Sonification of Large Datasets in a 3D Immersive Environment: A Neuroscience Case Study

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***Abstract*—Auditory display techniques can play a key role in the understanding of hidden patterns in large datasets. In this study, we investigated the role of sonification applied to an immersive 3D visualization of a complex network dataset. As a test case, we used a 3D interactive visualization of the so called, connectome of the human brain, in the immersive space called "eXperience Induction Machine (XIM)". We conducted an empirical validation where subjects were asked to perform a navigation task through the network and were subsequently tested for their understanding of the dataset. Our results showed that sonification provides a further layer of understanding of the dynamics of the network by enhancing the subjects' structural understanding of the data space.**

Keywords-sonification; XIM; networks; neuroscience; complex data; auditory display.

I. Introduction

Visual representations of data (also called visual displays) have a long successful history in scientific research. They have been employed widely and commonly in most of the traditional HCIs [1] playing a key role in uncovering hidden structures and meaning in massive collections of data. However, relying solely on visual representations of information can present some limitations when dealing with large amounts of multidimensional data [2]. In some cases, visual representation of data can also lead to cognitive saturation [3].

Humans have the capability to detect subtle temporal patterns in sounds [4]. Due to the auditory system's integrative properties, sound can be efficiently used to enhance visual representations without creating information overload for the user [5]. In addition, sound might be more appropriate to convey dynamical information as opposed to vision [6].

For this reason, in the last few decades, scientists have been introducing auditory cues as a means to convey information, giving rise to a new field called auditory display. As a subset of this, the field of sonification has emerged with the purpose of providing a new tool for the comprehension of complex data and generate new insights. A number of sonification models and techniques have been developed [7], [8], [9] with the purpose of converting data into meaningful information.

Many studies have investigated the role of sound for the representation of complex datasets [10], [11], [12], [13]. However, most of these studies focused on the effectiveness of visual and auditory displays separately, yet a few among them have investigated the role of sound as enhancer of a graphical visualization (i.e., multimodal display) [14], [15], [16], [17].

Here, we investigated how sonification may function when integrated in a multimodal display of large neuroscience datasets such as the connectome [18]. We previously developed the so called XIM Neuroscience application[19], a 3D interactive framework to visually represent and explore the massive connectivity of the human connectome, which is "a comprehensive structural description of the network of elements and connections forming the human brain"[18]. For the purpose of our experiment, we displayed the Neuroscience application in XIM, an immersive room equipped with a number of sensors and effectors that have been constructed to conduct experiments in mixed reality [20].

Our hypothesis was that the introduction of sound in a multimodal display could enhance the understanding of complex data describing the brain.

We paired the 3D visualization of a connectome dataset [21] in XIM with a sonification system intended to represent the changes in the dynamics related to different regions of the network, thus providing the user with an extra channel of information. For the empirical evaluation, we assessed whether sound could augment the understanding of the network's dynamics.

This paper is composed of three different sections. Section II introduces the methods and materials along with the sonification model that was adopted. Section III presents the results of the experiments and section IV provides an overview of the conclusions.

II. Methods

A. The "eXperience Induction Machine (XIM)"

The XIM [20] is a multi-user mixed-reality space covering a surface area of 5.5 x 5.5m equipped with a number of sensors and effectors. XIM effectors include computer graphics content projected via 8 projectors on 4 separate walls, a luminous

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interactive floor, movable lights and sonification system. For the purposes of this project, four projectors were used as a visual display of the connectome network on 4 separate walls and two speakers in the left and right corners of the room to project the auditory display.

B. The Neuroscience Application

The Neuroscience application is a system that was previously built in XIM [19] that uses multimodal input and output and permits the embodied exploration of connectome datasets. In this study, we adopted the connectome dataset from Hagmann et al. [21] (data source http://www.cmtk.org/datasets/homo_sapiens_01.cff). The dataset is composed of 998 regions of interest (ROIs), 28000 unidirectional connections and 66 anatomical subregions in the left and right hemisphere of the human brain.

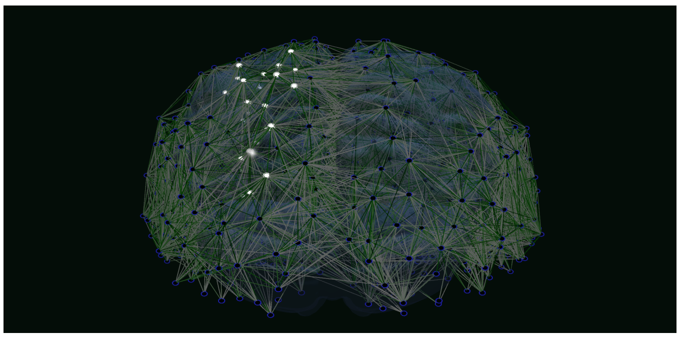

Figure 1. 3D visualization of the connectome in XIM.

The connectome network is visually represented in XIM. Edges are represented as tubes mapped to different shades of green in accordance to their strength. Nodes are represented as spheres and are highlighted when the region they belong to is selected by the user. The network's anatomical regions contain the nodes and are spatially organized in accordance with a standard brain atlas (Talairach coordinates of ROIs[22]) (Fig. 1). The system is implemented using Unity 3D (http://unity3d.com).

C. Sonification methods

The goal of our sonification was to acoustically represent changes in the connectome network's parameters while navigating through its different structures.

First, we analyzed the distribution of the values of the parameters in the network in terms of a) number of nodes, b) number of connections, c) average strength of each region and d) brain hemisphere.

Second, two distinct sound sources were chosen whose parameters were mapped to the network's parameters: a) a short sound sample (grain sound of 16 ms), acoustically perceived as a "click" and b) a soft multi-layered ambient sound, which could be characterized as a drone sound. For each one of the 66 brain regions, the sound parameters used for the sonification were: a) the repetition rate (playback frequency) of the grain sound, which was mapped to the number of nodes, b) the pitch of the ambient sound, mapped to the number of connections, c) the loudness of the grain sound, representing the average strength of each region and d) panning, to identify the brain hemisphere (Table I).

TABLE I. MAPPING BETWEEN THE NETWORK'S CHARACTERISTICS AND THE CORRESPONDING SOUND PARAMETERS.

Connectome Characteristics	**Sound source**	**Sound Parameter**
Number of connections	Sound grain of 16 ms	Rate of repetition
Number of nodes	Ambient sound at 380 Hz enhanced by a pure sine wave at the same frequency	Pitch
Average Strength	Sound grain of 16 ms	Loudness

The sonification engine was built using Pure Data (http://puredata.info/) and the communication between Unity and Pure Data was implemented using OpenSoundControl (OSC) messages.

1) Nodes: A narrow-band short sound sample with the duration of 16ms was chosen for the sonification of the nodes. The idea was to take inspiration from granular synthesis (a method that operates on the microsound time scale [23]) and simulate laboratory sound recordings of neural activity. These microsound characteristics allowed the auditory display of the micro-structures of the brain. By doing so, we associated the ROIs in the brain (i.e., the nodes of the network) to a sound texture composed of a large number of sound grains. The number of nodes determined the time interval between the grains, which defined the number of clicks that would be played back by our sonification engine.

The number of nodes was mapped to an interval that determined the metro (or rate) of the playback in an inversely proportional relation (i.e., lower number of nodes resulted in larger time intervals between the grains and vice versa). In order to avoid a mechanical and isochronous repetition of the grain sound, the output in milliseconds was also used as input for a random function. Likewise, a low number of nodes resulted in large range of intervals of the random function. The output of this function was used as a delay time, which was added to the final playback repetition.

2) Connections: Previous literature validated the role of pitch in the sonification of complex data for the purpose of different tasks [11], [12]. In addition, pitch offers large resolution since the human auditory system is capable of detecting very subtle changes in a very large range of frequencies [24]. For this reason, we mapped the pitch to the number of connections of each connectome region. A sound parameter with a large resolution, such as the pitch allowed for the auditory presentation of a wide range of number of connections.

We adopted a soft ambient sound sample to provide a more pleasant auditory experience to the user than a pure sine wave [25]. First, a spectral analysis was conducted with SonicVisualiser (http://www.sonicvisualiser.org), which revealed that the most prominent frequency of the sample was at 380Hz. This value was adopted to define the upper limit of the frequency range. Hence, the number of connections was mapped to a frequency range spanning from 60Hz to 1200Hz. Frequencies above 1200Hz would have resulted in an unpleasant and disturbing experience for the user.

To accomplish the sound mapping in our sonification engine, we used a pitch shift object in pure data. This object shifts the frequencies of the sound resulting in lower and higher final pitch. Three groups were defined for the whole range of numbers of connections. Each group was mapped separately into a subset of values using linear mappings, which depended on the distribution of the connections values in the network. These values were used to transpose the sound through the pitch shift function resulting in the final fundamental frequency. Finally, the amplitude of the sound was adjusted according to the equal - loudness contours [24]. This correction ensured that all the frequencies would present the same level of loudness.

3) Strength: Loudness is a perceptual sound parameter that has been used previously in sonification models [12]. For this reason, we used loudness to represent the strength of the connections in the network. Since the manipulation of the amplitude and the frequency of the same sound source simultaneously could lead to unperceived and confusing changes [26], we chose to modulate the loudness of grain sound used for the nodes, as opposed to the ambient sound of the connections.

We calculated the average strength for each region, which was mapped to the amplitude of the grain sound. According to the literature, "the most effective use of loudness change usually occurs when changes in loudness are constrained to two or three discrete levels that are mapped to two or three discrete states of the data being sonified. In this way, discrete changes in loudness can be used to identify categorical changes in the state of a variable or to indicate when a variable has reached some criterion value" [27]. For this reason, 3 groups of average strength were defined for low, medium and high levels of loudness so that the user would easily perceive the changes from one group to the other.

We adopted a linear mapping for the three groups. We defined a lower and upper limit for each group and implemented a scaling of the values of average strength into root mean square (rms) values of the sound wave. The rms values were then multiplied by the signal in order to determine the value of the amplitude of the grain sound. Additionally, a reverb was added to the higher values to enhance the perception of higher strength for the correspondent regions of the network. The scaling factor that was used for the mapping in rms depended on the distribution of the values in the network. Thus, for the first two groups the variation was smoother and for the third group it was more rapid.

4) Brain Hemispheres: For the brain hemispheres we used sound panning. This allowed for the discrimination between left and right hemisphere since the direction of the sound source makes the understanding of the location of the regions in the network more intuitive [24]. Binary signals were received from Unity, which were then mapped to the two speakers through the pan object in pure data.

D. Empirical Evaluation

The aim of this study was to assess whether sound could enhance the understanding of the network's characteristics displayed in XIM and their properties during a navigation task through the network.

Our hypothesis was that sonification would enhance the accuracy in the estimation of the characteristics of the connectome, thus providing a higher understanding of its dynamical changes and a more precise discrimination between the brain regions. By implementing a multimodal experiment using sonification, based on two contrasting sound textures (i.e., sound grains and a long drone), we aimed to empirically validate how sound could be used as an integrative tool to enhance the human ability to detect structural aspects of the connectome.

25 healthy adults (15 females, mean age=29.53, SD $\pm$5.6) with normal or corrected vision and hearing were recruited. The subjects had no prior knowledge of the connectome dataset that they were exposed to during the experiment.

To avoid between-subjects differences in auditory recognition skills, the experiment followed a paired-samples design, where each subject was exposed (in random order) to two conditions: a) only visualization and b) both visualization and sonification. The independent variable was the presence of sound (i.e., sonification condition) versus the absence of sound (visualization condition), while the dependent variable was the quantitative estimation of the properties related to different regions in the network during a navigation task.

E. Experimental setup

The subjects' task was to estimate the number of nodes, connections and the average strength of each brain region and to understand the changes of these values during the navigation. They were presented with different brain regions and were asked to mark their answers in closed-ended questions. The experiment consisted of a training session, followed by two experimental sessions.

The XIM was setup and equipped to provide an immersive experience to the subjects. The lights were dimmed, a table and a comfortable chair were placed in the middle of the room at a symmetrical distance from the speakers to allow a balanced auditory experience for all the subjects. The navigation was done with a standard keyborad and mouse.

1) Regions selection: We preselected a number of brain regions to be presented during the training and the first session. 14 regions of the network were chosen for the training session, resulting in 7 trials for each condition. The subjects were exposed to regions with similar properties (number of nodes, connections and average strength) in both conditions.

For the first experimental session, we selected 36 regions in total for both conditions resulting in 18 trials (9 pairs of regions) for each condition. For each one of the 3 parameters (nodes, connections, average strength) at least one pair of regions presented evident acoustical difference in the parameters (because of the high difference in their values).

2) Training Session: Visual information displays (e.g. graphs) are often familiar to the users given their former education (they are taught since young age) and informal experience [28]. However, complex auditory displays can be not as intuitive as visual representations. For this reason, most of the sonification studies indicate the importance of the training sessions [29], where the subjects can get acquainted with the network's characteristics and their corresponding visual and auditory meaning.

The task of the subjects during the training session consisted in the estimation of the values of the connectome's characteristics for the preselected regions. Specifically, the subjects

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were asked to estimate the number of nodes, connections and average strength of each region and in which hemisphere the region was located. The regions were presented in random order in both conditions. After the exposure to a region, subjects were asked to mark their answers in a closed-ended questionnaire presenting different value ranges in accordance with the properties of each area and their distribution in the network. Subsequently, subjects were given feedback on their answers so that they could learn their possible mistakes.

3) Session 1: In the first experimental session, the subjects were exposed to pairs of different regions (as specified in Section II-E1). First, they were informed about the characteristic they had to evaluate (number of nodes, connections or average strength). Then, they were asked to choose whether the second region presented had a higher or lower value of the parameter measured compared to the first region. After the presentation of each pair, they were asked to mark with plus or minus their answer in a questionnaire. Subjects where allowed to ask for a repetition of the trial in case they wanted to listen (and see) one more time the pair of regions.

4) Session 2: In the second experimental session, subjects were asked to navigate freely through the connectome. Their task consisted in finding a region with certain values (e.g., a region with low number of connections between 200-400 connections, a region with medium-high number of nodes between 20-30 nodes, etc.) as asked by the experimenter at the beginning of each trial. There were no time constraints and subjects were given a printed reference table showing the minimum and maximum values for each one of the parameters. After each answer, subjects were given feedback and proceeded to the following question. The task was repeated twice, once for each condition. Each subject completed 6 trials for each condition, resulting in a total of 12 trials.

5) Score attribution: We defined the score attribution criteria for the two experimental sessions. For each subject, we calculated a score for each one of the parameters, along with an overall score per condition. Table II summarizes the tasks and the score attribution criteria for each one of the sessions.

TABLE II. TASK FOR EACH SESSION AND SCORE ATTRIBUTION CRITERIA.

Session	**Task**	**Score Attribution Criteria**
Session 1	Estimation of higher and lower values between pairs of regions	Correct answers were attributed with 1, otherwise with 0
Session 2	Finding regions with certain characteristics in predetermined ranges of values	Error deviation from correct answer in predetermined scale designed ad hoc for the evaluation

For the first session, the score was based on the number of correct and wrong answers. A score of 1 was assigned to the questions answered correctly and 0 to wrong answers. A total score from 0 to 9 was calculated for each of the two conditions for each subject. In the second session, we measured the absolute distance from the correct answer [30] and divided the resulting value by the number of possible answers, thus obtaining normalized scores between 0 and 1, representing the maximum and the minimum score respectively. We computed these values according to the following formula:

$$\beta_i = 1 - \frac{|i-k|}{N} \tag{1}$$

where β is the normalized score, i the subject's answer, k the correct answer and N the total number of probable answers.

III. RESULTS

During Session 1, we measured the subjects' accuracy in estimating the higher or lower values for the three parameters of the network (number of nodes, number of connections and average strength) between pairs of regions. The data collected in session 1 was submitted to a Wilcoxon test between the two conditions (visualization and sonification). The correct answers for both conditions were calculated. The sonification condition obtained a significantly higher score (z=-2.96, $p < .05$) as opposed to the visualization condition (Fig. 2a). The means of the correct answers of the subjects for each one of the parameters of the network are presented in Table III.

Wilcoxon tests were conducted for each one of the parameters between the two conditions. Although not statistically significant, the means for the sonification condition were higher than their counterparts in the visualization condition (Table III).

Since the experiment followed a paired samples design, the data were tested for order effect. No order effect was found.

TABLE III. MEANS OF THE SCORES FOR THE CORRECT ANSWERS BETWEEN THE TWO CONDITIONS.

	Session 2 Estimation of higher or lower values			
	Visualization		Sonification	
	Mean	Standard Deviation (SD)	Mean	Standard Deviation (SD)
Nodes	2.32	0.80	2.41	0.60
Connections	2.12	0.97	2.48	0.82
Average Strength	1.76	0.66	2.16	0.99
Total	6.00	1.52	7.00*	1.57

We conducted a Spearman's correlation test between the musical background of the subjects and the their estimations for higher and lower values between pairs of regions in the sonification condition. The results revealed a significant negative correlation between the correct answers of the subjects and their musical background (ρ=-0.37, $p < .05$). Subjects with higher formal musical training scored lower than subjects who didn't have a musical background. These results explain the skewness towards the lower score of the score distribution in the sonification condition (Fig. 2a). As a follow up, we conducted a further Wilcoxon test by excluding from the analysis the scores of the subjects with higher formal music training, seven subjects were excluded. We obtained significantly higher scores for the sonification condition as compared to the visualization condition (z=-2.44, $p < .05$) and a normal distribution in the scores (Fig. 2b).

During Session 2, we measured the accuracy of the subjects to find a region that would present specific values of each one of the three parameters (number of nodes, connections and average strength). For this experimental session, a dependent

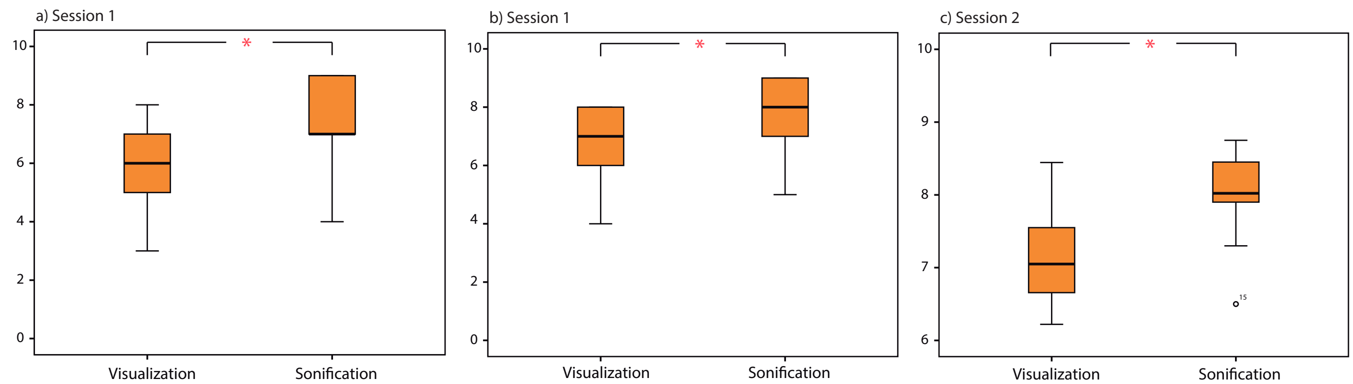

Figure 2. a) Boxplot showing the significantly higher score ($p < .05$) obtained for the sonification condition in Session 1. b) Boxplot showing the reduction of skewness in the data for Session 1, after the exclusion of subjects with high level of musical background. c) Boxplot showing the significant score obtained for the sonification condition in Session 2 ($p < .001$).

T-test was conducted for the total scores obtained from the error deviation measurements. The normalized scores for each subject were calculated for each one of the regions successfully found by the subject through the navigation in the network. The average score was calculated for each subject in both conditions. A significantly higher score was obtained for the sonification condition (t(24)=-5.03, $p < .001$) when compared to the visualization condition (Fig. 2c).

Wilcoxon tests for the scores of the separate parameters were conducted. The scores obtained were higher for the sonification condition for all the parameters.

TABLE IV. MEANS OF THE SCORES OBTAINED FROM THE ERROR DEVIATION FOR THE CORRECT ANSWERS IN BOTH CONDITIONS. THE STATISTICALLY SIGNIFICANT RESULTS ARE INDICATED WITH AN ASTERISK.

	Session 3 Error deviation			
	Visualization		Sonification	
	Mean	Standard Deviation (SD)	Mean	Standard Deviation (SD)
Nodes Low	0.94	0.09	0.96	0.10
Nodes High	0.90	0.14	0.95	0.11
Connections Low	0.48	0.35	0.85*	0.21
Connections High	0.83	0.21	0.87	0.13
Strength Low	0.77	0.29	0.87	0.13
Strength High	0.83	0.16	0.84	0.14
Total	7.15	0.62	8.03*	0.54

In addition, we found a statistically significant difference in score between the two conditions for the regions with low number of connections. The sonification condition obtained a significantly higher score (z=-3.42, $p < .05$) compared to the visualization (Table IV).

IV. CONCLUSION

In this study, we investigated the effect of sonification on the visualization of a complex network dataset. As a test case, we used a 3D interactive visualization of the human brain connectome displayed in the mixed reality "eXperience Induction Machine (XIM)".

We added a dynamic sonification to the 3D visualization of the connectome dataset and we conducted an experiment, where subjects were asked to perform a navigation task through the network and subsequently were tested for their understanding of the connectome dataset.

The parameters of the connectome network (i.e., nodes, connections, average strength and brain hemisphere) were mapped to repetition rate, pitch, loudness and panning, respectively and the estimation of the values in the two conditions (absence and presence of sound) was measured.

The empirical validation consisted of a training session followed by two experimental sessions. After the training, in the first session we measured the accuracy in estimating the higher or lower values of the three parameters between pairs of regions in the network. In the second session, we measured the accuracy of the subjects in finding regions within given range of values in the network parameters. The sonification condition obtained significantly higher scores in both experimental sessions.

Furthermore, the analysis of the data collected in the second experimental session showed that subjects obtained higher scores for the regions with low number of connections in the sonification condition during the free navigation through the network. In complex networks, such as the human connectome, connections (or edges) can't be easily discriminated visually. Here, we have shown that the pitch sound parameter can act as an enhancer in the understanding of structural connections.

The analysis of the results collected during the second session revealed that subjects obtained lower scores for the strength in the sonification condition for specific regions. This may be due to the interaction of the sound parameters (repetition rate and loudness). When an area presented high number of nodes associated to low strength, the interactions of these two parameters could have confused the subjects and these regions may have been associated to higher values of average strength. Further research on the interaction of the sound parameters will provide better understanding of the auditory perception.

In addition, we found a negative correlation between the scores obtained in the sonification condition and the musical formal training of the subjects. In the literature, there is no agreement about the relation of the musical background in auditory tasks. One explanation of this apparently counterintuitive result, as suggested by Walker and Nees [31], may lie on the fact that the skills acquired while undertaking musical studies, especially during the childhood, could be removed after many years. Another explanation for this result could be due to the fact that the measurement of musical background through a single question does not account for an accurate assessment; a more specific test to measure musical abilities should be administered.

In conclusion, the presence of sound enhanced the performance of the subjects (in terms of structural understanding of a network), hence we retain our alternative hypothesis.

Further improvements will include the sonification of additional parameters of the networks (hubs, clusters, etc.) along with the use of audio descriptors and spectral modelling techniques to validate which features, among the sound parameters, are more effective in the understanding of a complex network dataset.

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