Volume Cracker: A Bimanual 3D Interaction Technique for Analysis of Raw Volumetric Data

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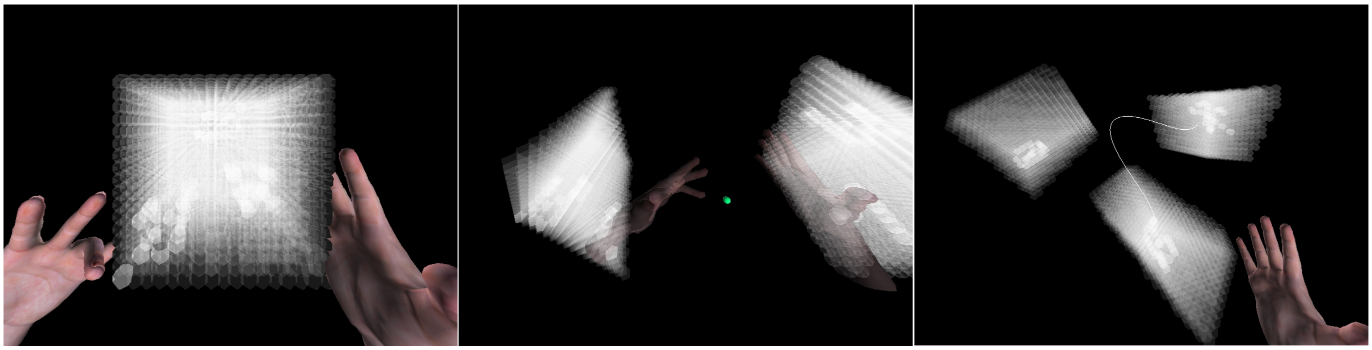


(a) A simulated volume dataset **(b) Cracking preview** **(c) Cracked and connected sub-volumes**

Figure 1: The Volume Cracker interaction technique.

ABSTRACT

Analysis of volume datasets often involves peering inside the volume to understand internal structures. Traditional approaches involve removing part of the volume through slicing, but this can result in the loss of context. Focus+context visualization techniques can distort part of the volume, or can assume prior definition of a region of interest or segmentation of layers of the volume. We propose a new bimanual 3D interaction technique, called Volume Cracker (VC), which allows the user to crack open a raw volume like a book to analyze the internal structures. VC preserves context by always displaying all the voxels, and by connecting the sub-volumes with curves joining the cracked faces. We discuss the design choices that we made, based on observations from prior user studies, input from domain scientists, and design studios. We also report the results of a user study comparing VC with a standard desktop interaction technique and a standard 3D bimanual interaction technique. The study used tasks from two categories of a generic volume analysis task taxonomy. We found VC had significant advantages over the other two techniques for search and pattern recognition tasks.

Categories and Subject Descriptors

I.3.6 [Computer Graphics]: Methodology and Techniques—Interaction techniques; I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism-Virtual reality; H.5.2 [Information Interfaces and Presentation]: User Interfaces-Input devices and strategies.

Keywords

3D interaction; 3D visualization; volume data analysis; bimanual interaction; virtual reality.

1. INTRODUCTION

Volume data comes from several domains, like medical imaging, geophysical sciences, engineering science and mechanics, and paleontological sciences. The sheer amount of volume data getting generated is increasing exponentially in these various domains [20]. It is generated through processes like computed tomography (CT), microscopic CT (micro-CT), magnetic resonance imaging (MRI), functional MRI (fMRI), positron emission tomography, and ultrasonography.

Volume data, in its raw form, is composed of voxels (x, y, z, v) in a 3D grid, instead of 2D pixels. Each voxel has one or more numeric values, representing color, density, refractive index, or other material properties. Generally, one of these properties is mapped to the transparency of the voxels (see Figure 1-a) in the rendering using some transfer function [10]. Scientists analyzing volume data often need to peer inside the volume [14, 15]. For example, a biologist may wish to follow a blood vessel through a CT scan to determine how many times it branches. This process involves finding the voxels representing the structure they are looking for, either by disregarding or removing the unwanted voxels, and then joining all the desired voxels to understand the structure. The analysis could also involve understanding in context, when the other voxels and relevant neighboring structures play an active role in the analysis [10].

The most standard method for analysis is called segmentation, in which the transfer function for mapping is adjusted manually or automatically based on some thresholds, to mark out the region of interest (ROI) in the volume accurately. Although segmentation produces very good results, it is quite time-consuming and often requires very precise selection of ROI in every slice of the volume. Thus, it would be useful to have alternative techniques that allow analysis of volume data and viewing of an ROI without requiring segmentation. Alternative analysis techniques such as axis-aligned slicing (AAS) cause users to lose context partially, and focus+context visualization and interaction techniques have several drawbacks (as discussed in section 2).

To address these problems, we propose a bimanual 3D interaction technique called the Volume Cracker (Figure 1), which preserves all the voxels, and the relative geometric shape and size of the various internal structures, but provides the flexibility to focus on any ROI chosen by the user. Our approach is inspired by the exploded views technique [4] that cracks open a volume into pre-defined selection objects, which could be refined interactively in real-time by volume painting [5]. The novel feature of our technique is that it is designed to be used with raw volume datasets, prior to any form of segmentation or any definition of selection objects or ROI. Our technique is aimed to contribute towards the suite of interaction techniques scientists are designing for interactive coarse segmentation of raw volume datasets [13].

We discuss the design and development of the Volume Cracker and present a user study comparing this tool with the desktop standard axis-aligned slicing (AAS) technique and a corresponding 3D standard arbitrary slicing (AS) technique. For evaluating the Volume Cracker, we chose different tasks from specific categories in a volume analysis task taxonomy [13].

2. RELATED WORK

Previous approaches to exploring volume data can be broadly divided into two categories. The techniques or tools in the first category remove part of the volume to reveal hidden structures inside, like orthogonal or axis-aligned slicing (AAS), in which the user controls cutting planes aligned with the three orthogonal axes, and can also obtain axial, coronal, and sagittal views along the three axes. The AAS technique has been widely used as part of various software packages like Amira[1] and 3D Slicer. Commercial 3D imaging hardware manufacturers, like Xradia[2] and GE healthcare, provide the AAS interaction as a de facto technique in their factory packaged software.

Hinckley et al. designed a bimanual asymmetric interface allowing arbitrary 3D slicing [8], based on Guiard's framework [7], using real world props. Going beyond simple cutting planes, researchers have used deformable cutting planes [12], clipping based on arbitrary geometry [26], and a filterbox tool [19]. Sculpting metaphors have also been proposed [25], and various sculpting tools like cutaway and ghost tools [5], and for erasing, digging, and clipping were explored [9]. All these techniques, although allowing the user to explore the volume in very useful ways, cause the user to lose spatial context.

This problem is addressed by the techniques of the second category, Focus+Context techniques. They seek to preserve the entire volume at all times, while letting the user focus on the ROI in various ways. One such approach is to use a 3D magnification lens metaphor, such as the Magic Volume Lens [24]. Some researchers have proposed focal-region-based feature enhancement [27] or importance-driven volume rendering [23]. Such magnifying or enhancing techniques, although highlighting the ROI over surrounding areas in the volume, distort the volume or the ROI at least partially with respect to its neighboring structures. Also, many of these techniques are intended for use with segmented datasets. Thus they assume a partial and existing solution of the problem they are trying to address.

Other Focus+Context visualization techniques include layered browsing of volume data, promoted through an array of deformation tools [17]. These assume semantic layers in the volume data, which may not always exist [17].

Our approach relies on using the two hands of the user for interaction with a volume. Both symmetric [1] and asymmetric [7] bimanual interaction techniques have been designed, but few researchers focused on designing or standardizing bimanual techniques for volume data analysis (Hinckley et al. [8] is an exception). Ulinski [22] found that symmetric and synchronous techniques were best for selection tasks in volume data. Recently, there has been some effort in leveraging symmetric asynchronous bimanual techniques for medical data exploration [19]. Researchers are also exploring bimanual gestures for various direct touch interaction metaphors for exploring volume data [11].

3. VOLUME CRACKER DESIGN

3.1 Goals

We set out to design a new interaction technique for volume data analysis that would address the problems of existing techniques. We wanted to allow the users to view internal structures while keeping all the voxels visible and not distorting the dataset in any way, and not requiring any prior segmentation.

During our interviews with researchers and our prior empirical studies for evaluating task performance with volume data, the researchers expressed a strong desire for 3D interaction techniques to directly interact with and analyze volume datasets for various research tasks they perform on a regular basis. They were of the opinion that having a technique where they could use their hand(s) would be more natural, faster, and easier than using indirect tools. Thus, our goal was to design 3D interaction technique(s) using direct manipulation.

3.2 Design

3.2.1 High Level Metaphor Selection

We used design studio sessions in the context of a university course to seek innovative ideas for interaction techniques mapped to a set of task categories [13]. We asked participants to brainstorm ways to use two hands to carry out such tasks in the real world (e.g., searching for seeds in cotton is similar to search tasks in volume data). We also drew inspiration from techniques found in the literature [9, 17, 19] In particular, Zhou et al's magic story cube [28] inspired our use of a cracking metaphor.

This resulted in a shortlist of metaphors to analyze more closely. These included knife, cracker, peeler, hinge spreader [17], and box spreader [17] techniques. In the knife metaphor, the dominant hand cuts open slices from a volume held by the non-dominant hand. The cracker technique uses two hands to crack open a volume, like cracking open a book. The peeler uses the fingers to peel off outer layers from a volume, revealing the inner layers. The hinge spreader uses a hinge, while the box spreader uses a resizable box to open up the volume. We created paper prototypes or storyboards of each technique to understand and discuss the

[1] *http://www.amira.com/*

[2] *http://www.xradia.com/solutions/index.php*

affordances that each technique provides. To select the final metaphor, we looked at a set of usability criteria.

3.2.2 Usability Criteria

For the requirements of our technique, we had good reference from prior empirical studies in the literature with volume datasets [14, 15], and from our interview sessions with domain scientists, from various domains such as geophysics, paleontology, medical biology, and biomechanics. The usability criteria were, in decreasing order of importance:

1. Allow the user to understand what is hidden inside a volume
2. Allow the user to look at smaller chunks of a volume more closely, to identify the regions of interest (ROIs)
3. Allow the user to maintain the spatial context
4. Do not distort any part of the volume
5. Do not assume that the data has predefined semantic layers
6. Make the results of user actions clear and predictable
7. Allow the user to quickly reverse or cancel their actions

Of the shortlisted metaphors, the hinge spreader and the box spreader remove occluding voxels, making the ROI more clearly visible, but violating the criterion to maintain the spatial context.

The cracker, peeler, and knife metaphors preserve all the voxels in the volume, while breaking it in useful ways for the user to analyze. The peeler, however, is based on the assumption of semantic layers in the volume.

The knife technique allows cutting along specific lines through the volume, like we cut open an apple using a knife, while we hold it with the non-dominant hand. The cracker allows cracking open a volume with two hands, and also cracking sub-volumes recursively. Both these techniques satisfied the first five usability criteria. The cracker technique, however, offers the possibility of informing the user of the result of the cracking action prior to cracking (see section 3.2.3 below), through a "cracking preview," satisfying the sixth usability criterion. It was difficult to see how a knife metaphor might offer such a feature, since multiple cuts may be required to cut out a piece of the volume.

Further, while an asymmetric technique (knife) might offer more precision in the cut that we make to analyze the ROI closely, based on Guiard's framework [7], a symmetric technique (cracker) could be faster, as we use the degrees of freedom offered by two hands instead of one [16].

Based on this analysis, we chose to design and develop the cracker metaphor. The next section discusses various design decisions that we incorporated in the Volume Cracker, and how those address the various usability criteria.

3.2.3 Design Details

The basic idea of cracking emerged from the first usability criterion—to understand what is inside a volume. Intuitively, like we crack open a book, we wanted to crack open a volume with our two hands, to look at the things inside. Cracking preserves all the voxels in a volume, and does not assume layers in a volume. It also does not distort any part of the volume.

We designed a cracking preview (see Figure 1-b), which showed up as long as the midpoint between the two hands was within the volume. This was created and updated in real time by dividing the volume into two halves on either side of the plane orthogonal to the line joining the two hands, and then by displacing each voxel

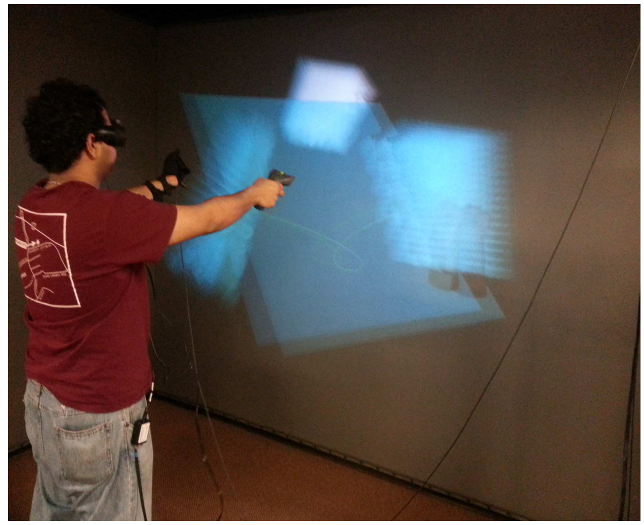


Figure 2: User inspecting a dataset with Volume Cracker.

by a fixed distance along that line, towards the hand closer to the individual voxel. The preview showed how the voxels (along with the internal structures that they form) moved from one sub-volume to the other interactively as the position and orientation of the crack moved. It was designed to make the resulting sub-volumes fully predictable, and ties back to the sixth usability criterion above. Interestingly, from user feedback, we found that the cracking preview also provided a quick and dirty analysis of the various internal structures as well.

Cracking required simultaneous closing of both fists, and broke the volume into two sub-volumes as shown by the preview. The user could choose to crack recursively, until she had separated out the internal structures in blocks of ROIs, which she wanted to analyze separately. To preserve the context after cracking (as per Balakrishnan and Hinckley [1]), we displayed a line joining the two sub-volumes (third usability criterion). Separating the ROIs in connected sub-volumes served the second usability criterion—looking at smaller chunks of volume or ROIs more closely.

To address the final usability criterion, we introduced a bimanual grab function in the Volume Cracker. This allowed the users to grab connected sub-volumes, move them farther apart or closer together, and also join them back (when their bounding boxes overlapped, and the grab was deactivated). We added visual feedback for activation of bimanual grab (blue), and joining of sub-volumes (green).

If the user cracked a sub-volume into two sub-sub-volumes, the line joining the original sub-volumes disappeared, while a new line joining the two new sub-sub-volumes appeared. The users could only rejoin connected sub-volumes, which maintained the hierarchy of sub-volumes.

The other action available in the original design was a single-hand grab on the entire dataset, cracked or otherwise, for manipulating its position and orientation directly. The fist did not need to be within the volume to activate the single-hand grab.

From demo sessions, we found that there were structures on the newly revealed surfaces of both sub-volumes that users wanted to analyze simultaneously, but they were having trouble because the surfaces were facing each other. This became another important usability criterion as even the domain scientists want to look at separate ROIs together. Also, this would help to figure out if there was an internal structure that got split in two during cracking.

We thus introduced rotations of the sub-volumes in the bimanual grab function, which gets activated right at the time of cracking. This allowed the users to grab the connected sub-volumes with both hands, and open those up like a book (while cracking) to look at the interior surfaces simultaneously. We connected the rotated sub-volumes with Hermite curves, defined and updated in real time by the normal vectors coming out of the two hands at any point during a bimanual grab (see Figure 3-c).

We initially allowed the users to reposition and reorient the sub-volumes however they wanted. This easily got confusing because if a structure is broken in two parts, it will be almost impossible to understand it as a whole if the divided structures get rotated about the axis running longitudinally through the unbroken structure, as in that case, the outlines of the structure on the broken faces would align improperly against each other.

In the final design, therefore, we use constraints to preserve the relative orientation of the structures between the two sub-volumes. We limit the movements of the sub-volumes to be along a plane and rotations of the sub-volumes to be around the normal vector to this plane (Figure 3-c). We define the plane at the time of cracking, as the plane containing the vector joining the two hands, and the vector joining the center of the original volume to the viewpoint. We selected these vectors, as at the time of cracking, the resulting plane allows the user to open up the sub-volumes like a book, so that the interior surfaces can face the user. This also serves the seventh usability criterion much better, as the users can quickly reverse the action of cracking if desired.

To avoid confusion, the cracking preview only shows where the crack will be, and not how the sub-volumes can be rotated after cracking. In other words, the preview shows what sub-volumes will be created, and then the separation and rotation of the sub-volumes is done after cracking. Although this means the cracking preview does not show the final state of the sub-volumes after cracking, the user can still quickly reverse the action if desired.

We use head tracking in combination with the Volume Cracker, since it helps the user to get different viewpoints very easily around a volume [15], and serves the first three usability criteria well. We also use stereoscopic display for better depth perception.

4. EVALUATION

4.1 Goals and Hypothesis

Our primary goal was to find out whether the Volume Cracker (VC) would improve quantitative task performance for volume data analysis, as compared to standard techniques. Thus, our first research question was:

1. How does VC perform as compared to a standard 2D and a standard 3D interaction technique for volume data analysis?

Further, we also wanted to gather qualitative insights on the usability and the design of VC, represented by our second research question:

2. How usable and easy to learn is VC?

Corresponding to the two research questions, we had two hypotheses:

1. *VC will produce significantly better task performance than other standard techniques for volume data analysis.* The design choices that we made while designing VC were all geared towards making volume analysis task performance faster and more accurate.

2. *VC will have comparable usability and learnability to existing techniques for volume data analysis tasks.* Based on the real-world metaphor of cracking with human hands, we believed VC would be easy to learn and intuitive to use.

To test our hypotheses, we designed an experiment to evaluate the VC and compared it against two existing interaction techniques for volume data analysis.

4.2 Preliminary Evaluation by Experts

Before running a more formal study, we invited four domain experts to evaluate VC. They included: a biomechanics professor who analyzes micro-CT scans of beetles and snakes, a medical biology doctoral student who works with micro-CT and nano-CT scans, a molecular biology doctoral student working with volume datasets generated from proteins, and an engineering science and mechanics doctoral student working with volume datasets.

We demonstrated a VC prototype to the experts. They appreciated being able to crack open a volume and segregate any region of interest to analyze the internal structures. All of them gave us examples of analysis tasks from their research domains where they felt the technique would be an improvement over the standard tools and techniques they use regularly.

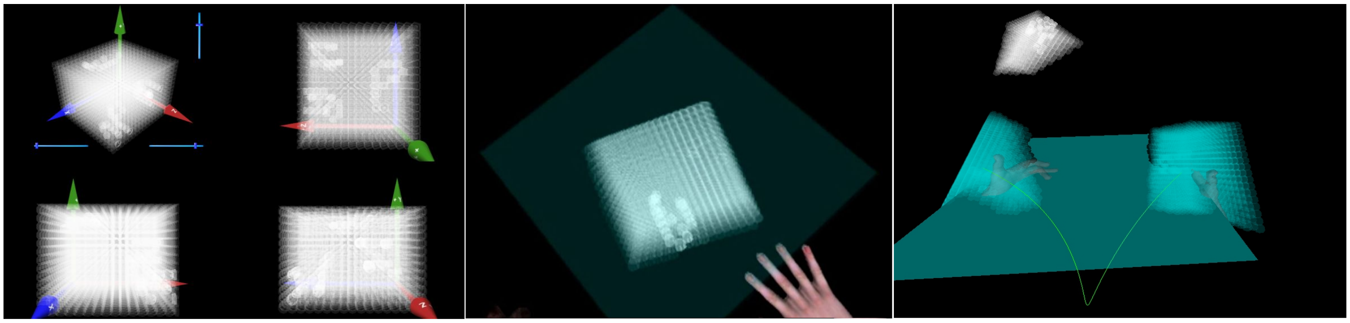
We also verified with them that the rendering of our simulated volume datasets (see section 4.4) were comparable to the real datasets they are used to. We made the simulated datasets as large as we could (17^3 voxels) without sacrificing real-time interactivity, which is needed for VC to work smoothly. They opined that if we observed any benefits in the speed of task completion by using VC with these datasets, it would further improve with real volume datasets. Based on their feedback and input, we created structures inside the simulated datasets similar to the ones in real datasets, and we used realistic analysis tasks from a volume analysis task taxonomy [13].

4.3 Study Design

There are several existing interaction techniques for volume data analysis (see section 2). The wide variety of available techniques makes it difficult to evaluate the benefits of a new design in an absolute sense, but it highlights the need for empirical studies to compare the designs. We chose to compare VC against the most widely used desktop 2D interaction technique, and a widely known 3D bimanual interaction technique [3, 8].

We called the desktop 2D interaction technique the “axis-aligned slicing (AAS) technique.” In AAS, the user looks at four views of the same data simultaneously. One is a 3D view of the volume. The user can slice it along three orthogonal axes, the views along which are called the axial, sagittal, and coronal views.

We termed the 3D interaction technique the “arbitrary slicing (AS) technique.” AS is currently used by several 3D volume visualization software packages like 3D Visualizer [3]. In the AS, the user can rotate the volume data to any arbitrary 3D orientation. The user also has a slicing or cutting plane, which can also be rotated to any orientation, and can be used to slice through the volume to look at any arbitrary cross section of the volume.



(a) Axis Aligned Slicing (AAS) technique **(b) Arbitrary Slicing (AS) technique** **(c) Volume Cracker (VC) technique**

Figure 3: The three interaction techniques we compared in our study.

4.4 Implementation

We implemented each of the three techniques in Vizard[3]. Because of implementing techniques like VC that manipulate individual voxels, we chose to create simulated volume datasets in the shape of a cube with 17^3 simulated voxels (represented by spheres). We varied the transparency between the various simulated voxels just like in real volume datasets. We verified with domain scientists that these datasets were comparable to the ones they use (see 4.2).

In our AAS technique (see Figure 3-a), we created four views, showing the simulated volume from four different viewpoints. The top left view showed a perspective view; the top right view looked down the vertical axis; the bottom left view looked down the left horizontal axis; the bottom right view looked down the right horizontal axis. We placed three sliders in the top left view, for slicing along the three axes. The three sliders and the corresponding cutting planes could be used in combination, by clicking and dragging with a wireless desktop mouse, placed on a table in front of the display. The handle of each slider bar spanned 20x10 pixels. None of the participants reported or appeared to have any trouble selecting them with the mouse pointer.

In our AS technique (see Figure 3-b), the user could grab using her left hand. She had a cutting plane attached rigidly to a six-degree-of-freedom (6DOF) tracked IS-900 wand, held in her right hand. The plane removed the voxels from the simulated volume that were on the rear side of the plane. The user could also make the cutting plane static with the wand, and use the left hand grab to analyze the various cross sections easily. Mapping the cutting plane to a wand held in the user's hand allowed the user to manipulate the plane easily to orientations difficult to achieve with just the human right hand.

The VC technique used in our study (Figure 3-c) was implemented as described in section 3.

We ran the evaluation with a rear projected Visbox-X2 display, a 10 by 7.5 foot display wall with passive stereo capabilities provided by Infitec. An Intersense's IS-900 tracking system provided 6DOF position and orientation tracking of the head and hands of the users in the AS and VC techniques, with a hand tracker for the left hand, and a wand held in their right hand. We used a 5DT data glove for detecting the grab action with the left hand. The right hand grab action in the VC technique was mapped to the trigger button click of the wand.

We used the same display (see Figure 2) in our study for all three techniques. We used stereoscopic rendering and head tracking in AS and VC. However, we used monoscopic rendering with no head tracking in AAS, trading off the experimental control for ecological validity. Since three of the four views in AAS showed just 2D slices, it is unlikely that stereoscopic rendering, and head tracking would have made much impact.

4.5 Participants

We recruited 17 unpaid voluntary participants, of whom three were pilot participants, one had equipment problems, and one retired due to sickness. The final study thus had 12 participants, of whom two were female. Their ages ranged from 19 to 33 years, with an average of 22 years. All the participants were graduate or undergraduate students, either native or fluent in English, and self-reported no prior background in volume data analysis (see selection of novices vs. experts in section). The ordering of the three techniques (AAS, AS, VC) was counterbalanced, giving six different orderings. We had two participants with each ordering.

4.6 Tasks

Researchers are designing an abstract volume data analysis task taxonomy incorporating tasks from various domains under one umbrella [13]. The experts we invited in our lab for a qualitative evaluation of the VC reflected upon some of these task categories (see 4.2). Based on their suggestions, we initially chose four categories in which we hypothesized VC would improve task performance. After running three pilot participants, and informally testing the tasks ourselves with the three techniques, we chose two task types for the final study.

The first was a search task. In a real volume dataset, scientists search for blood vessels, joints in a tracheal network, bones, soft floating tissues, tumors, and many other structures [14]. We chose to use letters from the English alphabet as an abstraction for such structures. This allowed us to recruit novice participants (see 5.1). We believed this task was valid, because a task defined by experts, and used in a prior study of volume data analysis [15] also asked participants to describe the shape of an internal structure as a letter from the alphabet. In each dataset, we created 13 letters, of various size and thickness, randomly oriented, and distributed in the simulated volume. Of the 13 letters, four letters were the same. The participants were told that there were at least two, but no more than six of that particular letter, and were asked to find all the instances of that letter.

The second task was a pattern recognition task. Domain scientists often seek patterns in different parts of volume datasets. For this they try to match complex shapes and clusters—they correlate and compare them to shapes in other parts of the dataset. To simulate this task, we created three closely matching coiled structures, all randomly oriented in 3D. We made the structures

[3] http://*www.worldviz.com/products/vizard*

overlapping and interweaving in 3D, like in real volume data. One of these was a little different from the rest. The task was to find the odd one out.

We did not repeat the datasets between techniques to avoid learning effects. We also wanted to have two trials for each task, for each technique. Thus, we created six datasets for search tasks, and six more for pattern recognition tasks. We also created a training dataset with many letters and two coiled structures.

4.7 Procedure

The study was approved by the Institutional Review Board of our university. After arrival, the participant signed an informed consent form, and filled out a background questionnaire. Then she was given a short introduction of the motivation behind the study, and went through a training session in the technique that would be used first. During the training, she spent three minutes practicing a search task, and three minutes practicing a pattern recognition task, with the training dataset. Next, she used the first technique to complete two search tasks and two pattern recognition tasks, each with different datasets. We created multiple simulated datasets of the same complexity level to avoid any learning effects between the techniques, and the datasets were counterbalanced between the participants and techniques. She was provided three minutes to complete each task. The experimenter used a stopwatch to record the time taken to complete each task. The same experimenter recorded the time for each participant, and we assumed that any time measurement errorrs were distributed evenly among the participants and techniques. The same experimenter recorded the response of each participant for each search task. For the pattern recognition task, the experimenter directly recorded whether the answer was correct or incorrect.

During the search task, the participants were asked to confirm their answer if they sounded unsure of what they were answering. This was done to make sure that the novice participants were not making passing guesses at what apparently looked like the structures they were searching for, but it also avoided over-counting. The experimenter reminded the participant before every search task that the letters could be big or small, and thick or thin.

After completing the tasks with the first technique, the participant had a short round of training with the second technique, with the training dataset. Then she completed the two search tasks and two pattern recognition tasks with the second technique. The participant then repeated the cycle with the final technique. Following that, the participant completed a post-questionnaire capturing her feedback on ease of use, ease of learning, and preference, all rated on a 1-7 scale for each technique, in addition to a few other usability and strategy-related questions for VC. The experimenter also recorded the participant's responses to different usability and design-related questions in a free-form interview.

From the pilot participants, we gathered useful strategies for the three techniques, which we passed on to the participants in the main study, in a way to give them a little bit of expertise that they wouldn't have. For the search task with VC, we recommended that the participants crack through the middle of the simulated volume to reduce the clutter of the dataset. For the pattern recognition task with the VC, we recommended that the participants separate the three structures into three sub-volumes, for easier comparison. For the AS, we recommended that they orient the plane towards the back of the simulated volume, so that the structures or letters towards the front became more distinguishable. We also suggested that they keep the plane static, parallel to the view, and through the middle of the dataset, and then use head tracking to look at both sides of the sliced dataset. With the AAS, we recommended using all three sliders together.

4.8 Results

The score metric was of ordinal numeric type, while the time was continuous numeric. The quantitative metrics in the post questionnaire (ease of use, ease of learning, and liking) were all of ordinal numeric type. For the time metric, we ran a one-way analysis of variance (ANOVA). For the other metrics, we ran an ordinal logistic regression based on a Chi-square statistic. If we found significant difference between the techniques, we employed post-hoc Tukey's HSD tests (for differences in least square means) for the time metric, and the two-sided Wilcoxon Signed rank test (with Bonferroni corrections), for all other metrics.

4.8.1 Search Tasks

The score metric for the search tasks had responses ranging from zero to four. We took the difference of the participants' response from four, which gave us the error produced by the participants. We found a significant effect of technique ($\chi^2_{df=2} = 25.6202$; $p < 0.0001$) on error. Post-hoc tests indicated that the errors decreased significantly from AAS to AS ($p=0.0348$), AAS to VC ($p=0.0003$), and AS to VC ($p=0.0027$), as illustrated by the graph in Figure 4-a. The mean errors of participants with the three techniques are in Table 1.

We also found a significant effect of techinque ($F(2, 69) = 3.3915$; $p = 0.0394$) on time. A post-hoc test indicated that VC was significantly faster than AAS for search tasks, as seen in Figure 4-b. There was no significant difference between the AAS and AS, or the AS and VC pairs. Mean times are in Table 1.

Table 1. Mean errors, scores, and time taken for the task types

Interaction Technique	Search Task Mean Error	Search Task Mean Time (seconds)	Pattern Task Mean Score	Pattern Task Mean Time (seconds)
AAS	1.833	175.00	0.2917	149.46
AS	1.208	164.08	0.7500	150.88
VC	0.583	154.45	0.8750	168.92

4.8.2 Pattern Matching Tasks

The score metric for the pattern recognition task was either 1 (correct) or 0 (incorrect). We found a significant effect of technique

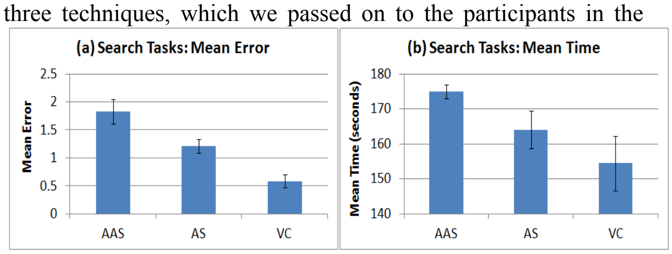


Figure 4: Performance metrics for search tasks.

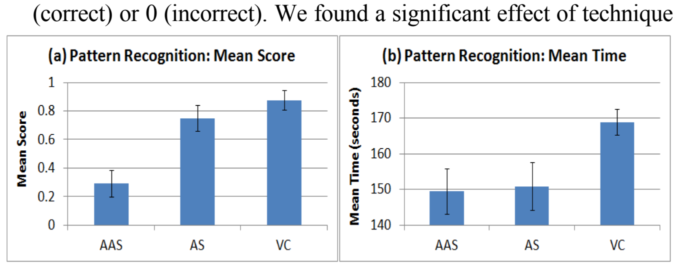


Figure 5: Performance metrics for pattern recognition tasks.

($\chi^2_{df=2}$ = 20.1322; p < 0.0001) on score. Post-hoc tests indicate that the score increased significantly from AAS to VC (p=0.0003), but neither AS and VC nor AAS and AS scores were significantly different (see Figure 5-a; mean scores in Table 1).

We found a significant effect of technique on time ($F(2, 69)$ = 3.5537; p = 0.0340), although post hoc tests found no significant difference in the time taken between the different techniques (also see Figure 5-b). Mean time spent is in Table 1.

4.8.3 Post Questionnaire Results

The participants reported no significant difference between the techniques for ease of use or ease of learning. However, the participants reported a significant difference ($\chi^2_{df=2}$ = 17.5265; p = 0.0002) in their preference for the three techniques—they liked VC significantly more than AAS (p=0.0411).

5. DISCUSSION

Looking back at our research questions, we have found evidence that partially supports and partially refutes our first hypothesis that VC improves task performance over standard techniques for search tasks and pattern recognition tasks. For the search tasks, VC had the lowest mean error and was also the fastest, which strongly supports the first hypothesis for the search tasks.

For the pattern recognition tasks, VC had the highest absolute score (0.875), but was the slowest, which could have been due to a speed-accuracy tradeoff. With VC, participants took quite some time to crack the volume such that the three structures were in separate sub-volumes. We believe the time spent on this would reduce with more practice. The AAS had significantly lower times of completion because several participants gave up on the pattern recognition task with AAS, as they felt it was really difficult. The graphs plotting the mean scores and errors (Figure 5-a, Figure 4-a) indicate that in the AAS the participants scored very close to the score that would have resulted from random chance (2.0 for search error, 0.33 for pattern recognition score).

We believe that the specific design choices that we made (section 3.2.3) supporting our different usability criteria (see section 3.2.2), contributed to the observed benefits of the VC technique, like the basic function of cracking a volume in two halves served to instantly reduce the clutter inside the volume, so that several participants could identify all the letters inside correctly in as little as 40 seconds. Most of them took the remaining time just to join the sub-volumes back, break at some other point, and recount to confirm to themselves, before giving a final answer.

For the pattern recognition task with the VC technique, once they had broken the volume to separate out the shapes in distinct sub-volumes, it was quite easy to determine the right answer. Out of 24 trials, they were incorrect in only 3 cases. Looking back closely at the results, we found that in two of those three incorrect cases they ran out of time. Also, we constrained the bimanual movement only on a plane as described in section 3.2.3. For the pattern recognition task, if we removed the constraints, the participants could actually rotate the sub-volumes so that they could align the coiled structures to verify visually if they matched.

The post-questionnaire results support our second hypothesis. The participants liked VC significantly better than the standard AAS technique. Even though the VC technique challenged the participants with more gestures to recall and use (single-handed grab, crack, bimanual grab, join) than both the AAS (orthogonal slicing) and the AS technique (unconstrained slicing, single-handed grab) combined, the participants reported no significant difference in learning or usability for the three techniques. VC was easy to learn, it was preferred by participants, and it had good performance in most cases. We believe that the use of a real world metaphor that was natural to the users contributed to these results.

Participant comments included concerns about the lack of precision while cracking, blocking of the view by the hands, and difficulty in understanding the depth of the hands. The lack of precision might have also contributed to the slow task performance with VC. We are planning to address these issues in the next iteration of VC, by using an asymmetric interface, and reducing visibility of the 3D models of hands.

5.1 Novice vs. Expert Participants

We initially evaluated our design with experts (see 4.2), but chose to run the main study with novice participants (see 4.5). This decision is in line with arguments made by researchers running empirical studies for evaluating task performance with volume datasets [6, 14, 15]. There are not very many expert users of volume datasets, and researchers find it hard to locate domain scientists as study participants. The field of micro-CT is relatively new, domain scientists have little experience in analyzing volume data [21], and training activities are actively being pursued [18]. Laha et al. found that none of the experts in their study self-reported as *experts* in the background survey questionnaire [15].

We could argue that experts might perform better than novices with the AAS technique. But the results of our study provides evidence that AAS at the least requires a lot of training for *search* tasks, much more than what is needed for AS and VC. Also, as discussed in 4.7, we gave the novices useful interaction strategies in each technique in a way to give them a little bit of expertise when they began to use each technique.

5.2 Simulated Datasets vs. Real Datasets

Using simulated volume datasets for evaluation studies is not ideal, but given our rendering hardware constraints, we believed it to be a reasonable choice. We kept the size of the datasets as big as possible (17^3) without sacrificing real-time interactivity, but they were much smaller than real data (256^3 or higher). We verified that the design of the simulated datasets closely corresponded to real datasets by evaluating them qualitatively with scientists from four different domains (see 4.2). We designed the simulated structures inside these datasets to be similar to those from real data, with internal objects coiling and overlapping in 3D. All four scientists who verified the structures opined that they closely resemble structures from real datasets that they work with. They were also of the opinion that the results we found would translate to their individual domains, but also encouraged us to find ways to work with real datasets. Currently, we are working on rendering real datasets in such a way to access and manipulate individual voxels interactively as needed by the VC, to prototype and evaluate VC with real datasets.

6. CONCLUSIONS AND FUTURE WORK

The contribution of this paper is a bimanual interaction technique for generating exploded views of volumes [4], which works directly on raw volumetric datasets, prior to any form of segmentation or definition of selection objects or ROI. We discussed in detail the various decisions that we made while designing the Volume Cracker, and reported the results of a user study comparing VC with the AS and the AAS techniques. We found that VC had significant advantages over both of these for search and pattern recognition tasks. We have contributed a deeper understanding of the usability criteria for volume data analysis interaction techniques, and a proven exemplar design satisfying those criteria.

We are currently working on creating an asymmetric interface for VC, based on Guiard's framework [7], to increase the precision. The literature suggests preference of symmetric designs over assymetric [2], and vice versa [1] for different task types, and factors affecting task performance. But we need more evidence for performance, and preference of one design over the other. We plan to evaluate the new VC design with real volume datasets, using the task categories from an abstract task taxonomy [13].

We have just started exploring the design space of 3D interaction techniques useful for volume data analysis. As we do not have standardized techniques mapped to the various tasks that domain scientists perform, we need to design, develop, and evaluate further novel 3D interaction techniques for volume data analysis. A bigger goal is to map the various techniques together in a suite of tools for coarse but interactive volume segmentation [13].

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8. REFERENCES

[1] Balakrishnan, R. and Hinckley, K., "Symmetric bimanual interaction," in *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pp 33-40, 2000.

[2] Balakrishnan, R. and Kurtenbach, G., "Exploring bimanual camera control and object manipulation in 3D graphics interfaces," in *ACM CHI conference*, pp 56-63, 1999.

[3] Billen, M. I., Kreylos, O., Hamann, B., Jadamec, M. A., Kellogg, L. H., Staadt, O., and Sumner, D. Y., "A geoscience perspective on immersive 3D gridded data visualization," *Computers & Geosciences,* 34(9):1056-1072, 2008.

[4] Bruckner, S. and Groller, M. E., "Exploded Views for Volume Data," *IEEE Transactions on Visualization and Computer Graphics,* 12(5):1077-1084, 2006.

[5] Bruckner, S. and Groller, M. E., "VolumeShop: an interactive system for direct volume illustration," in *IEEE Visualization*, pp 671-678, 2005.

[6] Forsberg, A., Chen, J., and Laidlaw, D. H., "Comparing 3D vector field visualization methods: A user study.," *IEEE Transactions of Visualization and Computer Graphics,* 15(6):1219-1226, 2009.

[7] Guiard, Y., "Asymmetric division of labor in human skilled bimanual action: The kinematic chain as a model," *Journal of motor behavior,* 19:486-517, 1987.

[8] Hinckley, K., Pausch, R., Goble, J. C., and Kassell, N. F., "Passive real-world interface props for neurosurgical visualization," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp 452-458, 1994.

[9] Huff, R., Dietrich, C. A., Nedel, L. P., Freitas, C. M. D. S., Comba, J. L. D., and Olabarriaga, S. D., "Erasing, digging and clipping in volumetric datasets with one or two hands," in *ACM international conference on Virtual reality continuum and its applications*, pp 271-278, 2006.

[10] Kaufman, A. E., "Volume visualization," *ACM Computing Surveys,* 28(1):165-167, 1996.

[11] Klein, T., Guéniat, F., Pastur, L., Vernier, F., and Isenberg, T., "A Design Study of Direct-Touch Interaction for Exploratory 3D Scientific Visualization," *Computer Graphics Forum,* 31(3):1225-1234, 2012.

[12] Konrad Verse, O., Preim, B., and Littmann, A., "Virtual resection with a deformable cutting plane," in *Proceedings of simulation und visualisierung*, pp 203-214, 2004.

[13] Laha, B. and Bowman, D. A., "Interactive Coarse Segmentation and Analysis of Volume Data with a Suite of 3D Interaction Tools," presented at the IEEE VR Workshop on Immersive Volume Interaction, 2013.

[14] Laha, B., Bowman, D. A., and Schiffbauer, J. D., "Validation of the MR Simulation Approach for Evaluating the Effects of Immersion on Visual Analysis of Volume Data," *IEEE Transactions of Visualization and Computer Graphics,* 19(4):529-538, 2013.

[15] Laha, B., Sensharma, K., Schiffbauer, J. D., and Bowman, D. A., "Effects of Immersion on Visual Analysis of Volume Data," *IEEE Transactions on Visualization and Computer Graphics,* 18(4):597-606, 2012.

[16] Leganchuk, A., Zhai, S., and Buxton, W., "Manual and cognitive benefits of two-handed input: an experimental study," *ACM Transactions on Computer-Human Interaction,* 5(4):326-359, 1998.

[17] McGuffin, M. J., Tancau, L., and Balakrishnan, R., "Using deformations for browsing volumetric data," in *IEEE Visualization*, pp 401-408, 2003.

[18] Mishra, S., Sensharma, K., Lee, S. J., Fox, E. A., and Wang, G., "SLATE: Virtualizing multiscale CT training " *Journal of X-Ray Science and Technology,* 20(2):239-248, 2012.

[19] Mlyniec, P., Jerald, J., Yoganandan, A., Seagull, F. J., Toledo, F., and Schultheis, U., "iMedic: a two-handed immersive medical environment for distributed interactive consultation," in *Medicine Meets Virtual Reality 18: NextMed*, 163:372-378: IOS Press, 2011.

[20] Ritman, E. L., "Micro-computed tomography-current status and developments," *Annual Review of Biomedical Engineering,* 6:185-208, 2004.

[21] Stock, S. R., *Microcomputed tomography: Methodology and applications*: CRC Press, 2008.

[22] Ulinski, A. C., "Taxonomy and experimental evaluation of two-handed selection techniques for volumetric data," Department of Computer Science, The University of North Carolina, 2008.

[23] Viola, I., Kanitsar, A., and Groller, M. E., "Importance-Driven Volume Rendering," in *Proceedings of the conference on Visualization*, pp 139-146, 2004.

[24] Wang, L., Zhao, Y., Mueller, K., and Kaufman, A. E., "The magic volume lens: an interactive focus+context technique for volume rendering," in *IEEE Visualization*, pp 367-374, 2005.

[25] Wang, S. W. and Kaufman, A. E., "Volume Sculpting," in *ACM Symp. on Interactive 3D Graphics*, pp 151-156, 1995.

[26] Weiskopf, D., Engel, K., and Ertl, T., "Interactive clipping techniques for texture-based volume visualization and volume shading," *IEEE Transactions on Visualization and Computer Graphics,* 9(3):298-312, 2003.

[27] Zhou, J., Hinz, M., and Tonnies, K. D., "Focal region-guided feature-based volume rendering," in *First International Symposium on 3D Data Processing Visualization and Transmission*, pp 87-90, 2002.

[28] Zhou, Z., Cheok, A. D., Pan, J., and Li, Y., "Magic Story Cube: an interactive tangible interface for storytelling," in *Proceedings of the ACM SIGCHI International Conference on Advances in computer entertainment technology*, pp 364-365, 2004.