Volumetric selection techniques for 3D data

Sub-volume Selection of Astronomy Data in virtual reality

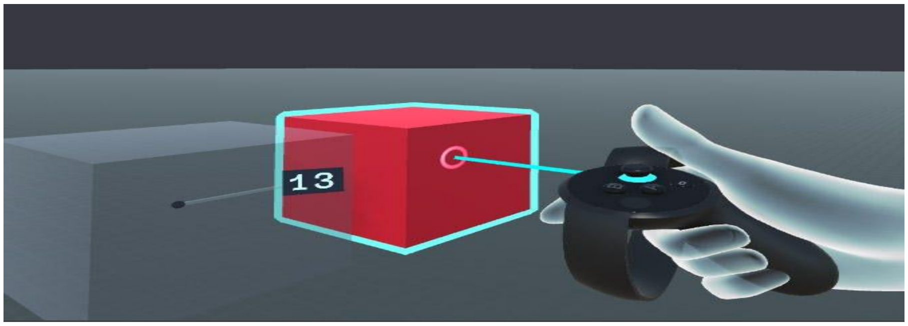

Figure 1: Data selection in virtual reality

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ABSTRACT

Large amounts of data is being produced by current radio telescopes which means that the amount of data needing to be visualized and analyzed is increasing. Using spectral 3D data cubes to visualize this data is an effective way to allow it to be viewed in virtual reality, which gives an extra edge in the visualization effectiveness. While in this virtual reality environment, the user may wish to select data being represented such as galaxies. Multiple selection techniques were analyzed, and it was found that if the data is dense with large amounts of noise then the CloudLasso technique is best. If the data is simplistic then the box selection is the most effective. Additionally, using SOFIA, a 3D line spectral source finding algorithm, objects can be masked and then the masks refined using other selection techniques.

KEYWORDS

Object selection, volumetric data, selection techniques, astronomy, virtual reality.

1 INTRODUCTION AND MOTIVATION

Astronomy and radio astronomy in general creates massive datasets that astronomers wish to reduce and extract valuable information from for various purposes. Recent radio astronomy surveys are picking up even fainter structures in the vicinity of known galaxies, which were not seen before [4]. Traditional visualization on a 2D screen can be very limiting in the data that is displayed, especially when this data is by nature 3D and multidimensional [1]. Visualizing this volumetric data in virtual reality, allows for previously unnoticed aspects to be brought up and analysed, while also giving the user of the visualization a more intuitive view of the data. It allows for depth to be determined by a glance and easier traversal through the 3D space. Studies have shown that using virtual reality to explore data has resulted in fewer inaccurate insights and has an increase in user satisfaction [12]. However, the current use of virtual reality to display 3D volumetric data has not come without its shortfalls.

Current examples of selection and masking techniques using SOFIA involve creating a box around the desired object (such as a galaxy) and then analyzing the target, which is automatically selected by the voxels it contains being highlighted or not. The issue arises as the voxels are by nature cubic shapes and do not have that natural movement often found in nature. This means that the masking of a desired object sometimes results in certain parts of the object not being selected or vice-versa where unwanted voxels are included. It is possible for the mask to be cleaned up, using painting for example but this is a manual process [15]. A lot of time can be saved with a more effective masking technique as well as a more effective cleaning up technique. Additionally, certain parts of the desired object, such as the faint outlines or interconnections, are not always picked up by the source finding technique and thus not included in the following mask [15].

A more effective method of source finding, data selection and masking in a virtual environment, would allow for data areas to be selected more accurately with less tedious brushing up needed by the user. A less rigid automatic mask would also make uses outside of selecting galaxies an easier process (as more precision would be needed for selecting areas in brain or CAT scans).

This review starts by looking at the different types of selection techniques being used. This will establish the basis for the paper, which is the comparison between various source finding and selection techniques (collectively called selection techniques onwards). These selection techniques are broken into three main categories: Lasso selection techniques, Shape selection techniques, and Automatic pipeline selection techniques. The techniques discussed within each section often have overlaps but the classification into these three sections will allow for easier comparison between similar techniques. These three categories will then be compared to each other to gain insight into what technique, or combination of techniques, is the most effective in selecting 3D volumetric data in virtual reality.

Comparisons between the techniques will focus on the accuracy of the selection when it is applied, as well as the cognitive load on the user when that technique is used. This is important as reducing the cognitive load has been shown to increase user satisfaction and overall usability of the technique and thus programme implementing the technique [9]. Where possible, the target acquisition rate (speed of selection) will also be compared. However, as will be discussed, the comparison between selection techniques is not always easy.

The results from this comparison will help guide the choice of which techniques to implement in a controlled environment to see how they can improve the current methods for volumetric data selection being used in certain applications.

2 SELECTION TECHNIQUES

2.1 Automatic Pipeline Selection

As the amount of astronomical data being created daily was exponentially growing, so did the need for techniques that could analyze this volumetric data without the need of human intervention for the main process of source finding. These techniques needed to be accurate in being able to identify sources and applying a mask on them. The detection of low-intensity sources by a human was not possible as the task would have been insurmountable, partly due to the fact of sources having low intensities similar to that of surrounding noise [13, 7]. This began paving way for the development of automatic source detection algorithms that would assist in reducing the manual workload of astronomers and scientists alike and create a sense of large data sets.

These source finding techniques had to find the optimal noise (which obstructs real sources and replicates the look of fake sources) reduction by finding the balance between accepting false positives (i.e. saying the voxel is part of the object when it is not) and rejecting true voxels that are part of the object [7]. While automatic source finding algorithms did exist, such as SExtractor which was developed in 1996, it was not designed for the levels and type of data modern instruments were creating [10, 5]. In particular, the expected increase in expected demands from ASKAP, led to the development of DUCHAMP, one of the first publicly available generic 3D source finders [10].

DUCHAMP is a general-purpose 3D source finder that was designed to find H1 (neutral hydrogen) data sources in the input it receives. The rough process of DUCHAMP is the intake of an image or 3D volumetric data cube, the loading and preprocessing of the cube (where inversion, smoothing and multilevel wavelet reconstruction to enhance smaller sources, takes place), the threshold source finding technique is used and is set to either flux or signal-to-noise ratio, and finally sources are extracted and formed into objects [10]. This can then be displayed to the user in a FITS image which contains a mask over the identified objects, allowing for further analysis and manipulation. DUCHAMP then is able to attempt to pick up faint features that may have been missed. This is done by growing the objects to a second threshold and using a binary mask of voxels either being selected or not, where faint features are picked up and included and if it contains a voxel about the primary threshold [10]. Thus, DUCHAMP effectively assesses the noise level inside a data cube and uses this to efficiently identify and source objects within the data cube and apply a mask over them. DUCHAMP, however, only applies a single algorithm and thus is more favorable to a certain type of astronomical dataset. The introduction of SOFIA, a newer and more flexible source finder, solved this issue [7].

SOFIA is considered more flexible as it contains a variety of source finding algorithms [11]. This has the benefit as it means the user does not have to stick with the given algorithm, as is the case with DUCHAMP, but can instead choose which one to use. This is useful as it has been mentioned that what specific algorithm is most useful for a dataset is mostly influenced by the type of astronomical data being looked at [7]. Thus, the development of SOFIA brought across this benefit with several other improvements. SOFIA searches for line emissions on more than just one scale to detect sources, it can estimate the reliability of sources detected and is able to find signal in very large data cubes [11]. Once sources have been detected, SOFIA automatically masks the data objects within the data set much like DUCHAMP. It does this by using a weighted data cube in addition to the analyzed data cube to reduce variation in noise to assume uniform noise and applies the relevant source finding algorithms (threshold, S+C, CNHI) [11]. It also does reliability checks to ensure bad masks and sources are removed [7]. This is useful for the user as it means the sources are identified and masked, with the voxels all selected, which can then be used for analysis of the source. However, SOFIA is not perfect and will sometimes miss out on identifying certain sources or have the mask of the actual source to large (i.e. voxels are selected when they do not actually belong to the source). To help this, mask optimization is done using binary dilation or using an elliptic cylinder to try and select the fainter areas of the source [11]. This does not promise a perfect mask, and touchups are still needed on occasions, but despite this, SOFIA is still largely used today for all its benefits and customization (it has the added benefit of being modular which will allow for future expansion [11]). Apart from SOFIA, another very common source finding technique is used, and it is called MTObjects.

MTObjects came about as an improvement to SExtractor, which was developed to automatically detect and classify sources from astrological images [5]. SExtractor was based on thresholding which brought across a disadvantage of having to know which optimal threshold was best for which pixels would be considered on object or not, as well as being faulty at detecting faint sources [13]. MTObjects was the solution to this. MTObjects is Max-Tree-Based method of extraction, that is better at finding faint sources than its predecessor SExtractor [13]. At its core, MTObjects works using a Max-Tree of nodes to represent an astrological image. The statistical models used are then run to determine if a node should be marked as significant, based on the power attribute that is associated with each node, where a significant node is considered part of a source [13]. Further testing is done to make sure that these nodes are split or connected depending on if they are the same object. This technique allowed MTObjects to detect fainter sources better, without affecting the shape of the selection. There are never more nodes than voxels in the image, which allowed for the masking to be effective [7]. An additional benefit of MTObjects was that each node could be assigned attributes for further filtering, such as volume and flux density [7]. MTObjects is however not without its problems, and it was shown to struggle with detection of sources when these sources tended to overlap each other or were in a dense environment [13]. Thus, we are left with two leading techniques for automatic pipeline source finding and selection.

While the publication of MTObjects found that it was able to pick up on a galaxy that was missed by SOFIA [13], this was the only metric used to compare the two together in that paper. A study was done in 2023 that directly compares MTObjects with SOFIA, as well as introduced a post processing technique that could improve both automatic pipeline techniques [7]. This study used 3D neutral hydrogen data cubes to determine which of these two source finding techniques was more effective. The same data cubes were given to both techniques to allow for a fair comparison. The results were straightforward and showed that SOFIA was the quicker in detecting sources than MTObjects [7]. Additionally, SOFIA was able to find the most real sources, showing on average SOFIA has better and faster source detection and masking. What is interesting to note, is that the study showed the application of a classical machine learning classifier (in this case a random forest classifier), led to an improvement in both SOFIA and MTObjects object detection [7]. The study also introduced a deep learning algorithm trained on astronomical data. However, this review is intended for selection techniques, and this is more along the realms of source finding but should be noted for future work in the field of volumetric data visualization and interaction.

2.2 Lasso Selection

As has been mentioned and will be mentioned again, selecting visualized volumetric data can be a simple task when data objects are few and large, however, when there are more of them packed into a small area, selection becomes more complicated. These data objects are not always known, and thus spatial selection of the object is required if the user wants to investigate that particular object. Detecting low density objects is a hard task for users to do manually and will often involve many steps, thus more effective selection and masking techniques are needed [7]. Thus, the development of CloudLasso and TeddyLasso came about, to assist with the spatial selection of objects within a chosen area of interest [17]. These two techniques aim to reduce the number of manual steps required by the user by using a structural aware selection method that finds and masks these objects in the data cube. These two methods build on what is known as CylinderSelection, which selects data by using a freehand lasso to build a cylinder that extends in 3D and selects all the objects within it. The newly proposed TeddyLasso and CloudLasso built on the same premise of allowing the user to draw a 2D selection (in the 3D volume space) and then projecting that 2D selection into 3D to take the full object into account [17]. CloudLasso using the aforementioned threshold source finding method in particular the Marching cubes method which makes sure the selected voxels within the lasso are of a certain density.

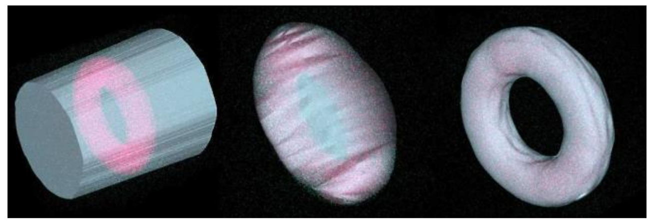

Figure 2: Object selection using Cylinder selection (left), TeddyLasso (middle), CloudLasso (right).

CloudLasso, TeddyLasso and CylinderSelection were all tested next to each other and it was found that CylinderSelection often selects more data than is required (as seen in Figure 2) [17]. Additionally, it was also found that CloudLasso and TeddyLasso were significantly faster and more accurate than CylinderSelection. Finally, CloudLasso took the edge over TeddyLasso as CloudLasso was shown to repeatedly have a smoother mask than TeddyLasso. CloudLasso was shown to have the ability to select disjoint objects without the inclusion of the noisy areas in between [4]. This provides the benefit of being able to select multiple objects in high density without having a large number of bad voxels which are not meant to be selected. In its essence, CloudLasso first selects the Volume within the data cube and searched for voxels above a certain threshold and then threshold tuning can be applied to highlight the correct area [4].

2.3 Shape Selection

Another group of selection techniques looked at are shape selections. These are talking about the techniques that use shapes to select certain areas in volumetric data and the selection of specific already identified objects. These methods were around very early on as a method to select an object that the user wants to analyze and have since grown in capabilities. Many techniques are now able to select multiple objects at once and select objects that appear behind each other and objects in denser environments. This is important as interaction with 3D clouds containing large amount of included data points is not a trivial task, when considering the occlusion and density of the of the data cubes and subsequent objects [2]. This section additionally highlights the benefits of hybrid systems when it comes to shape selections and the role they can play in volumetric data selection in virtual reality.

The first look as it two common ways of selecting already identified objects and these broad categories are hand extension selection techniques and ray cursors. The hand selection techniques will be ignored as in a 3D immersive space all objects may not be in arms reach [16]. Rather the focus is on ray cursors which developed from point cursors. These ray cursors allowed for faster selection in virtual reality but suffered from issues of selecting multiple objects at once when only one was intended, thus requiring disambiguation [16]. Grossman and Balakrishnan [16] improved upon this problem by designing what they called a depth ray, which has shown to decrease acquisition time as well as error rate in data selection. Depth ray improved upon this problem by projecting its ray where the user is pointing but then having a distance marker attached to the ray. That distance marker can then be moved forward and back and the object closest to it is highlighted in green. When the desired object (which may have been originally hidden) is highlighted, the user can choose to select that object, and thus has managed to remove the further step of disambiguation. An issue presented itself here where the selection must be of large objects (big enough for the user to be able to see) and only single objects. Which in an astronomical data set, means selection of galaxies and similar cloud like structures would be difficult. Thus, ray casting (such as the depth ray or other aperture-based selection methods) would not do well in selecting clouds [3], as they are made up of thousands of objects and time needed would increase as the number of overall targets increased [17].

A solution to this problem was looked at with the introduction of two-handed selection methods for data selection by Ulinksi et al., [3]. The techniques were divided into two categories, the first was bimanual selection where each hand had a different task and bimanual symmetric selection. Both categories had techniques that made use of a box metaphor, i.e. the method of selecting an area of volume. This was done as it was found that the best solution to selecting multiple objects at once was to create a box around it, thus selecting everything inside the box and encompassing the selected volume rather than one specific object [3]. This parallel technique of selecting multiple objects at once using a selection box was shown to be more effective than serial techniques such as the ray cursors [8]. The most effective asymmetrical technique was the Hand-In-Middle technique of creating the box, which had less accuracy but a lot more comfortability. The most effective symmetrical was the Two corner selection technique which had more accuracy but a higher cognitive load [3]. From this it can be concluded that if the task is not complex, i.e. the data area is not dense with high occlusion, the Two corner technique is most effective at selecting volumetric data. In cases where the environments were denser, a hybrid technique using a tablet and pen in addition to a virtual reality headset was proposed. SlicingVolume is a hybrid selection technique that takes a 3D volume selection and projects it into a tablet, where finer adjustments can be made and more precise selections [14]. This technique makes use of slicing panes which are projected in the virtual environment wherever the user decides. The area between the panes is what is then projected onto the tablet. This is useful for highly occluded areas as the projection onto the tablet provides more haptic feedback and thus was shown to increase the accuracy of the selection [14]. However, for less dense areas, it is still quicker to use a parallel technique such as the box selection as it is faster than using tablet tapping [16].

3 COMPARISON/DISCUSSION

The biggest issue that has appeared with attempting to compare various selection techniques, is that there is a large amount of overlap. It is often the case where some of these different techniques are used hand in hand with each other and compliment each other in completing the overall task of visualizing 3D volumetric data effectively and allowing the user to analyze the data and interact with it. This is seen for example by looking at SlicerAstro [4] which uses SOFIA as an automatic pipeline to generate the data cube blocks and identify the sources inside of them. Then, when further interactivity is desired, a modified version of the CloudLasso selection technique is used for selecting the mask for effectively. While SlicerAstro is more of an interactive platform for volumetric data visualization, it still shows the specific selection techniques that are being used out there. However, indirect comparisons are still possible and will be made and discussed now. Another issue presenting itself was how to compare these techniques and methods with each other. In all the papers certain metrics were used but that specific metric was not guaranteed to be common amongst all the other techniques. This means that direct comparison is not always possible and had to be done using what limited information was made available.

The analysis of shape selection techniques had some important findings. The evolution from point cursors to ray casting methods was highlighted and shown to have become obsolete due to the nature of astronomical data. This data typically has multiple data objects within a 3D data cube, and thus the selection of a single object that is occluded by many others would not be a simple task. Thus, the development of a box selection for an area of volumetric data was looked at. The best selection technique to implement this method was using the Two corner method, however, this is most effective for simple data that is not too dense and has objects not too complex in shape. A possible solution to this problem was brought up with the idea of a hybrid system that uses a pen and tablet to allow for the finer selection of selected data between two slices. This hybrid system called SlicingVolume shows a lot of potential for improving the accuracy of data selection. However, the focus is on selection techniques in virtual reality and while this method has a large virtual reality component, it is still relying on an additional physical tablet, which is not readily available. For this reason, more focus will be put on the box selection using the Two corner selection method. It is important to note that if the data presented is not of a cuboidal shape and is more organic such that found in nature, drawing a rectangle for selection is not necessarily the most effective means.

CloudLasso, which was built as an improvement to CylinderSelection is able to identify sources quicker than CylinderSelection and more accurately with less false selections. Additionally, it creates a smoother mask than its counter part

TeddyLasso. While CloudLasso is performance wise heavy, often requiring multiple seconds [18], it is able to perform complex masking especially in high density environments where the objects wanting to be selected will often have high occlusion.
When comparing CloudLasso (the top Lasso selection technique) with the Two-handed box selection (the top Shape selection technique), we can see a distinct difference in uses. While they could be directly compared to each other, it is important to see that they both have separate strengths. The box selection is much quicker than the CloudLasso but does not perform well in high density environments, compared to CloudLasso which has slower performance speeds, but can take on more difficult tasks. Therefore, to say one is better than the other depends on what is present inside the dataset. However, in the case of radio astronomy where most of the objects are made up of many data points such as galaxies, filaments, and gas tails, it would be more effective to use CloudLasso.

Both SOFIA and MTObjects are automated source finder pipelines and generate masks through their software, but these masks are not as shown, always perfect. In particular, the source finding methods used by SOFIA and MTObjects struggle when it comes to differentiating data in highly occluded areas [7]. This means there is room to add further object masking and touching up. A solution to this, and something that was mentioned, is a hybrid model, that makes use of both the automated pipeline and then a further selection method. This is already implemented in current systems [17, 18] and should be looked at as a possibility going forward. The use of multiple selection methods allows for more precision and touchups to be done. Another improvement to SOFIA and MTObjects which was brought up was the preprocessing using an object classifier. This has not been experimented with a lot and could prove to have interesting results when applied to a variety of source finding algorithms.

While this paper has looked at a critical comparison between different techniques, there was another avenue that could not be explored due to its more simplistic nature. The focus was on a large and complex algorithm choosing data or which platforms, or automatic pipelines should be used, but the manual aspect for data mask refining has not been researched a lot. This could mean the simplest improvements to improving the selection techniques may not lie in the type of technique, but rather in how the use of the technique in virtual reality could be improved. Aspects such as the size and the shape of the brush used for selecting and deselecting which voxels make up source (which is viewable by the human eye in virtual reality) may be the most significant improvement.

4 CONCLUSIONS

A couple of conclusions can be made from this literature review. Multiple selection techniques were looked at and divided into three sections depending on what their primary method was. The first section was automated pipeline source finding techniques, which looked at DECHAMP, SOFIA, SExtractor and MTObjects. From there it was concluded that SOFIA with its ability to use multiple source finding algorithms was the most effective in finding and masking objects in a 3D astronomical data space. It was also concluded that the application of postprocessing on these masks through a random classifier or through other selection techniques could be beneficial for increasing accuracy. The analysis of the Shape selection techniques looked at point cursors, ray cursors (particularly depth cursor), and multiple techniques for creating a selection box. It was determined that the box selection was more effective than ray cursors and point cursors as it allows for selection of multiple objects in parallel easily. Additionally, the Two-handed method was most effective even though it had a slightly higher cognitive load. Finally, three lasso methods were looked at, where both CloudLasso and TeddyLasso outperformed the CylinderSelection for speed and accuracy. CloudLasso was considered better than TeddyLasso due to its more efficient smoothing. Between selection categories it was concluded that the selection box is better for low density environment and CloudLasso is better for high density space environments. Additionally, using SOFIA in conjunction with other selection methods to brush up seems the most effective.

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