Psychophysical Scaling of Sonification Mappings

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determined preferred data-to-display mappings by asking experiment participants directly and then examined the hophysical scaling functions relating perceived data values to underlying acoustic parameters. Presently, we are nding and validating the scaled mappings in practical data interpretation tasks. The resulting scaling functions, in unction with the experimental paradigm developed here, should spark further research in this area and have implications he design of future sonifications.

words

hophysical scaling, auditory display, sonification, data-display mappings

RODUCTION

investigations focus on data sonification, or the representation of scientific data with sound [1]. In particular, this rch begins to determine the best way to vary auditory display dimensions (i.e., sound parameters such as frequency or o) in order to communicate a data set to a listener for interpretation and analysis. Little research has been done to mine exactly how to map data to sounds, despite the finding [5] that this mapping procedure is not necessarily ghtforward or intuitive. An effective and practical approach to sonification can only result from the determination of al listener preferences and performance. The most rigorous method for this is experimentation and validation of fication schemes through representative listening tasks.

ORTANT QUESTIONS FOR PRACTICAL AUDITORY DISPLAYS

egin to create auditory displays with widespread utility, three basic questions must be answered. First, we need to know auditory display dimensions best represent a given data dimension. Is it best to use frequency, tempo, or some other tory parameter to represent the data dimension of, say, velocity? Second, what is the direction or "polarity" of the erred data-to-display mappings? If frequency is used to represent velocity, one might postulate that increasing frequency d represent increasing velocity. However, when representing the dimension of size, increasing frequency might best esent *decreasing* size, since high-frequency sounds tend to come from small objects. And third, once we establish a ping and polarity, what is the scaling factor for that data and display pair? That is, exactly how much change in frequency we use to represent a given change in velocity?

ainly there are many more questions, but these three are primary and critical, and as yet have not been systematically stigated. We begin by answering these questions, and then we begin to validate the resulting mapping solutions in a esentative practical listening task.

VIOUS WORK

ping Choices

few of the sonification projects to date have systematically addressed the three questions we raise. Most systems rely on pings, polarities, and scaling functions determined either by system constraints (e.g., only frequency may be varied) or by gn decisions made by the system programmers (e.g., increasing frequency is always mapped to increasing data values). rtunately, the resulting solutions may not match listeners' preferences or expectations. This may lead to errors or slower ormance by users of the system [5]. Further, most sonifications have not taken into account the actual type of data being ayed, or the specific listening experience of the listeners.

ker & Kramer, 1996

e sonification of a fictitious "Crystal Factory," Walker and Kramer [5] showed that the specific choices of both mapping polarity can affect reaction time and accuracy in monitoring tasks. Three different sound designers agreed about what t to be the "best" mappings, however the data showed that such "intuitive" design decisions may not result in the best al performance.

e is a vast literature of auditory perception research, much of it important for sonification. However, one particularly ant line of research is the work of S. S. Stevens and others [3,4] in determining the psychophysical scaling functions een acoustic parameters and subjective perceptions of a stimulus. For example, if the physical amplitude is doubled, is the resulting change in the perceived loudness?

we adapt the psychophysical scaling paradigm known as magnitude estimation [4] to examine how changes in the ical sound attributes (e.g., frequency) result in different estimations of the data that the sound is supposed to represent. is, if temperature is mapped to the frequency of the sound, then what change in *temperature* will the listener report when requency is doubled? Is it simply the same as the change they report for *pitch* when frequency is doubled? Is it the same ge they would report for pressure or velocity or the value of the dollar when the frequency is doubled? The question thus lifies to whether it matters what data dimension the sound is supposed to represent, and if so, how.

ERIMENT 1: MAPPING PREFERENCES

ddress the question of which display dimension best represents a given data dimension, we sought a straightforward oach that would be very easy to apply by designers of new auditory displays. We simply presented pairs of sounds that red only along a single auditory dimension at a time, and asked listeners to indicate which sound best represented a cular data dimension.

aratus and Procedure

ners sat in front of a 17-in. Macintosh computer monitor in a sound-attenuated room, listening to sounds via Sony MDR-) headphones, and responded using the mouse.

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sounds were presynthesized at 16-bit, 44.1 kHz using Csound. They were composed of a one-beat long pure sine wave followed by a half-beat of silence. These elements were looped to create a continuous pattern. The sounds were esized with all nine combinations of the auditory dimensions of frequency (400, 1000, and 2400 Hz) and tempo (60, and 420 beats per minute or bpm; at 60 bpm, one beat lasts one second). The amplitude envelope of the tones included a econd linear ramp onset and offset. We normalized the stimuli for loudness, starting with relative amplitude values from l-loudness contours [2] then making minor adjustments based on pretesting.

d Cues

chose four data dimensions that were both widely known and commonly used in a variety of scientific fields perature, pressure, velocity, and size). For each dimension, matching cue questions were created to cover each end of the limension. An example pair of cues would be: "Which sound best represents something with a hotter temperature?" and ich sound best represents something with a colder temperature?"

l Structure and Task

maximum transportability the experiments were written in HTML and Javascript, and run with Netscape 4.6. On each a cue question was centered near the top of the screen, with two 1-inch squares centered just below, separated by two es horizontally. While the cursor was located over square A, sound A would play. While the cursor was over square B, d B would play. On a given trial, the two sounds would differ only along only one of the dimensions (e.g., frequency). participant would listen to each of the sounds, then simply click on the square whose sound they felt best answered the question. During the half-hour session, all sounds differing only in frequency (nine pairs) and all sounds differing only in o (nine pairs), were combined with all eight word cues, for 144 total trials presented in random order.

icipants

en Rice undergraduate psychology students (2 male, 9 female) participated for partial course credit.

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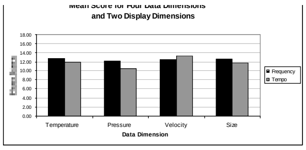
each cue (data) and sound (display) dimension pair, a signed preference score was determined for each subject. If, for ple, the higher-frequency sounds of a pair were always judged better for representing hot, and the lower-frequency ds were always judged better for representing cold, then the individual preference score would be +18. If, on the other , the higher frequencies always "matched" cold, and the lower frequencies always "matched" hot, then there would be ct agreement, but with the opposite polarity (i.e., a score of −18). Scores in between +/− 18 would indicate a less- istent or weaker preference. Average preference scores across subjects provided a measure of how effective a mapping and in what polarity it was preferred. Figure 1 shows the individual preference scores for each data and display nsion for the 11 subjects.



'igure 1. Mean preference scores from Experiment 1, across subjects. Black bars represent sounds differing only in requency; gray bars represent sounds differing only in tempo. None of the differences reached statistical significance.

ussion of Experiment 1

preference scores in this experiment were meant to indicate which display dimensions are preferred for representing the dimensions. However, it seems that most subjects just determined a mapping polarity and applied it consistently across ata dimensions. In debriefing the listeners, many reported simply trying to be consistent and "get a perfect score." Thus simple paradigm does not seem to be as effective as we had hoped in determining preferences. For example, increasing ı should map to decreasing size for at least some listeners (which would make the mean preference score lower, or even tive). It was clear that we required a more sophisticated, and perhaps less transparent, experimental paradigm.

'ERIMENT 2: SCALING THE DIMENSIONS

ldition to discovering mapping polarity preferences, we also need a way to determine what the scaling function is een the physical sound attributes and the data dimensions they are meant to represent. We turned to the psychophysical ng paradigm of magnitude estimation [4] to assess directly both the polarity and scaling function issues. We hoped that :ognitive twist on this well-established paradigm would be less transparent than Experiment 1, so it would be less likely listeners would respond in a particular pattern throughout the study (i.e., attempting to attain some "perfect" score).

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icipants and Stimuli

ı the same subject pool, 132 different listeners participated. Two sets of sound stimuli were created as in Experiment 1. set consisted of 10 stimuli that were all at a frequency of 1000 Hz, but varied along the tempo dimension (45, 60, 105, 210, 270, 420, 500, 550, and 600 bpm). The second set of 10 stimuli were all at the same tempo (60 bpm), but varied ; the frequency dimension (100, 200, 300, 400, 800, 1000, 1400, 1800, 2400, and 3200 Hz).

ı participant completed two blocks of trials, separated by a brief rest. In one block they heard only the sounds from ulus set 1, and in the other block they heard only the sounds from set 2. Block order was counterbalanced across subjects.

l Structure and Task

cipants read instructions like the following:

> 'ou will hear a series of sounds, one at a time in random order. Your task is to indicate what pressure they represent, y assigning numbers to them. For the first stimulus, assign it any number of your choosing that represents a pressure. 'hen, for each of the remaining sounds, indicate its pressure, relative to the first sound. For example, if the second ound represents a pressure that is 10 times the first pressure, assign it a number that is 10 times the number you ssigned to the first sound. If the second sound represents a pressure that is one fifth that of the first sound, assign it a ıumber that is one fifth the first number; and so on. You may use any range of numbers, decimals, or fractions that eem appropriate, as long as they are greater than zero.

:n. Listeners simply filled in their responses and clicked a "Next" button to proceed to the next trial.

block of 20 trials, each sound was randomly presented twice, with the constraint that the highest or lowest frequency or ɔo could not occur first, and subjects only responded to one data dimension per block. Following a brief rest, the rimenter introduced the second block with new instructions that indicated a different data dimension (e.g., size), but were :wise identical. Thus, for example, a particular participant might first listen to all the stimuli that differed in frequency nake judgments about temperature, and then in the second block listen to all the stimuli that differed only in tempo and e judgments about the size that the sounds would represent.

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ʻidual Data

ɜach subject, we kept the responses from each block (i.e., each data/display dimension pair) separate. We observed that in a block most of the listeners responded with a particular mapping polarity, and despite the random order of trials, ıced a set of responses that either increased or decreased monotonically with the stimulus dimension. When plotted on og axes, the typical results fall along a straight line. This is entirely in accordance with the findings generally reported sychophysical judgments [4], with the important difference that in our experiment the listeners were making *conceptual* ments.

ınalyzed each participant's data as follows. First we calculated the geometric mean of the two responses to each stimulus use of the geometric mean is justified in [4]). We then log-transformed the responses and the stimulus values (e.g., the ıencies), and calculated the Pearson correlation coefficient between the stimulus values and the geometric mean of the ɔnses. A large absolute value of the correlation coefficient meant that the participant had responded in a consistent and rally linear fashion. We decided to remove the data of those few whose correlation coefficients did not reach entional levels of statistical significance (i.e., for 10 data points and a = .05, $r_{critical}$ = 0.44).

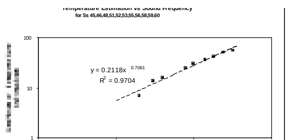
e listeners obtained highly significant, but negative correlation coefficients for some blocks. Positive correlations :ated that the listener had assigned increasing data values to increasing display values (i.e., increasing temperature ɔed onto increasing frequency). Negative correlations, on the other hand, indicated that increasing data values were ɔed to *decreasing* display values (e.g., increasing size was represented by decreasing frequency). Some listeners obtained ghly significant positive correlation in one block, and obtained a highly significant negative correlation in their other :. In debriefing some subjects, it was clear that this was intentional. For example, one reported, "It seemed obvious to me in the first part [of the experiment] hotter things were faster [in tempo], but in the second part bigger things make deeper er frequency] sounds." It appears, then, that this paradigm provided a better way to investigate mapping polarities. In s of our data, we considered the actual number of participants using a positive versus a negative polarity for a given data-ay dimension pair as a good and simple indication of the "popularity" or general preference of a mapping direction. :e values are included in Table 1.

ographic Variables

ldition to the magnitude estimation data, we recorded age, sex, handedness, and number of years of musical training for participant. We calculated correlation coefficients between these four variables and the slopes for each listener. None of lemographic correlations reached statistical significance for this group of listeners.

ension Scaling: Aggregate Slopes

next measure of interest was the actual scaling of the data dimensions. For this we sorted the total data set by display ɜnsion (frequency or tempo), data dimension (temperature, pressure, velocity, and size), and mapping polarity (positive or tive correlations). For each subset of data, the geometric mean of all responses was calculated for each stimulus (across ɜcts). These ratings of pressure, velocity, etc., were plotted against the actual values of the physical parameter that was ɜd (e.g., frequency) on log-log axes (see Figure 2 for an example). These graphs were all very linear, with high R^2 values. slope of each of these graphs, as indicated by the exponent of the x-term in the power-fit equation, provides the hophysical scaling function between the data and display dimensions. For example, if the slope of the temperature-ıency graph is +0.7, then a ten-fold increase in frequency represents only a seven-fold increase in temperature. If the ɜ were -0.8, then a ten-fold increase in frequency would represent an eight-fold *decrease* in temperature.



igure 2. Geometric mean temperature estimations made for sounds of different frequencies in Experiment 2. The line hrough the data is a power fit; the slope is represented by the exponent of x in the equation, in this case, 0.71 (s.d.= .02). If the frequency is increased by a factor of 10, the perceived temperature will only increase by a factor of 7.1.

able 1. Summary of slopes of graphs of data-display pairs. Slopes represent the psychophysical scaling function etween the data and display dimensions. Positive slopes (listed first) indicate that increasing data values map to ncreasing display values. Negative slopes indicate increasing data values map to decreasing display values. Slopes in old indicate the most popular polarity. The number of subjects contributing to each slope is indicated in parentheses.

Display Dimension: Frequency				**Display Dimension: Tempo**			
Data Dimension	**(N)**	**Slope (b)**	**SE(b)**	**Data Dimension**	**(N)**	**Slope (b)**	**SE(b)**
Temperature	(11)	**0.95**	0.12	Temperature	(11)	**0.43**	0.04
	(2)	-0.69	0.04		(6)	-0.48	0.05
Pressure	(8)	**0.78**	0.05	Pressure	(10)	**0.68**	0.06
	(4)	-0.49	0.08		(5)	-0.72	0.06
Velocity	(14)	**1.06**	0.03	Velocity	(11)	**1.04**	0.06
	(2)	-0.17	0.03		none		
Size	(7)	0.90	0.05	Size	none		
	(12)	**-0.76**	0.08		(16)	**-0.94**	0.07

ussion of Experiment 2

e 1 summarizes the data-display pairs and the obtained slopes, plus the numbers of listeners whose data contributed to lope. The fact that these slopes are different for each of the data dimensions, and that they are different from 1.0, is an emely important and interesting result. Thus it really does matter how the participant expects to interpret the stimuli, and paradigm is sophisticated enough to distinguish user preferences. It also provides the transfer function to be used to ert changes in a data dimension (e.g., pressure or velocity) into the appropriate changes in the display dimension (e.g., o or frequency). This is the key to effective data representation. These scaling functions provide the first experimentally mined, scaled sonification mappings.

i the results of Experiment 2, we now have the beginnings of a set of transfer functions to provide the basis for an tive sonification tool. Data can be translated into the appropriate sound dimensions for optimal comprehension. Of se, these findings are for a relatively small sample of listeners from a homogeneous cultural group. Using this paradigm, results will be replicated with new listeners with widely different musical and cultural experience.

es matter what the sounds are supposed to represent. Further, while some polarities could be guessed (e.g., increasing iency mapped to increasing temperature), there are clearly others that must be determined experimentally (e.g., :asing size to decreasing tempo). And of course, the actual slopes of the lines cannot be guessed.

y other interesting questions are raised by these findings. It remains to be seen how listeners would respond if they were ucted to use a certain polarity for a mapping, but otherwise free to respond. Also, one could ask whether participants d respond as systematically if they were asked to switch the polarity they used when responding the first time. Another e area awaiting investigation is that of the range of stimuli used, as well as the choice of modulus, or starting response. ens [4] recommends against introducing a starting value (i.e., the listener may choose any number whatsoever for the sound). However, it may matter if the listener is "seeded" with temperatures in different ranges. That is, if the uctions mention "outside daily temperatures" and ask the participant to call the first sound "70," a different scaling :ion might arise compared to "temperatures in a nuclear reaction" starting at "3000."

lly, many other display dimensions are yet to be tested, as well as an unlimited number of data dimensions. We are nuing with work in this area.

'ERIMENT 3: VALIDATION TASK

:rimentally derived mappings and scaling functions are presumably better than simply using "what sounds good" to ;n a sonification. However, the utility of the scaling functions still needs to be experimentally validated within a practical A sonification that takes advantage of the preferred mappings and scaling functions should result in better performance a sonification that does not.

:edure

undergraduate participants are performing data analysis and interpretation tasks with weather data. This domain allows ıstantaneous measurement ("What temperature is it?"), trend analysis ("Is the wind speed increasing?"), and integration ultiple data dimensions ("What is the wind chill factor?"). Accuracy and task completion speed can also be measured in way. The use of weather data provides a common task that is of interest to all listeners. It also requires little or no ing of subjects – virtually everyone is familiar enough with rain, wind and heat. In addition, the data dimensions used in orology (temperature, pressure, velocity, etc.) are the same dimensions commonly used in other sciences. This choice ld again help to make the results easily transferable to different scientific domains. This work is currently underway.

predict that performance on all tasks will be faster and more accurate when participants use the optimal mapping :ities and appropriate scaling functions. This will validate the experimental determination of sonification schemes.

NERAL DISCUSSION

ı the determination of optimal mappings and scaling functions, design of data sonifications need no longer rely on the tions and educated guesses of sound designers. More importantly, the development of a paradigm for quantitatively ıating the countless possible mappings between data and display dimensions advances the scientific foundations of the of auditory displays.

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