. Ten sets of sonifications were made for each of the six designs being evaluated in this study, resulting in a total of 60 sets of sonifications.

2.4. Setup & procedure

This study was conducted in the RIHM (Research on the Interface between Humans and Machines) laboratory at Texas A&M University. Volunteers who participated in this study used a pair of Sennheiser HD 280 headphones powered by a Focusrite Scarlett 2i2 audio interface to listen to the sonifications. The study was run locally through a browser using the XAMPP environment to run a MySQL database for recording participants' responses.

The first section of each experimental session consisted of an introduction to sonification. In it, participants were given a brief introduction to what sonifications are, what an auditory parameter is, how an auditory parameter can be mapped to trends in a data set, what sEMG is, and provided some examples of what a sEMG sonification might sound like. Once this section was complete, participants began the experimental trials. Participants listened to 6 different blocks with 10 trials in each block. Each block contained one sonification design and the presentation order of the blocks was counterbalanced. After listening to each sonification, the participants were asked to identify the following:

(1) Which muscle (A or B) activated (contracted) first (Task 1).
(2) Which muscle (A or B) exhibited a higher exertion (Task 2).

The participants were given two tasks to perform (as opposed to one) so that the sonification designs that resulted in the best listener performance for each task could be identified. This allowed us to determine if the design that yielded the best performance for Task 1 was the same design that yielded the best performance for Task 2 or if the designs which yielded the best performance for Tasks 1 and 2 were different.

These two tasks were chosen specifically because they are both relevant to sEMG sonification. Task 1 (determining which muscle contracted first) is relevant for those interested in using sEMG sonification for biofeedback. Auditory information is superior to visual information when portraying time-sequenced data such as muscle activation times [25], and determining muscle recruitment order with EMG is useful for athletic training because it promotes correct muscle recruitment, which reduces an athlete's risk of injury [26].

Task 2 (identifying muscle exertion level) is relevant for those interested in using sEMG to assess office ergonomics, a domain in which repetitive strain injuries can result from prolonged muscle exertion at low levels [27].

When participants were asked to identify which muscle activated first and which muscle had a higher exertion level, they chose one of the four options below and answers were saved into the MySQL database for evaluation.

- Muscle A
- Muscle B
- Both muscles had the same activation time (or exertion level)
- Unsure

2.5. Study design

The study was a fully within factorial design with 2 independent variables regarding auditory dimension: sonification design (3: Loudness/Attack, Pitch/Loudness/Attack, and Pitch/Loudness), and spatial location (2: Spatialized and Non-Spatialized). There are two dependent variables that were used to assess performance: judgment of muscle activation time (TIME) and judgment of muscle exertion level (LEVEL).

2.6. Measures

To measure participants' ability to identify muscle activation time (TIME), the proportion of correct responses given for each sonification design was calculated. For instance, if a participant correctly identified which muscle activated first in 4 out of 10 Pitch/Loudness, Non-Spatialized conditions, that participant's score for that condition would be 4/10 or 0.4. An identical process was done to measure the participants' ability to identify which muscle had the higher exertion level (LEVEL).

2.7. Statistical analysis

To explore the effects of spatialization and sonification design on the participants' ability to identify muscle activation time and exertion level, two separate fully within 2 (Spatialization: yes or no) $\times$ 3 (Auditory Design: Pitch/Loudness, Pitch/Loudness/Attack, and Loudness/Attack) Factorial Repeated Measure ANOVAs (RMANOVA) were conducted—one RMANOVA for each task measure, TIME and LEVEL. Post hoc analysis was conducted for significant effects using Bonferroni comparisons and One-Way ANOVAs were used to explore the effects of any interactions. Alpha was set at the standard level of 0.05. Further, given the design of the study, it was possible to calculate what performance would be if the participants were simply guessing each time (i.e., chance). Given that participants had 4 options (i.e., Muscle A, Muscle B, Both muscles had the same activation time (or exertion level), and Unsure) a chance performance would be 1 out of 4, or 0.25. Conditions that had very low performance scores were compared to chance to identify if this low performance reflected participants simply guessing.

3. Results

To describe the findings of this study, descriptive statistics as well as inferential statistics are provided below.

Table 1
Descriptive statistics for both performance measures (TIME and LEVEL) for all six of the sonification conditions (N = 36).

	Mean	SEM	Median	Min	Max
Activation time (TIME)					
Loudness/Attack, Non-Spatialized	0.12	0.02	0.1	0.0	0.5
Loudness/Attack, Spatialized	0.42	0.03	0.4	0.1	0.8
Pitch/Loudness/Attack, Non-Spatialized	0.18	0.02	0.2	0.0	0.6
Pitch/Loudness/Attack, Spatialized	0.43	0.04	0.4	0.1	0.9
Pitch/Loudness, Non-Spatialized	0.26	0.03	0.3	0.0	0.7
Pitch/Loudness, Spatialized	0.54	0.03	0.6	0.2	0.9
Exertion level (LEVEL)					
Loudness/Attack, Non-Spatialized	0.25	0.03	0.3	0.0	0.5
Loudness/Attack, Spatialized	0.64	0.03	0.7	0.3	0.9
Pitch/Loudness/Attack, Non-Spatialized	0.23	0.02	0.2	0.0	0.5
Pitch/Loudness/Attack, Spatialized	0.75	0.02	0.8	0.4	1.0
Pitch/Loudness, Non-Spatialized	0.29	0.03	0.3	0.0	0.7
Pitch/Loudness, Spatialized	0.64	0.02	0.7	0.3	0.9

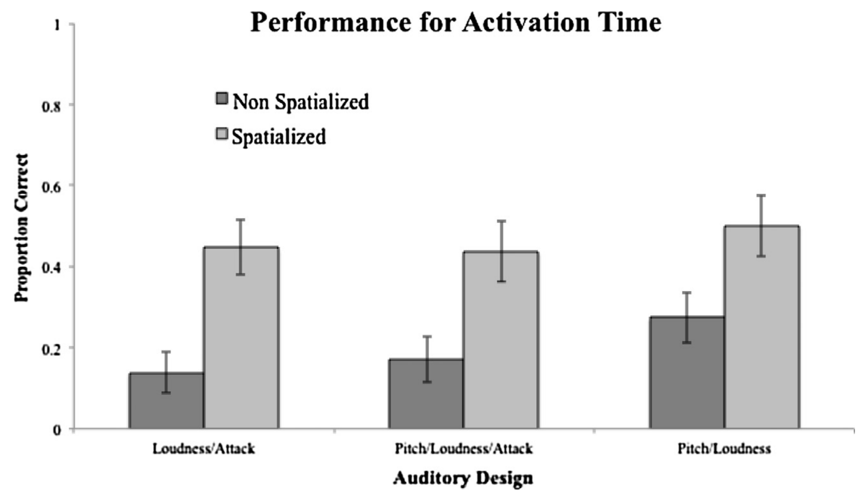

Fig. 1. Mean proportion correct for Activation TIME task by sEMG Sonification Design and Spatialization. There is a main effect of Spatialization ($F(1, 35) = 159.78$, $p < 0.001$) and Design ($F(2, 70) = 16.23$, $p < 0.001$) and no interaction ($p = 0.72$). Error bars represent the 95% confidence intervals.

3.1. Descriptives

Table 1 provides the descriptive statistics for both measures (TIME and LEVEL) for the six sonification conditions.

3.2. Activation Time

As seen in Fig. 1, participants were better able to identify which muscle activated first with the Spatialized conditions versus the Non-Spatialized conditions and this main effect was significant, $F(1, 35) = 159.78$, $p < 0.001$, $\eta_p^2 = 0.82$. Further, another main effect of Design, $F(2, 70) = 16.23$, $p < 0.001$, $\eta_p^2 = 0.32$, is seen in the figure with performance being better for the Pitch/Loudness conditions than either the Loudness/Attack (Bonferroni comparison: $p < 0.001$) or Pitch/Loudness/Attack conditions (Bonferroni comparison: $p = 0.001$). However, there is no interaction between Spatialization and Design for TIME ($p = 0.72$).

For the Non-Spatialized conditions, the performance was extremely low—near or below chance performance (chance performance = 0.25). To test for this, single sample t-tests were done for each of the three Non-Spatialized conditions and the Loudness/Attack and Pitch/Loudness/Attack conditions were both reliably below chance ($t(35) = -6.10$, $p < 0.001$ and $t(35) = -3.10$, $p = 0.004$ respectively). However, the Pitch/Loudness condition was not significantly different than chance ($p = 0.75$).

3.3. Exertion level

Fig. 2 shows the proportion correct for the exertion level task by Design and Spatialization and again there is clearly a main effect of Spatialization, $F(1, 35) = 220.79$, $p < 0.001$, $\eta_p^2 = 0.86$, with performance for the Spatialized tasks being higher. There is also an interaction between Spatialization and Design $F(2, 70) = 7.64$, $p = 0.001$, $\eta_p^2 = 0.18$. To investigate this interaction, one-way ANOVAs were conducted for the simple effects of Design for Spatialized and Non-Spatialized conditions separately. There was a simple effect of Design for the Spatialized conditions, $F(2, 70) = 8.02$, $p = 0.001$, $\eta_p^2 = 0.19$, and pairwise comparisons adjusted using Bonferroni found that the Pitch/Loudness/Attack condition was significantly better than the Loudness/Attack condition ($p = 0.04$) and the Pitch/Loudness condition ($p = 0.02$). However, for the Non-Spatialized conditions, there was no effect of Design ($p = 0.23$). Further there was no main effect of Design ($p = 0.18$).

4. Discussion

These results clearly indicate that designs of sEMG sonifications can impact performance and that effective designs will need to differ based on the task being performed with those sEMG sonifications. Specifically, the condition that resulted in

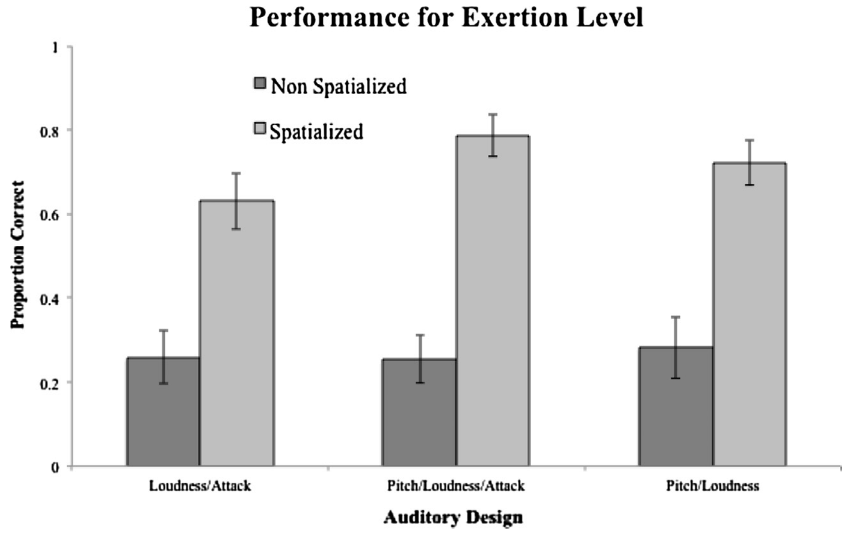

Fig. 2. Mean proportion correct for Exertion LEVEL task by sEMG Sonification Design and Spatialization. There is a main effect of Spatialization ($F(1, 35) = 220.79$, $p < 0.001$) and interaction between Spatialization and Design ($F(2, 70) = 7.64$, $p = 0.001$) and no main effect of Design ($p = 0.18$). Error bars represent the 95% confidence intervals.

the best performance for the TIME task (Spatialized Pitch/Loudness) was not the same as that for the LEVEL task (Spatialized Pitch/Loudness/Attack). Both tasks did show better performance with the Spatialization dimension, but interestingly, for the LEVEL estimation task, there seemed to be a floor effect on performance for the Non-Spatialized conditions (with performance at about chance) but not for the TIME estimation task. For the TIME task in the Non-Spatialized conditions, the Pitch/Loudness condition was better than the other two sound design conditions, further underscoring the potential effects of sonification design on performance. Given that all of the significant findings had effect sizes (η_p^2) that were medium (0.06–0.13) or high (greater than or equal to 0.14), these effects have practical significances as well [28]. Indeed the effect size for Spatialization indicates that this variable explains 74.9% of the variance for Time and 85.6% of the variance for Activation level. Although the effect sizes of Auditory Design are lower, explaining 15.6% and 10.3% of the variability in Time and Activation level respectively, these effects can still be considered impactful on performance.

The specific implications regarding the dimensions and combinations of dimensions used in this study are noteworthy as well. At a very basic level, if it were merely adding more dimensions of sound to a sonification that improved the listener's performance, the Spatialized Pitch/Loudness/Attack conditions would have resulted in the best performance for both tasks. However, this design was the best for identifying exertion LEVEL but not activation TIME. Given that the best performance for TIME was in the conditions without attack, it could be that instead of having this dimension, which is presenting an attribute of time, facilitate the interpretation of time, it somehow seemed to interfere with it. This may be because attack time was mapped inversely to sEMG—specifically an increase in sEMG amplitude resulted in a decrease in attack time. This result may also have to do with the perceptual properties of these dimensions. Previous research found that when integral dimensions of sound were used redundantly for auditory graphs, performance was better than when separable dimensions of sound were used but there was no redundancy loss with separable dimensions [21]. These results essentially mean that if a sonification designer uses redundant dimensions there may be a benefit, but there should not be a loss if separable dimensions are used. The dimension of attack time is not clearly integral or separable from Pitch and/or Loudness as it is typically considered a component of timbre [29]. However, given Peres and Lane's results of no redundancy loss with separable dimensions [21], the lower performance in the conditions with attack time for TIME estimation are surprising and warrant further study. Peres and Lane's study also only examined one task that involved participants evaluating the statistical components of the auditory graphs which is a task that is cognitively more similar to the task of estimating exertion LEVEL. This may be the reason that the effects of Design for the LEVEL task more closely follow the results of the Peres and Lane [21] study than the effects of Design on the TIME task.

The benefit of Spatialization is very clear and indeed not surprising given the nature of the tasks and display. Specifically, the tasks required the user to compare activation times and exertion levels of the two muscles, which requires selective attention to the display for each muscle. In the Non-Spatialized design, it is likely remarkably difficult for the listener to selectively attend to the information for each muscle as they are both presented equally in each ear, requiring the listener to sonically distinguish one muscle from another. This difficulty is clear in the LEVEL task where participants performed at essentially chance (i.e., chance performance being a mean proportion correct of 0.25) for all three Non-Spatialized design conditions. However, Spatialization made attending to the muscles individually easier since each muscle was presented specifically in one ear or the other and thus may have made the comparison of the muscles' properties easier.

These findings in combination strongly support the notion that not only do sonifications of the same type of data need to be designed differently based on the task that the user is trying to accomplish, but also that the design of the sonification for that task needs to be created in a manner that measurably supports performance. However, for those who are designing sonifications for sEMG, it would be very difficult if not impossible to empirically test every possible combination of auditory dimensions for every type of task and environment. Therefore, it is necessary to develop a systematic approach for developing and testing sEMG sonification designs to ensure that they meet the needs of the users.

5. Future work

Exploring the space of task-specific sonification design will not be easy. There are still hurdles within the field of sonification that have yet to be overcome. The most prominent hurdle is referred to as "The Mapping Problem (TMP)" [30]. TMP is generally specific to PMSon and results from the phenomenon of auditory parameter perceptual entanglement (e.g. an increase in loudness will be perceived by the listener as an increase in pitch unless frequency is controlled for). This can result in unpredictable artifacts within the sonification that can impair the listener's performance. Researchers have begun to explore the realm of sonification aesthetics in order to address this problem [31]. Sonification aesthetics is primarily concerned with meaning-making, that is, the ability of the listener to derive meaning from the sonification [31]. Embodied sonification designs have been explored as a promising way of improving sonification aesthetics and getting away from PMSon in order to address the mapping problem [31].

We are also interested in exploring the realm of sonification aesthetics and investigating how aesthetics could be leveraged to create meaningful real-time sEMG sonifications for motor learning and data monitoring applications. We believe that sonification designs (not necessarily PMSon) that are tailored to the task at hand are crucial to improving sonification aesthetics and meaning-making. But the question remains: how does one go about designing a sonification specifically for the task at hand? This will certainly not be easy, however, there are tools available that could aid in the process of refining sonification design that we intend to explore in future work. One such tool is the task analysis, a rigorous exercise that comes from the domain of Human Factors. Human Factors is a field that seeks to integrate a user with their task and environment in order to optimize safety, efficiency, and performance. A task analysis asks, and attempts to exhaustively answer, three questions:

(1) Who is the user?
(2) What is the user's environment?
(3) What is the task to be performed?

It is our opinion that the answers to these questions could be used to inform sonification design for a given task and that doing so would improve the quality of the sonification design which could enhance a listener's ability to derive meaning from the sonification.

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