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A stereoscopic system for viewing the temporal evolution of brain activity clusters in response to linguistic stimuli

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Abstract

In this paper, we present a novel application, *3D+Time Brain View*, for the stereoscopic visualization of functional Magnetic Resonance Imaging (fMRI) data gathered from participants exposed to unfamiliar spoken languages. An analysis technique based on Independent Component Analysis (ICA) is used to identify statistically significant clusters of brain activity and their changes over time during different testing sessions. That is, our system illustrates the *temporal evolution* of participants' brain activity as they are introduced to a foreign language through displaying these clusters as they change over time. The raw fMRI data is presented as a stereoscopic pair in an immersive environment utilizing passive stereo rendering. The clusters are presented using a ray casting technique for volume rendering. Our system incorporates the temporal information and the results of the ICA into the stereoscopic 3D rendering, making it easier for domain experts to explore and analyze the data.

Keywords

stereoscopic visualization; fMRI; independent component analysis; time-series data; language acquisition

1. INTRODUCTION

Imaging has become an essential component in many fields of medical, laboratory research, and clinical practice.[1] Advances in modern medical imaging numerous techniques, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), are now available for acquiring complex multi-modal data. One technique, known as functional Magnetic Resonance Imaging (fMRI), has enabled neuroimaging researchers and clinicians to detect metabolic changes within the cerebral tissue. This effect is known as the Blood-Oxygen-Level-Dependent (BOLD) signal and is the result of an increase in oxygen delivery to active cerebral tissue, which in turn results in changes to the local magnetic field.[2] This provides for high spatial resolution of active brain regions which, when combined with an anatomical reference such as MRI data enables researchers to glean important insights into the complex

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operations of human cognitive processes, such as learning. However, fMRI data is time-dependent and highly complex, requiring immense preprocessing in order to extract viable signal from the data.

Computer-based visualization techniques have become a valuable part of medical imaging.[2] In particular, direct volume rendering has demonstrated that it can be a valuable technique in not only the analysis of multi-modal 3D brain data but also allows for more in depth discussion with domain experts and acts as a proxy for outreach with the general public. Visualization has grown in importance as advances in technology bring about decreases in cost both in terms of price and computation time.

In this paper we present a novel visualization system prototype, dubbed the *3D+Time Brain View*, which focuses on the temporal aspects of fMRI data to visualize distinct neural networks as they evolve over time. To our knowledge, this type of visualization has yet to fully exploit the issue of time-varying visualization in multi-modal 3D ensemble brain data. To illustrate the utility of our application, we apply it to fMRI data from a language learning experiment that included three sequentially-obtained scans designed to illuminate the process of language learning over time.[3]

A prevailing question in the domain of language learning research is what kinds of neural networks are involved in language acquisition.[4–6] While neural regions involved in language processing have been well described, little is known about the neural networks recruited during the process of language learning. In the presented experiment, researchers used fMRI and ICA to examine the brain's response over time as adult participants were asked to identify individual words embedded in Norwegian, a language that was initially unfamiliar to all of the participants.

The experiment was repeated in three consecutive scans representing three time points in the learning process. The resulting data was analyzed using independent component analysis (ICA). The ICA approach separates complex signals into simpler component signals that are statistically independent (see Refs. 7 or 8 for overviews of the technique). The separate signals, or independent components (IC) are model-free estimates in that the analysis does not assume a shape or duration of the BOLD response. Because ICA separates the complex fMRI signal into component waveforms, this analysis can reveal correlated regions of activation, as well as separate time courses for activation that occurs within a single brain region.[9–11] For this particular experiment, ICA yielded five functionally independent clusters of brain activation that were present across the three time points. These data clusters serve as the source materials for the visualization tool described here.

The issue of volumetric neurological data visualization is not new, and techniques for the combined visualization of multi-modal image data and multi-volume rendering have been well described.[12–15] Advances in hardware acceleration and programmable GPU's have made it easier to develop high-resolution multi-volume rendering, and numerous applications have been developed to take advantage of this., both commercial[16,17] and non-commercial.[18] Ray casting[19,20] is a common volume rendering technique[21,22] due to its high precision in visualizing the various medical images.[23]

2. VISUALIZING TEMPORAL DATA CLUSTERS

The main advantage our system has over other applications visualizing fMRI data is its focus on the *temporal evolution* of the data. Given that the process of learning can be reasonably expected to involve change over time, and imaging studies which employ learning based paradigms must devise clever approaches to modeling temporal effects. One approach is to incorporate multiple back-to-back scanning sessions in the hopes of capturing brain activities that demonstrate the intended learning effects over time.[24–27]

In typical fMRI visualization applications, multiple volumes are rendered individually or in conjunction with one another in an overlaying fashion. This is acceptable if the image(s) in question are static, or represent the averages of multiple sessions. However, there are situations where it would be useful to analyze the temporal evolution of multiple clusters of brain activity. In these cases, existing tools can be cumbersome and limit the user's ability to explore and analyze the dynamic aspects of their data. Our system by contrast incorporates the temporal elements of these imaging experiments and allows the researcher to examine the functionally connected clusters across multiple sessions.

The obvious benefit of this is that this visualization tool offers better insights into time-linked data, providing visual confirmation of their experimental effect. Further, the visualization acts as a tool which helps domain experts to reason effectively about their data. It also may presents unforeseen opportunities by providing views of the data that may not have been recognized otherwise. This has the added benefit of expanding outreach opportunities with the general public and non-domain experts, both in terms of developing an appreciation for the complexity and subtleties of the data and the research it is intrinsically linked to.

3. DESIGN AND IMPLEMENTATION

Our system presents a anatomical brain image overlaid with ICA clusters. All provided datasets had a dimension of 109×91×109 voxels. We had access only to the post-processed data (and not the raw individual fMRI scans) which gave us 15 files in NIfTI-1.1[*] format[28] representing 5 clusters over 3 time periods. The files are single channel with a 16-bit range representing a possible 65536 values, i.e., a statistical intensity map. Higher values represent a higher likelihood of being associated with the specific experimental task. Clusters were selected following a multiple iterative process ensuring component cluster stability. Following component identification, significance testing was performed to ensure reliable correlation with the component activation and the experimental task.

The researcher can use our interface to investigate the the different experiments. By moving a slider from left to right, the researcher is able to control which experiments are currently displayed. In our prototype, we visualized the results from a study taken over three sessions at different times. Thus, the researcher can view the first, second, or third time periods by positioning the slider at the left, in the middle, or at the right, respectively. If the slider is positioned between two time periods, we display the clusters from *both* of the time periods,

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weighting their opacity using a linear interpolation applied to the alpha channel of the clusters. Figure 1 shows multiple clusters at different sessions.

The second main feature of our interface allows the researcher to to assign unique colors to each cluster, and to turn on or o particular clusters within the image. In our prototype, we visualized up to five clusters simultaneously. The researcher could, for instance, turn o all but one cluster to view how a single cluster changes over time, or they could view multiple clusters to see the degree of spatial overlap or independence among clusters. Figure 2 shows the temporal evolution of a single cluster between two sessions.

The user can also change the rotation of the brain in real-time along the x, y, or z axes, and also zoom in or zoom out. This allows the user to more easily examine a particular cluster or set of clusters.

Finally, the user can change the opacity of the anatomical brain image. The default value is set to 0.5 so that it provides a contextual visual cue for how the clusters are situated within the brain. However, this can be changed as needed, for instance, if the anatomical brain image obscures details about the clusters.

The *3D+Time Brain View* is created with an open source graphics framework called *Aluminum*[29] which makes it easy to port applications between desktop (2D) and stereoscopic (3D) environments. Custom programmable shaders are implemented using the *GLSL* language, and our main volume rendering technique was based on a ray casting algorithm described by M.M. Movania and modified from an implementation presented in Refs. 21, 22. Figure 3 shows an overview diagram of our system.

4. EVALUATION

To evaluate the *3D+Time Brain View*, we conducted a cognitive walkthrough with 7 domain experts (1 professor, 2 research scientists, 2 doctoral students, and 2 undergraduates) from the Speech and Hearing Lab at University of Arizona. We were specifically interested in how these experts responded to our main contribution: the interactive visualization of the ICA clusters changing over time. All the participants of the cognitive walkthrough indicated that they found our prototype application potentially useful for evaluating how spatial relationships change over time.

One participant told us: “It’s really interesting to see the loyalty of the particular ICA components to their regions over time.” Another remarked: “This is useful, I like that you have incorporated the blending between time points to get a sense of how the clusters evolve over the course of the experiment.” A third user said: “I think it is a novel application in terms of the fact that you can view datasets from one session to the next, Ive never seen another application that can do that.” Other participants also commented positively on the application’s ease-of-use and their ability to control of rotation and zooming of the brain and the ICA clusters. Figure 4 depicts a domain expert examining the stereographic output of the *3D+Time Brain View*.

Although we were mainly interested in the utility of visualizing temporal aspects of their fMRI data, we also recorded feedback regarding secondary aspects of our application. Some users noted that the interface and the sliders were confusing and needed be explained better. Other participants told us that they wished there were metadata and analytical data associated with the samples and the clusters. Another user indicated that some indication of the data provenance would also be useful. One discerning participant who was familiar with the experiment and the specific data set hoped that future iterations of the application would provide "better precision in terms of mapping clusters to the anatomical brain image."

Although these results are encouraging, especially in regards to the main component of the system, future work will more rigorously evaluate the effectiveness of our system in facilitating reasoning about the temporal evolution of brain activity clusters. We will also consider the suggestions made regarding improvements to the interface and the desire for added functionalities.

5. CONCLUSION AND FUTURE WORK

We have described a unique framework for GPU-based multi-volume rendering which explores the temporal component of fMRI data in the context of a language learning experiment. Our method incorporates direct volume rendering using single-pass ray casting in order to visualize changes within a dynamic neural network across time. Future use cases offer broad applications beyond the current data set, and could be applicable to other temporally-linked or static data sets and not just linguistic stimulated ICA clusters but also Arterial Spin Labeling (ASL) functional imaging data or fMRI data analyzed with the more traditional General Linear Model (GLM). It is the hope of the authors that this tool will support cognitive neuroscientists and medical imaging experts in experimental studies.

Future work will incorporate more advanced volume rendering and shading techniques in order to improve the visualization of clusters, which could be especially important when there are numerous datasets to be viewed simultaneously. Presently, blending between two time periods is accomplished using a linear interpolation. However, it would be worth exploring whether applying blending concepts, such as "tweening" between the clusters, would improve the clarity of the visualization. Our group has also been experimenting with simple gesture controls so that the user does not have to use the keyboard or mouse to move through time, to rotate and scale the volume rendering, to change opacity, to update the selection of clusters, or to change any other parameters of the visualization. We have been experimenting with low-cost, off-the-shelf interaction technologies (such as the Kinect and the Leap Motion) that are easy to implement with our passive stereo set-up. We are also interested in further explorations that utilize the CAVE system installed at University of Arizona's Laboratory for Immersive Visualization Environments.[†]

[†]http://rc.arizona.edu/az-live/home

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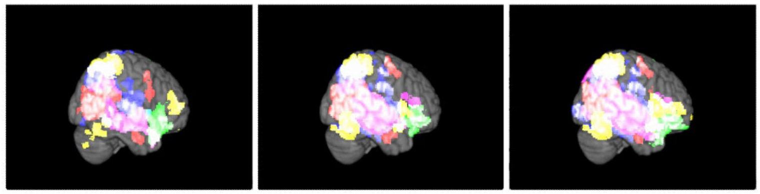

Figure 1.
Screenshots of the *3D+Time Brain View* showing all five components as they appear at session 1 (left), 2 (center), and 3 (right).

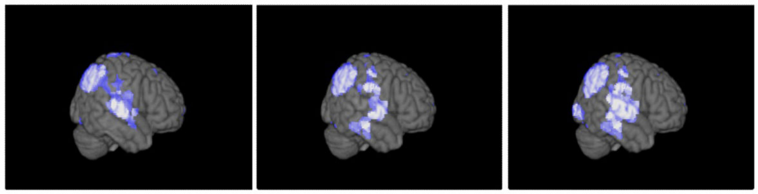

Figure 2.
Screenshots of the *3D+Time Brain View* showing the temporal evolution of a single cluster over time. At t_1 (left), only the cluster related to the first time period is shown. At t_2 (center), the time has been positioned halfway between the first and second time period, so both clusters are shown at equal opacity. At t_3 (right), only the cluster related to t_3 is shown.

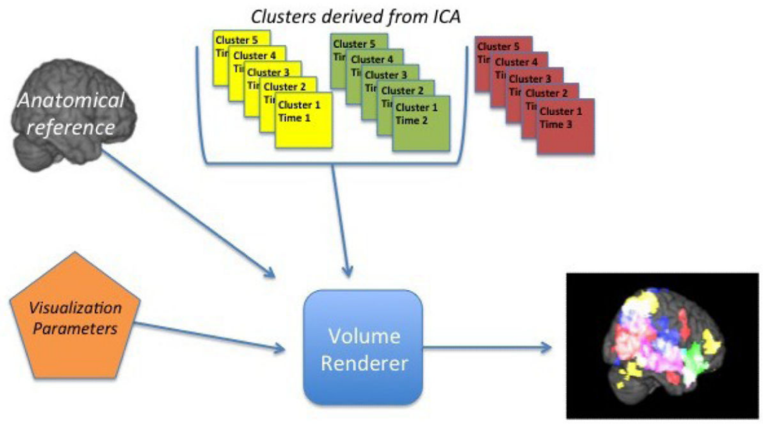

Figure 3.

Diagram showing a high-level overview of the main components of the *3D+Time Brain View*. Inputs to the volume rendering shader program include: a selection of clusters and a particular range of time (top); the anatomical reference image (top left); visualization parameters, including the amount of temporal blending, coloring, eye separation, and opacity (left). An example output image is shown on the bottom-right of the diagram.

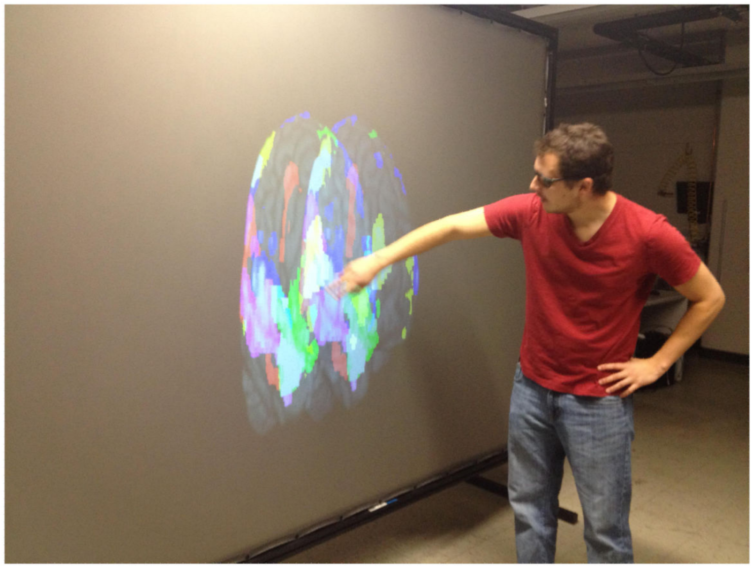

Figure 4.

Photo of a user wearing polarized lenses which allow him to see the passive stereo projection of the volume-rendered brain and temporal clusters in 3D.