Figure 1: From selection to suggestions of region grown based on attribute similarities.

VolSelectAware: Visual-Cognition Coupled Non-Visual Data-Driven Volume Selection for Immersive Scientific Visualizations

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ABSTRACT
There are benefits to visualizing and exploring scientific data in immersive display systems. Interactive data analytics further exploit these benefits. Direct interaction techniques enable scientists to leverage their visual-cognitive skills for identifying and selecting visually rendered data. However, fatigue, data density, rendering, and visual encoding issues may result in reduced usage of immersive scientific visualizations. In this paper, we present algorithmic details of a novel volume selection interaction, implementation details, and discuss use case scenario. Our technique seeks to improve usage of immersive visualizations for scientific discovery and insight.

CCS Concepts
• **Human-Centered Computing→ Human Computer Interaction** • **Human-Centered Computing→ Visualization** • **Information Systems → Decision Support Systems**

Keywords
Volumetric selection; Data-aware; 3D Selection; Regions of Interest; Region-Growing, 3D Interaction; Semi-Automated;

1. INTRODUCTION AND MOTIVATION
The challenge of selection, or identifying regions of interest or data points which make up a volume for selection, for immersive visualizations remains to be solved. Selection techniques which are driven by direct user interaction help the users to harness these skills [1,3,12]. However, when utilizing immersive visualizations, there are challenges that can hinder this human-visual process, such as dense data rendering, rendering ambiguity, limitations to visual

channel, and/or occlusion of data points [10]. We can automate this process instead [4], but many scientists are well trained in visual identification skills that have yet to be replicated by computer vision techniques. There are few techniques which combine both [15] but often remain task-specific [6]. Our novel technique (Figure 1) takes advantage of both scientists' visual-cognitive processing skills and automation that learns about the users' actions to feed back into the automation technique. Our work will have impact in how we can better augment human visual-cognitive skills to improve interactive visual analytics and usage of immersive visualizations.

2. RELATED WORK
Previous work provides a predefined volumetric area to the user and enables manipulation of that area in order to define the selected set of points [3,5,10]. A predefined shape may not accommodate to the data shape and positions. Progressive refine selection from multiple objects to single sets [7,11] may not be suitable for dense data points in a visualization. User-directed techniques were designed specifically for volumetric selection [8,14], but may cause physical fatigue. A few techniques reduce fatigue in how the tasks are mapped [2,13]. Other techniques use a combination of 2D user input in 3D to reduce fatigue [9]. One technique combines automation, by performing an initial selection and then adding or removing similar neighboring streamlines [6]. Our technique differs from this one in that we use several variables simultaneously while growing regions. In two 3D selection techniques, TeddySelection and CloudLasso, an initial selection is done in a 2D plane, this shape is then extruded to form a 3D cylindrical shape, and the structure of the selected data is analyzed [15]. Our technique is different in that it permits interactive 3D selection from the user and that our technique grows the selection from inside the volume of interest following the data structure. Additionally, our technique does not use spatial proximity as a default parameter for growing the selection set and rather it could be a selected or learned parameter as proximity is not always primary task component.

3. VolSelectionAware Technique
Our technique VolSelectionAware is composed of two real-time continuously repeating stages: (A) Growing/shrinking selected

regions, and (B) Searching similar regions. In stage A, a user selects a point (or set of points) from the data based on how the visualization is rendering these data points. These points serve as the seeds for stage B, the growing/shrinking algorithm. In stage B, the input is the selection from the user in stage A. In this step the system analyzes the currently selected region, among visually encoded parameters, and extracts a data-pattern. For example, if temperature is encoded visually from blues to reds, and a user selects more red elements, then the pattern results from data points with higher temperatures. This data-pattern is then matched against the remaining points to find similar points. The process of extracting a data-pattern consists on averaging the values of each attribute (both visual and non-visual) of every selected point. If we find a percentage of attributes of this point lies between a certain range of the data-pattern, then this point is considered to match the pattern and is added to the set. A set of similar points are suggested back to a user, who can accept, reject, or refine. We define this set as the future volume selection set, or volume suggestion set. These patterns help define and adjust the weights used to define similarity metric. VolSelectionAware will add to or remove from the set of data points within the selection set based on the similarity metric defined by these weights and commonalities among the non-visual variables. The region reduction works in an analogous manner to the region growing. This process continues iteratively, finishing only when the users are satisfied with their final volume selection set. When the current selection is modified, VolSelectionAware works in the background to identify similar regions in the non-selected data. When regions are found, they are highlighted (Figure 1) so a user can decide to add to the current selection. While growing regions a user may discover that unexpected points are added to the selection set and refine those.

4. IMPLEMENTATION AND USE CASE

VolSelectionAware is being used to display a dataset which contained atmospheric data (Figure 1). The current implementation uses Qt for the GUI and OpenGL for the graphical rendering. The assumption is that identification of the points can use any technique generalized for volume selection [1,2,5,8,12,13]. We implemented simple drag-and-swipe for our prototype. This implementation can work with one of two input devices: (1) a common Mouse+Keyboard combination, or (2) a Razer Hydra. The communication between the RazerHydra and Qt was achieved using VRPN. Currently 4-dimensional Network Common Data Format (NetCDF) datasets are supported. The datasets can have any arbitrary number of attributes. Implementation can be enabled in a scientific visualization application, VRUI. To locate the initial points in space the users utilize the tracker data provided by the RazerHydra. A user presses the trigger and moves the joystick to start identifying initial points/areas, releasing the trigger confirms the action. This enables us to use a spatial data-structure such as an Octree to narrow the selection area, thus decrease lookup duration. To grow the initial volume, users move the joystick of the RazerHydra to one side, and to shrink it, to the other side, of volume tool. The system tracks the location of the previous points of a growing/shrinking, so when it grows/shrinks a region it can determine the direction in which it should move (a growth occurs when the selection-frontier is moved in the direction of the normals of the previous selection-frontier). When a user turns the joystick to the base position, the system calculates and shows the suggestion set. Users can adjust parameters using the GUI.

5. CONCLUSION AND FUTURE WORK

In this paper, we have presented our novel volume selection technique, VolSelectionAware. Users can leverage their visual-cognitive skills and expertise in visually identifying elements to select regions of interest, then VolSelectionAware finds patterns in the features that the graphical rendering was based on. VolSelectionAware then finds patterns among non-visual features to suggest data sets that users may have missed due to visual limitations, occlusion, density or vastness of data. We will conduct a user study to evaluate the selection benefits of our technique.

6. ACKNOWLEDGMENTS

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