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Abstract

The quantity of information we are producing is soaring: this generates large amounts of data that are frequently left unexplored. Novel tools are needed to stem this "data deluge". We developed a system that enhances the understanding of large datasets through embodied navigation and natural gestures using the immersive mixed reality space called "eXperience Induction Machine" (XIM). One of the applications of our system is in the exploration of the human brain connectome: the network of nodes and connections that defines the information flow in the brain. We exposed participants to a connectome dataset using either our system or a state of the art software for visualization and analysis of connectomic data. We measured their understanding and visual memory of the connectome structure. Our results showed that participants retained more information about the structure of the network when using our system. Overall, our system constitutes a novel approach in the exploration and understanding of large network datasets.

Index Terms: I.3.7 [Three-Dimensional Graphics and Realism]: Virtual reality—; E.1 [Data Structures]: Graphs and networks—;

1 Introduction

The quantity of information we are producing is soaring. This generates the, so called, "data deluge" [2]. Large chunks of these data are left unexplored due to their heterogeneity and to the lack of tools to effectively visualize and analyze them [10].

These data are frequently organized semantically and stored hierarchically using standard formats, such as XML [22]. One of the most effective approaches to represent large amounts of data is the use of network (or "graph") structures. Networks allow to symbolize the relationships between objects at different scales by visually displaying datasets as a series of nodes connected through edges that express different properties and can reveal the behavior and characteristics of complex systems shaped by the interactions among its components [16].

In context of large network visualization and understanding, immersive environments offer unique benefits when compared to standard desktop environments. Previous studies have shown that large screens promote the use of more efficient cognitive strategies [24]; surrounding displays, in particular, offer kinetic depth cues (e.g. 3D rotation) thus allowing the user to amplify the understanding of graphs [1]. Moreover, immersive environments increase the performance in data analysis tasks that involve spatial relationships (e.g. volume, geometry, common features) thus enhancing spatial understanding [18].

For these reasons we built an immersive system that uses multimodal input and output and permits the embodied interaction with large network datasets. To do so, we used the eXperience Induction Machine (XIM), a mixed reality space equipped with a number of sensors and effectors that we constructed to conduct experiments in mixed reality [3].

Using the XIM infrastructure we have previously shown the impact of different navigation modes on the understanding of complex neuronal data designed through a neuronal network simulator [6]. Here we present a new mixed reality application capable of handling large and complex network structures in real time.

As a test scenario we used the human brain connectome, "a comprehensive structural description of the network of elements and connections forming the human brain" [21].

With our system the user can be fully immersed in this complex data seeking to understand its dynamics and to discover new patterns. We provide an ecological form of interaction since the user can literally grab data clusters and manipulate them.

In addition, physiological measures (electrodermal activity, heart rate and respiration) are collected through wearable and unobtrusive sensors. These implicit responses are analyzed in real time to detect the user's interest and suggest to the user new relevant areas in the dataset.

To validate empirically our system, we compared it to the Connectome Viewer, a state of the art software for visualization and analysis of connectome data [9].

2 Methods

2.1 The eXperience Induction Machine

The eXperience Induction Machine (Fig. 1) is an immersive space constructed to conduct empirical studies on human behavior in complex, ecologically valid situations that involve embodied interaction in mixed reality [4].

The XIM covers an area of about 25 m^2 and is equipped with a number of sensors and effectors. XIM effectors include 4 projection screens, a luminous interactive floor [8] and a sonification system [13]. The sensors include a marker-free multi-modal tracking system [14], floor-based pressure sensors, microphones as well as wearable and unobtrusive sensors that measure the user's physiological state. A glove prototype is used to measure electrodermal activity (EDA), finger gestures and hand position in the space [12], whereas the Smartex™ WWS shirt measures electrocardiogram, respiration and body movements [17].

In XIM the game engine Unity 3D [25] is used to render 360 degrees 3D content.

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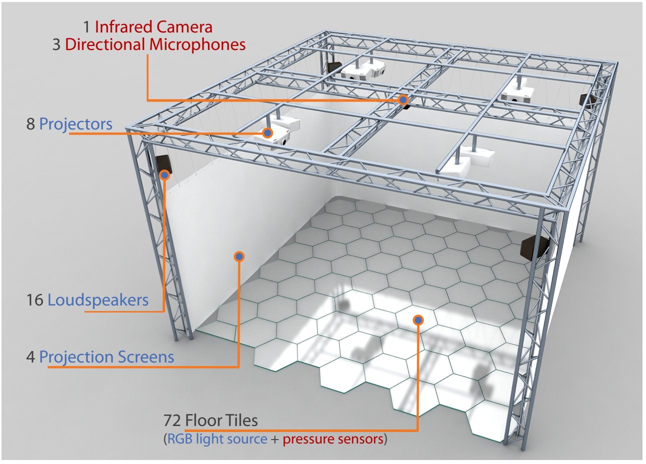

Figure 1: Schematic illustration of the eXperience Induction Machine (XIM). The space covers an area of 5.5x5.5m and is equipped with a number of sensors (labels in red) and effectors (labels in blue).

2.2 The connectome

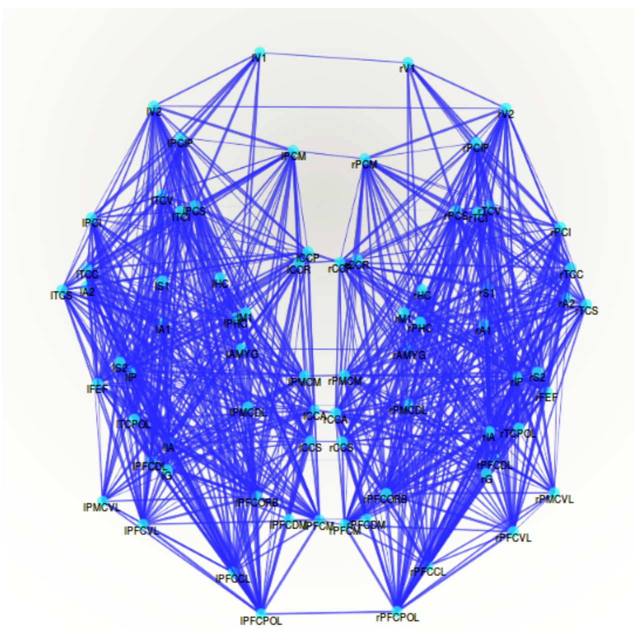

Figure 2: Visualization of the dataset we used in our study (subject B from the "human cortex connectivity dataset" [11]). The network is composed of 998 regions of interest and approximately 28k connections distributed according to 66 anatomical areas.

The connectome constitutes a large and complex dataset [19] and scientific research can benefit from its understanding in several ways. These detailed maps of structural connectivity have already led to quantitative characterization of various aspects of the brain architecture and the basis of common brain disorders [21]. Moreover, the effects of developmental variations and aging, the impact of lesions and the recovery from traumatic brain injury are progressively determined thus opening new opportunities for therapy and prevention (see [20] for a review).

One of the applications of our system is in the exploration of the human brain connection matrix (the human "connectome"), the network of nodes (denoting neural elements or anatomical regions) and edges (denoting structural connections) that provides a description of brain connectivity across different scales (single neurons, neuronal populations, brain regions).

As a benchmark to validate our system we used the "human cortex connectivity dataset" [11]. This dataset is publicly available [1] and constitutes a reference for network analysis of the brain (Fig. 2).

The human cortex connectivity dataset was originally available in Connectome File Format (CFF)[2], a standardized container format that includes multi-modal datasets (in this case, the term multimodal refers to different types of data rather than measurement modalities). From the CFF we extracted the connectivity data stored in GraphML format, a standard XML-based structure used for the representation of graphs composed of nodes and edges with extra attributes (e.g. strength of edges) [7].

By default our system is capable of parsing GraphML files. To plot a 3D representation of the network each node is associated with an X, Y, Z coordinate tuple in accordance with the Talairach coordinates of ROIs [23].

The function of the brain is closely coupled to its structure. For this reason we coupled the structural representation of the connectome network with `iqr`, an open source real-time neuronal network simulator [5]. This allows the user to stimulate data clusters in the dataset and visualize the resulting activation propagated through the network.

2.3 Technical description of the system

2.3.1 Graphics

To achieve an optimal real-time visualization of large network structures, we developed three software components: a) a graphML parser, b) an atlas and c) a "geometry provider". These components have been implemented in C# using Unity 3D and following a Model-View-Controller design pattern.

The *graphML parser* is responsible for the generation of a data structure that allocates all the graph elements (i.e. nodes and edges).

The *atlas* is responsible for reading the meta data associated to the elements that compose the model. These meta data are stored in XML format and typically consist of spatial information (e.g. 3D coordinates for each region and node of the network). However, they can also include extra properties (e.g. color, size, hyperlinks). Multiple sets of meta data can be used (e.g. distinct sets of coordinates), thus allowing to switch between different representations and layouts of the same dataset. In our test case, we fed the atlas with the Talairach coordinate system of the brain [23] to associate each node of the connectome dataset to its brain region in the virtual world.

The *geometry provider* is responsible for plotting the final result as a 3D visualization by combining the instances generated through the parser with the coordinates specified within the atlas. The geometry provider gives flexibility to the visualization of the dataset since each node or connection is associated to a separate object instance: this allows to visualize and manipulate the network in real time by including or excluding objects in accordance to their properties (e.g. specify threshold values to show/hide connections) while maintaining a high performance in the system.

2.3.2 Real-time activity

We coupled the structural representation of the network with `iqr` to allow the user to manipulate data clusters and visualize in real-time the resulting activity.

Similarly to the connectome structural networks, neuronal systems in `iqr` are specified using the XML format and composed of

[1] Human cortex connectivity dataset: http://cmtk.org/viewer/datasets
[2] http://cmtk.org/cfflib/

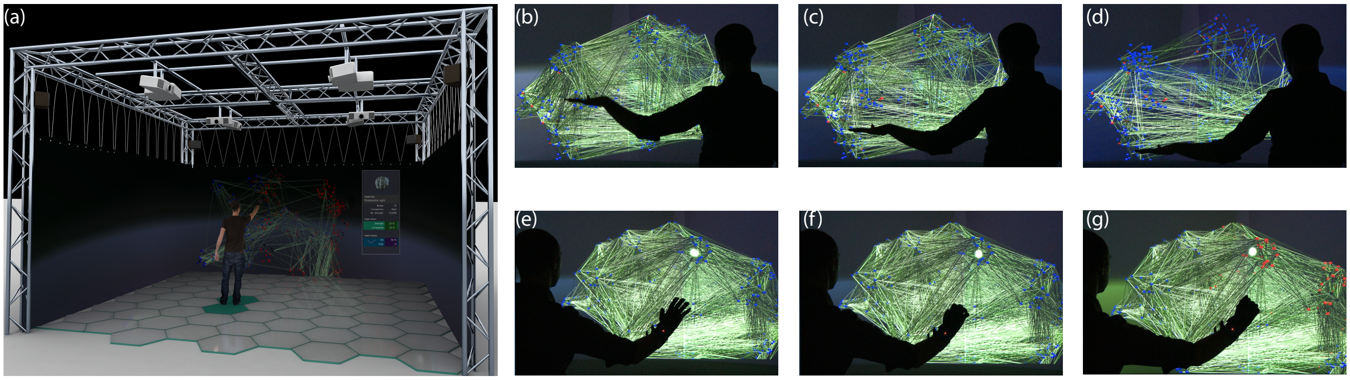

Figure 3: Illustration showing our system in the eXperience Induction Machine (XIM) (a). The user can explore the network dataset by physically walking in the XIM space. A graphical user interface displays properties of the selected area (i.e. name, number of nodes, average strength, filters applied) as well as the user's heart rate and electrodermal activity in real time. Through natural hand gestures the user can filter the connections by complexity or strength (b,c,d) or manipulate data clusters by grabbing them (e,f) to see the resulting activation and propagation within the network (g).

processes, groups and connections. For this reason we converted the connectome dataset into an `iqr` system format. We mapped the brain areas to `iqr` processes, the regions of interest to groups and the edges to the connections.

To visualize the propagation of this activity in our system `iqr` and Unity communicate bidirectionally through the YARP platform [15].

The default status of the `iqr` simulation is driven by a stochastic process (Gaussian random noise). When a user in the XIM selects a specific brain region and grabs it, a signal is sent to `iqr` and the corresponding neuronal group is activated by an excitatory current. The resulting simulated activity generated by `iqr` is fed back in real time to the system, leading to a visual change of the updated activity in the 3D network (Fig. 3e,f,g).

2.3.3 Physiological measures

We enhanced our system with the user's physiological states measured through wearable and unobtrusive sensors. The glove measures electrodermal activity, while the Smartex$^{\text{TM}}$WWS shirt measures heart rate and respiration.

These implicit responses are analyzed in real time using the SSI framework [26] to detect the peaks of arousal thus allowing the system to create a discovery map of the user based on the areas in the dataset associated to these peaks and suggest relevant associations in the dataset (e.g. areas with similar properties such as average number of ROIs and strength) by highlighting them in the visualization with a yellow halo.

2.3.4 Performance

Using the human connectome dataset as a benchmark, our application in the XIM reaches an average rate of 70 frames per second with the highest quality settings available in Unity 3D (real-time shadows, antialiasing, best quality texturing). The performance increases up to 170 frames per second by lowering the quality settings without observing a significant quality loss. Moreover, a standalone version of our system works without loss of performance on latest generation laptops and desktop PCs.

2.4 Visualization in XIM

We use 180 degrees immersive projections to visualize the network dataset (Fig. 3a). The edges are represented as tubes mapped to different shades of green (RGB values: min 143,188,143, max 34,139,34) in accordance to their strength value. This allows the user to visually inspect the strength of the connections and have an overview of their density and dynamics in the distinct areas of the network.

The nodes are represented as spheres colored in blue when the network is in a quiescent state. As soon as they are stimulated with real-time activity they become red (Fig. 3g). The saturation of red is directly proportional to the activity level (Section 2.3.2).

On the main screen a graphical user interface displays in real time the following information taken from the dataset:

- Name of the selected area;
- Total number of nodes and connections in the selected area;
- Average strength of the connections in the selected area.

In addition, the GUI shows to the user the filters applied to the dataset (i.e. strength and complexity) and the electrodermal activity and heart rate measured in real-time using the wearable sensors.

2.5 Interaction

We adopted the Mircrosoft Kinect$^{\text{TM}}$and the glove prototype to track the user's gestures and position in the XIM space and map them to the virtual environment thus allowing real-time embodied interaction.

To interact with the system the user can perform two main actions: navigation and manipulation.

2.5.1 Navigation

With our system the user can navigate the dataset by physically moving in the XIM space. This embodied navigation is achieved using either the Kinect or the XIM tracking system. By default we use the Kinect and map the position of the user's torso to the first person virtual camera in Unity.

The user starts the navigation in the center of the XIM. The network is initially scaled to fit the main screen and no filters are applied (i.e. all the edges are shown). The user can walk forward or backward to zoom in and zoom out the network (shifting the virtual camera on the Y axis). Left or right movements produce a rotation of the network on the X axis. The perspective of the virtual camera is corrected in the lateral displays to maintain the original proportions of the model. This mapping provides an immersive visualization by allowing the user to be inside the data space and explore the different areas.

2.5.2 Manipulation

The user can explore the different areas of the network through natural hand movements. The right hand acts as a pointer and allows to select areas and visualize their properties (Fig. 3e). Left hand movements allow to operate on the parameters of the network and filter the number of visible connections by strength or complexity (Fig. 3b,c,d).

In addition, the user can literally grab data clusters and activate them to observe the resulting activity that is propagating through the network, leading to an appreciation of structural and functional interaction (see Section 2.3.2).

2.6 Empirical evaluation

2.6.1 Sample and protocol

We compared our system to the Connectome Viewer, a state of the art software for visualization and analysis of multi-modal connectome data [9].

20 participants (11 females, mean age 27.3 $\pm$3.45 SD) equally divided into two groups, were asked to explore a complex connectome structural dataset. We exposed the participants in both groups to the human cortex connectivity dataset (subject B, see Section 2.2). This dataset is composed of 998 ROIs and approximately 28 thousands connections distributed upon 66 anatomical brain areas.

The first group was exposed to the dataset using the Connectome Viewer and a latest generation desktop PC, while the second group experienced the connectome network in XIM.

To measure the structural understanding of the dataset we designed a questionnaire aimed to assess the recollection of the main structural components of the connectome such as the brain areas, their interconnections, and their properties (e.g. most populated brain areas, patterns of stronger connections, etc...). In addition we measured the participants' visual memory by asking them to draw a sketch the network ("drawing task").

The experimental protocol comprised 1-participant sessions and followed an independent samples design. During the sessions participants in both conditions were exposed to the same connectome dataset without having any pre-learned knowledge of it. No training session was required.

Prior to the session, participants were asked to fill out a form with demographic information and were also instructed to explore freely the connectome dataset trying to remember as many aspects of the network as possible. Participants in the XIM were additionally instructed to enter the XIM and place themselves at the designated starting point in the center of the room. Immediately after the experiment, participants in both conditions filled out the questionnaire and were asked to draw a sketch of the connectome structure with as many details and information as they could remember.

The average duration of each experimental session was 30 minutes.

2.6.2 Score attribution

The questionnaire included 6 questions to assess the participants' understanding of the connectome dataset structure. We assigned a score of 1 to questions that were answered correctly and a score of 0 to incorrect answers. Thus, we calculated a total "structural score" from 1 to 6 for each participant.

To quantify the participants' performance for visual memory in the drawing task, we attributed to each participant a score on a scale from 1 (highly inaccurate) to 5 (highly accurate) in accordance to the criteria in Table1.

3 Results

We conducted an independent samples T-test to evaluate the differences between the two conditions (XIM and Connectome Viewer Toolkit) in strucural scores collected through the questionnaire. We found a significant main effect for the independent variable ($t(18)$ = -2.53, $p < .05$). Participants performed significantly better (in terms of structural score) using the XIM system (mean = 4.30 $\pm$0.95 SD) as opposed to the Connectome Viewer Toolkit (mean = 2.80 $\pm$1.62 SD) (Fig. 4a).

To evaluate the differences in the visual memory task, we conducted a Mann-Whitney test. The result of the test was significant (U = 20.50, z = -2.36, $p < .05$). Participants completed the task more accurately when exposed to the connectome dataset in XIM (mean = 2.5 $\pm$0.7 SD) as opposed to the Connectome Viewer Toolkit (mean = 1.5 $\pm$0.97 SD) (Fig. 4b).

Table 1: Score attribution criteria for the drawing task.

Score	Criterion
1	Highly inaccurate: the sketch doesn't present any component of the network.
2	Partially inaccurate: the sketch presents the main components of the networks (nodes and edges) distributed according to a non-structured or random disposition.
3	Fairly accurate: the sketch presents the main components of the networks distributed upon the main lobes (i.e. frontal lobe, parietal lobe, occipital lobe and temporal lobe).
4	Very accurate: the sketch presents the main components of the network distributed upon the main areas and includes at least 5 correctly placed labels of anatomical brain areas.
5	Highly accurate: the sketch presents the main components of the network distributed upon the main areas and includes more than 5 correctly placed labels of anatomical brain areas.

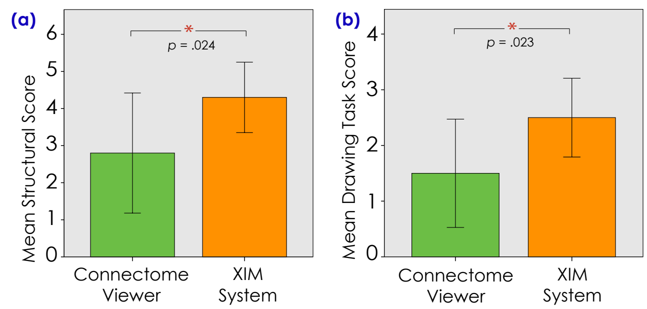

Figure 4: (a) Histogram representing the differences in structural score between the XIM system and the Connectome Viewer Toolkit. (b) Histogram representing the differences in score for the drawing task between the XIM system and the Connectome Viewer Toolkit. The error bars represent the standard deviation.

4 Conclusion

To address the question of how to understand large datasets we developed a system to explore and manipulate complex networks in real time using the mixed reality space eXperience Induction Machine (XIM). Through this system the users can explore and manipulate the network while immersed in the dataset.

Furthermore the system measures the user's electrodermal activity, heart rate and respiration with wearable sensors to detect peaks in interest and arousal of the user and suggest relevant associations in the dataset by highlighting them.

As a test scenario we used a human connectome dataset composed of approximately 28 thousands connections and 1 thousands nodes.

We conducted an empirical evaluation by comparing our system to the Connectome Viewer.

Firstly we measured the participants' understanding of the dataset structure through a questionnaire. Participants retained more structural information on the network using the XIM system. Secondly we measured the participants' visual memory by means of a sketch drawing task. Participants showed a significantly higher accuracy in recalling the network when exposed to the XIM system, as opposed to the Connectome Viewer.

The results we obtained show the effectiveness of our system in the understanding of large network datasets. Besides the intrinsic features of immersive environments such as the XIM (as described in section 1), the introduction of physiological measures from the user accounted for the differences we observed by adding a further layer of (implicit) interaction thus boosting the exploration process. To quantify and validate empirically the role played by the suggestions based on the user's physiological signals, further experiments are needed.

Our system constitutes a novel approach in the visualization and exploration of large network datasets (in our case, the human connectome) and it provides an ecological form of interaction where the user is immersed in the data space and can navigate through the dataset by physically moving in the XIM space, by using natural gestures and by literally manipulating data clusters.

Future improvements will consist in the enhancement of the user interaction (in particular the mapping of implicit signals) and in the integration of new algorithms (e.g. network complexity measures) to achieve practical applications of our system (e.g. medical). A neurosurgeon, for instance, could simulate the lesions provoked by brain surgery and observe the resultant changes in connectivity in the areas involved.

The exploration process will be further guided by a synthetic "Sentient Agent" that will enhance our system with suggestions based on the collective experience of past users.

Finally, we aim to generalize and validate our mixed reality system to support large and complex networks from a wide range of different domains (e.g. social networks).

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