A literature review of the various selection methods for volumetric data in a virtual environment.

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ABSTRACT

The scientific field of astronomy shares the overlying issue of how to best analyze astrophysical data despite technology generating large amounts of data. It is a field wide challenge due to the typical astrophysical dataset consisting of three dimensions. One potential manner to ease the process is to reduce the dataset to subsets, to be analyzed and rendered in a feasible fashion. The identification of subsets would require the use of a selection tool. The typical methods of selection struggle in terms of efficiency when faced with irregular data volume. As such this literature review will establish a foundation of criteria to assess the usability and effectiveness of the various selection methods. After which insight will be provided on data visualization of volumetric data to elaborate on the context of the selection techniques. Followed by the focus on previous methods for volumetric selection in virtual environments. They will be evaluated according to the criteria of comparison, focusing on both the performative and user experience aspects. The aim is to draw conclusions from the studies conducted on the selection techniques to identify and implement a more efficient selection method pertaining to the volumetric selection of subsets of volumetric data in virtual environments.

CCS CONCEPTS

• Data visualization • Selection Methods. • Virtual Reality.

KEYWORDS

Astrophysical datasets, Virtual Reality selection, Volumetric selection.

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1 Introduction

With the astronomy field consistently increasing the technology and methods to obtain astrophysical data, the matter of how best to interpret and analyze this data becomes of greater significance as said by Comrie et al. [5]. As the instruments to collect astrophysical data become more advanced so does the quantity of data.[2] As a result of large amounts of finely detailed data, one way to manage the data is to select subsets of the datasets [6]. The purpose of this literature review is to identify previously established selection methods for subsets of volumetric datasets in a virtual environment and compare their efficiency in selecting specific voxels (which are three dimensional pixels) in the context of astrophysical data. Volumetric data consists of three dimensional datapoints, two of its dimensions are spatial dimensions and the third is the spectral dimension. Moreover, multi-dimensional data sets link them self strongly to the use of virtual reality [2]. This is due to virtual reality's ability to utilize the concept of depth and space. The selection techniques will be compared according to completion time, accuracy, TLX and fatigue. The volumetric selection methods will comprise of three sub-groupings based on the principles behind the selection methods. They first be compared to other selection methods in their groupings before cross evaluating the different groupings. The selection sub-groupings are lasso, source detection and 3-D shape volume-based selection.

Table 1: Table depicting the evaluation criteria used in the different studies to outline the similarities.

Source	Accuracy	Completion Time	TLX	Fatigue	Rate of learning	Under/ Over Selection
Two handed Selection techniques for volumetric data.	x	x	x	x	x	
The Design and Evaluation of Selection Techniques for 3D volumetric Displays		x			x	
Hybrid Touch/ Tangible Spatial 3D Data Selection.	x	x	x	x		
Slicing-Volume: Hybrid 3D/2D Mulit-target Selection Technique for Dense Virtual Environments.	x	x	x			x
Frequency of Usage:	3	4	3	2	2	1

2 Criteria to compare selection methods

Before one is able to evaluate and assess the existing selection methods, one must have some measure of assessment for the comparison to be of meaning. [17]

Across various studies conducted to determine selection techniques with the least intensity in terms of usage and learning, as well as those that perform most efficiently there are consistent parameters used in evaluation. The completion time has been used in each source as a measure of performance, furthermore accuracy, TLX, and level of fatigue have been frequently utilized [3][4].

Overall, it is evident that there exist two subcategories that the evaluation measures belong to. These being performance and user experience. These two categories will be further expanded in this section.

2.1 Performative measures

The performance category encapsulates the measurements pertaining to how effectively a user can accomplish the specified task(s). The measurements that fall into this category are completion time, accuracy, and under/over selection.

2.1.1 Completion time

The concept of completion time refers to the total time taken for an individual performing an assessment to complete it [4]. In the context of this literature review, completion time will refer to the cost of time in using each selection method. The use of completion time across all papers strengthens the significance of it as if the selection method is more time intensive, the effectiveness is reduced. Completion time is one of the main criteria of measurement as the aim of the study is to identify the strengths of selection methods with one desirable quality being speed **[14]**. This focal point of completion time is further enforced as it is the sole metric to be used across the four papers used in deriving the metrics.

2.1.2 Accuracy

Accuracy measures the precision with which one selects items, in this context volumetric data. Accuracy is built off the notion of correctly and incorrectly selected items referred to as True or False in Besançon et al. [3] and this is further expanded into the notion of if the data was supposed to be selected (Positive if it was and negative if not) [14]. From this a True Positive (TP) is when data correctly selected while False Positives (FP) occur when data is incorrectly selected [3]. Similarly, this notion is applied to Negatives or data that is not supposed to be selected to obtain True (TN) and False Negatives (FN). These concepts can be used to construct the Matthews Correlation Coefficient (1) (MCC) [14].

$$\boldsymbol{MCC} = \frac{\boldsymbol{TP}\,.\,\boldsymbol{TN}-\boldsymbol{FP}\,.\,\boldsymbol{FN}}{\sqrt{(\boldsymbol{TP}+\boldsymbol{FP})(\boldsymbol{TP}+\boldsymbol{FN})(\boldsymbol{TN}+\boldsymbol{FP})(\boldsymbol{TN}+\boldsymbol{FN})}} \tag{1}$$

The closer the MCC value is to one, the more accurate the selection method.

2.2 User experience focused measures

The user experience focuses on how the user felt when completing the task(s) and whether it is feasible to use the proposed selection technique. As such the domain of the user experience field encompasses the TLX, fatigue, and rate of learning. With these elements providing insight into the user's experience, the information has to be obtained through surveys and questionnaires returned by the user. Further information can be obtained through the process of interviews and direct user feedback.

2.2.1 TLX or Task Load Index

One of the standardized methods for collecting user feedback is the NASA TLX. The TLX is a hybrid of performance and user experience as it measures subjective mental workload of participants. It factors in both physical and mental demands Hart and Staveland [10] and other measurements of user experience such as frustration and effort [4] in a weighted rating scale. The TLX obtains its weighted rating through users rating the pairs as to which one is more important in specific tasks [10] and the frequency of the subset determines the weighting. Furthermore, it considers the users' views on their own performance which offers a unique perspective into the feasibility of the selection methods. Moreover, in substantiating the usage of TLX in evaluating selection techniques, it had the second highest frequency of usage in the referenced papers.

2.2.2 Fatigue

The concept of fatigue is introduced under the TLX with the physical demand section [4] and is furthered by the frustration aspect, as fatigue is both a mental and physical experience. The evaluation of selection techniques takes fatigue into account [3] due to the importance it plays in the long-term usability of a selection method. It is also noted that the gain in performative measures should outweigh any increase in fatigue for the selection method to be an improvement. This is further emphasized in a research context, as it often requires long hours of data sifting.

2.2.3 Rate of learning

The rate of learning is another factor of importance when evaluating selection techniques due to the role it plays in the usage of selection techniques. For selection techniques with high learning curves, there is yet another obstacle to overcome [12] as individuals would have to learn how to use the technique before trialing it. As such this aspect of learning is taken into consideration in the evaluation of selection techniques.

Going forward with the criteria of evaluation, it will consist of completion time, accuracy, TLX, fatigue and rate of learning in descending order of priority.

3 Visualizing Volumetric Data and its difficulties

Visualizing volumetric data has become more important than ever due to large quantities of data being generated and stored daily. Furthermore, one does not want to simply store the data, they aim to analysis and understand it to draw conclusions or knowledge from it. In the context of volumetric data, there exists data cubes which are a means of storing volumetric data. According to Norris in [7] there are four outcomes from the visualization of data cubes and that we as humans struggle to organize this data in a palatable manner. The four outcomes according to Norris in [7] are: intuitively understanding the data, observing otherwise unknown properties of data, obtaining quantitative results from the data and communicating the qualitative and quantitative results to others.

Norris [7] states that the difficulty arises when users attempt to gain value from the data but are limited by the translation from human to machine in viewing the data. More specifically, there exists a difficulty in presenting 3-Dimensional data in a 2-Dimensional plane. Despite advances in technology which have enabled us to plot this volumetric data in a 3-D space such as virtual reality it again raises the issue of how best to present and study this data. Norris elaborates in [7] on how the easiest method of understanding 3-D datasets is the notion of movement. In terms of virtual reality, the notion of the data being 3-D is established through the movement of the user in the spatial sense, which tends to overcome the problem mentioned by Norris.

4 Existing selection methods

The term selection method refers to defining target properties or functions, finding those befitting the criteria and verifying the sought-out targets [8]. However, in the specific context of astronomy datasets it can be more generally defined as the means to identify and choose a subset of some larger dataset for further analysis and manipulation.

The aforementioned subsets take shape in two forms, object and volumetric. The difference in the forms depends on the aim of selection. Object selection refers to identifying and selecting one or many objects from a space, whereas volumetric selection subsets an area and selects the contents within. Another way to view volumetric selection is how Beasçon et al. [3] defined it as a function that returns a region of interest and the contents within. In the context of this literature review only volumetric selection techniques will be considered going forward. Going forward the volumetric selection methods will be grouped according to their formative principles. The groupings will be lasso, masking and volume defined by 3-D shapes. In each sub-group the individual selection techniques will be compared against each other according to the criteria evaluations established previously.

4.1 Lasso

The lasso selection principle is the idea of encircling an item or area within a drawn shape and taking the data either within or outside of the boundary. The notion of using a lasso was established in the use case of image editing of 2-D images according to Bowman et al. [13] in which it is referred to as the freehand lasso. The user can manipulate the shape of selection granting an additional element of control in selection and this is one of the main benefits in using this approach.

To implement the theory of lasso in volumetric selection Bowman et al. [13] created the Tablet Freehand Lasso Tool (TFLT). The purpose of TFLT was to map a user drawn 2-D shape from the camera's point of view to the area in a virtual environment, creating a 3-D volume to be used for selection. Despite Bowman et al. [13]'s studies finding no superiority between their Tablet Freehand Lasso Tool and 3-D techniques, their development of the Tablet Freehand Lasso Tool set the groundwork for many significant improvements on lasso selection such as Teddy Selection, CloudLasso, SpaceCast, and Tangible brush selection.

Some of the earlier improvements on the Tablet Freehand Lasso Tool include Teddy Selection and CloudLasso both introduced by Yu et al. [9]. Teddy Selection briefly explained consists of two levels of "binning" where the first reduces the volume of the cone to identify the volume more accurately according to a certain density. Through using triangulation, the cone's area is decomposed into smaller triangles to define the target volume more accurately. Then the areas with a low enough density are discarded to better identify the desired volume, resulting in a mesh selection of the volume. According to the study by Yu et al. [9] Teddy Selection was found to deliver undesirable results by including the sparce space between dense cluster and the difficulties that arise from using it in complex environments. To improve on Teddy Selection Yu et al. [9] developed CloudLasso which like Teddy Selection identified regions of interest through density calculations. However, CloudLasso differs by utilizing the Marching Cubes algorithm to select dense clusters within the lasso region whilst disregarding the sparce areas between dense clusters. CloudLasso overcomes Teddy's problem in identifying and selecting multiple dense clusters thanks to the Marching Cubes algorithm. In comparison to the Tablet Freehand Lasso Tool, both Teddy Selection and CloudLasso perform better in terms of selecting less undesired space according to Yu et al. [9]'s study. Furthermore, CloudLasso tended to increase the speed of selection when compared to the Tablet Freehand Lasso Tool across 4 varying datasets, with the smallest time difference being 48 seconds and the largest being 83 seconds. With regards to accuracy CloudLasso ranked above Tablet Freehand Lasso Tool in all datasets according to the MCC (1), although the difference bordered on insignificant with the greatest difference being by two decimal places. Assessing CloudLasso from the user experience it was clearly easier and more convenient to use compared to Tablet Freehand Lasso Tool as many users completed the CloudLasso selection task in one step. This was further strengthened by Yu et al [9]'s study where it was noted that CloudLasso got the correct result more reliably than Teddy Selection and TFLT as it did not include the sparce space between dense clustering's. CloudLasso was also faster than TFLT by 70%.

Despite CloudLasso being the best performing of the lasso methods mentioned thus far, it had the issue of depending on the camera's view during the selection definition. Realistically, this often hinders the results obtained with CloudLasso, as such Yu et al. [14] developed SpaceCast to improve upon CloudLasso. With respect to the user interaction, SpaceCast closely follows suit with CloudLasso. SpaceCast improves CloudLasso by identifying clusters in the specified region and then selecting the clusters resembling the original shape of the lasso input. It was noted by Yu et al. [14] that in some cases depending on the lasso shape, SpaceCast's output will equate to CloudLasso's. Similarly, this is SpaceCast's strength in that it enables the user to target a single cluster through more specific input through the lasso. Additionally, in Yu et al. [14]'s study SpaceCast was found to be almost two times faster than

CloudLasso which itself was two times faster than TFLT. In the Yu et al. [14] study it was found that all selection techniques had an accuracy according to the MCC equation(1) of great than 0.96 implying there was indifference with regards to accuracy. Another selection technique to take inspiration from THLT is the Tangible Selection Brush developed by Besançon et al [3]. The Tangible Selection Brush differs from all previously mentioned lasso selection techniques by making use of both 2D and 3D inputs, in where a lasso is drawn (known as the brush) and the brush is extended into 3D by physically moving the screen to give a sense of direction and space. The defined volume is the result of multiple rapid Boolean operators where an area is either added, redacted, or intersected with an existing volume. According to Besançon et al. [3]'s study the Tangible Brush was more time intensive than SpaceCast by a factor of 2 on average. While in the same study, SpaceCast was found to be three times timelier than TFLT and twice more than CloudLasso. These comparisons place the Tangible Brush selection on par with CloudLasso with respect to time taken until completion. Tangible Brush proved to be more accurate than SpaceCast in the MCC accuracy as it scored a 0.95 compared to the 0.92 for SpaceCast. Furthermore Besançon et al. [3] determined that there was no significant difference in fatigue levels between SpaceCast and Tangible Brush. Although the TLX score for the Tangible Brush was lower due to a higher mental demand.

It appears that an ideal improvement in lasso selection would be to combine multiple of the already existing techniques such as SpaceCast and the Tangible Brush to leverage their individual strengths resulting in more timely and accurate selections that do not come at the expense of the user.

4.2 Source Identification and Selection

An alternative method of selection would be to automate the input used to define the selection region. Instead of depending on a user input as is the case with the lasso methods, the following methods focus more on automated source identification and selecting the volumes pertaining to them.

One such source identification and selection method is SoFiA. According to Serra et al. [11] SoFiA was designed to function regardless of how the data was obtained for any data cubes. This modularity of SoFiA strengthens the use case for it as in Barkai et al. [15] the ideal source finder factors the properties of the astronomical data itself. SoFiA better caters to the properties of the data by offering many combination of data filtering options and source detection algorithms. Most notably SoFiA offers the use of the smooth and clip method as according to Barkai et al. [15] it can find sources in terms of the spatial and spectral dimensions of a data cube. However SoFiA also offers the simple threshold detection which simply identifies voxels with a property greater than some specified threshold. After source voxels have been identified, [11] describes the grouping of voxels into sources as an algorithm akin to a friends of friends algorithm. This groups all selected binary voxels together if they are within a specified distance of each other. SoFiA is beneficial as [11] says that users can search along multiple scales of the sky for spectral line signals. Additionally, SoFiA can roughly determine the reliability of individual detections, helping in detection of many sources.

One of the main contenders to SoFiA is the MTObjects region-based source finding software. MTObjects use the notion of Max Trees which according to [16] refers to a set of connected components and Barkai et al. [15] describes it as a tree structure representing an image such that the leaves pertain to the maximas. The primary advantage of Max Trees is their capability to sort cubes without the loss of information. Furthermore, the usage of a Max Tree as said by Barkai et al. [15] improves the source finding by working with a preprocessed image whilst keeping the original intact.

In the study done by Barkai et al. [15] it was found that SoFiA had the highest accuracy when it came to detecting both genuine and test galaxies. In this test SoFiA scored above 0.6 when in comparison MTObjects scored slightly over 0.3, these results indicate that SoFiA was more sensitive and correct in detecting the test data. Additionally, in the study done by Barkai et al. [15], it was found that SoFiA was the fastest source finding software. SoFiA was faster than MTObjects by a factor of five, where SoFiA completed in under five minutes while MTObjects completed running slightly under 27 minutes. SoFiA is not only more accurate than MTObjects but is also faster, and one must consider the difference in speed when processing large volumes of data. Moreover, SoFiA has the advantage of modularity to increase the robustness of the software as well as an increased ability to fine tune detection algorithms for specific data.

4.3 3D shape volume selection

The premise of selecting a volume of area is most intuitively accompanied by the idea of selecting a volume of area defined by a three-dimensional shape such as a cube or a sphere and selecting the contents within the volume.

When selecting volumes bound by a six-sided box, there exists numerous ways to size, orientate, position, and rotate the selection shape. In 2007 Ulinski et al. [4] conducted a study to determine the most efficient way to go about manipulating a shape-based volume. In their study, they compared three selection techniques: Hand On Corner, Hand in Middle and the Two Corners techniques in terms of their performance and user experience. The Hand On Corner technique in [4] describes attaching the non-dominant front facing bottom corner of the box to the user's non-dominant hand. This positioning centers the box between the user's virtual hand where intuitively the user controls the placement of the box with their non-dominant hand. To aid in orientating the box, the top back dominant corner is attached to the dominant hand and as such controls the sizing with the dominant hand. Whereas the Hand In Middle technique similarly attaches the box to the non-dominant hand. However, it attaches the middle of the box to the non-dominant hand whilst not attaching to the dominant hand. The size is determined by the distance between the hands. In Ulinski et al. [4]'s study the Two Corner's method was positioned the same as the Hand on Corner technique, however both hands are simultaneously responsible for positioning, orientating, and sizing the box. With respect to completion time Ulinski et al [4] found the Hand In Middle technique consistently took less time than the other two techniques. However, in terms of accuracy, the Two Corner technique and Hand In Middle technique outperformed the Hand On Corner technique significantly. Despite the Two Corner technique performing best in accuracy, the Hand in Middle technique scored lowest on the Task Load Index. This in conjunction with the Hand in Middle technique scoring lowest in terms of fatigue is indicative of it being the least straining to use whilst still performing best or close to in the performative aspects.

One other volume-based selection technique is Slicing Volume. One such implementation of Slicing Volume can be found in Montano et al. [1] where a hybrid of 2-D and 3-D inputs and viewing is used to select data. Similarly to the selection techniques above a volume box is used and controlled through hand movements, except in this case the volume box and its contents are mapped to a 2D plane to display on a tablet. The thickness of the volume box refers to the thickness of the slicing volume. On the tablet a pen is used to select 3D points where the depth is defined by the thickness of the slicing volume. Montano et al. [1] decided on a pen in order to offer the precision selection that is lost when using hand movement inputs. In all test cases conducted by Montano et al. [1] the addition of the tablet improved accuracy when compared to the mid-air input. The increase in accuracy was 10% according to Montano et al. [1] on average. This finding implies that the tablet hybrid approach is more accurate than the two-handed selection techniques studied by Ulinski et al [4]. Although the mid air selection in Montano et al. [1] was found to be significantly less time consuming compared to the implementation of the tablet, in some cases by almost 20%.

5 Discussions regarding current selection methods

After assessing the three groupings of selection techniques for volumetric data there are clearly established grounds for cross comparison of these groupings according to the criteria of evaluation elaborated on in section 2. Furthermore there are definitive advantages to each grouping of selection techniques some of which are amplified in some use cases.

With regards to the lasso methods mentioned in 4.1, the use case for such techniques comprises of time where a user aims to make manual selections of data while observing it. Additionally, the implementation of lasso techniques may occur after having automatically detecting celestial bodies according to some threshold criteria as in 4.2, after which an individual can manually touch it up with more precise selection techniques such as the tangible brush. It is noted that a more optimal usage of the lasso techniques would be to use the differing techniques interchangeably in order to utilize their respective strengths. Furthermore, lasso techniques are superior to automated selection techniques in the cases of selecting specified subsets of data while automated selection is more useful when searching through data for information.

With respect to the automated detection and selection of sources, one can determine that the TLX will be substantially lower compared to the other two selection groupings. This is due to the nature of automation, and it is reducing many negative aspects of technology usage such mental and physical demand as it is now automated. Furthermore, the reduction in time from human observation to machine observation is increasingly large as computers become more powerful. This effect is further amplified when considering the amount of data that can be processed during the time it would take for a human to evaluate it.

Both the lasso and identification and selection of sources are superior to volume-based selection techniques when assessing the accuracy of the selection techniques. This is in part due to the rigid form of the volume-based selection techniques and the fact that few data would naturally take the shape of something like a cube. This implies that the volume-based selection techniques select areas that would be unselected by either of the other two groupings. This problem is worsened by the fix to the cubic selection being multiple iterations of Boolean operators as this becomes a frustrating and time-consuming task. The volume-based selection techniques do leverage the ability to directly show the user what is being selected before selecting.

Lastly, the idea of utilizing many if not all forms of volumetric selection should be explored. In the process of doing so, one may be able to select volumetric data with otherwise impossible precision and speed, as doing so would be to leverage each strength to one's advantage.

6 Conclusions

After evaluating and assessing the numerous volumetric selection techniques, first within their groupings and then across the different groupings it is evident that no one such selection method is always the best. Each of the groupings have their use cases and often within their groupings the individual selection methods have their strengths.

The lasso selection techniques operate with great accuracy typically above 95%, however they tend to be more time consuming and require more technical knowledge on the data being studied. The overall most effective lasso technique is the SpaceCast technique due to the speed and accuracy with which selection is achieved, without sacrificing workload or fatigue.

In terms of the automatic detection and selection of sources, SoFiA is the more effective of the two compared. Not only is SoFiA faster than MTObjects, it was also found to be significantly more accurate at detecting both real and test galaxies. Furthermore, the automation of source detection allows for people studying the data to spend less time observing the data to identify points of interest and instead focus on the detected points of interest.

Lastly the simplicity of volumetric selection with volume-based selection shapes allows for common use cases and works as a broad measure with which to compare more complex selection methods.

In the end, no one selection method is best for all use cases. However, if one were to implement them in unison and make use of their strong points, they would be closer to arriving at the optimal selection method.

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