TimeTubes: Visual Fusion and Validation for Ameliorating Uncertainties of Blazar Datasets from Different Observatories

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ABSTRACT

Astronomers have been observing blazars to solve the mystery of the relativistic jet. A technique called TimeTubes uses a 3D volumetric tube to visualize the time-dependent multivariate observed datasets and allows astronomers to interactively analyze the dynamic behavior of and relationship among those variables. However, the observed datasets themselves exhibit uncertainty due to their errors and missing periods, whereas periods interpolated by TimeTubes result in a different type of uncertainty. In this paper, we present a technique for ameliorating such data- and mapping-inherent uncertainties: visual fusion of datasets for the same blazar from two different observatories. Visual data fusion with TimeTubes enables astronomers to validate the datasets in a meticulous manner.

CCS CONCEPTS

•**Human-centered computing → Information visualization; Visualization design and evaluation methods;** *Visualization; Visualization toolkits;*

KEYWORDS

Time-varying multivariate visualization, uncertainty visualization, astrophysics, blazar.

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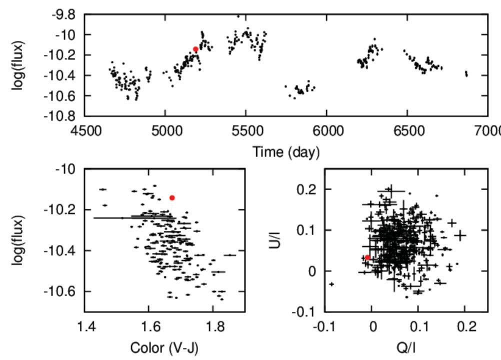


Figure 1: Animated scatterplots: A conventional way to visualize a time-dependent multivariate blazar dataset [10].

1 INTRODUCTION

Astronomers have been observing blazars to solve the mystery of the relativistic jet ejected from the central black hole of an active galactic nucleus [1]. Their goal is to analyze time-dependent multivariate observed datasets for extracting universal patterns in the trajectory of the object in polarization parameters, which may correlate with the intensity and color variation. However, the commonly used animated scatterplots, as shown in Figure 1, suffers from visual clutter and low interactivity. Thus the limitations compromise astronomers' ability to carefully scrutinize the original dataset.

Our previous study [20] presented a new visualization method, termed *TimeTubes*, which allows astronomers to analyze the dynamic behavior of and relationship among the multiple time-varying variables geometrically by visualizing a dataset as a 3D volumetric tube (see Section 3). TimeTubes indeed enables astronomers to communicate effectively with these datasets. Accordingly, some new behaviors of blazars have been found based on this method and reported in [19].

In this paper, we improve the technique to help astronomers analyze datasets more effectively and obtain more information at one time by incorporating a novel mechanism, *visual data fusion*, into the previous 3D visualization. By visually fusing into the originally targeted dataset, another dataset for the same blazar from a different observatory, TimeTubes can ameliorate two types of uncertainty, which are not mainly focused on in the previous work [20]: data-inherent uncertainty, which arises from errors and missing periods in the dataset, and mapping-inherent uncertainty, which arises as a result of interpolation when TimeTubes transforms the data into a continuous geometry. This visual data fusion enables astronomers to validate the datasets in a meticulous manner. We also discuss the new kinds of findings that are enabled by the latest version of TimeTubes. Note that this paper is an extension of our previous poster [16].

2 RELATED WORK

We briefly review related research on time-dependent data visualization, uncertainty visualization, and visual data fusion.

2.1 Time-dependent data visualization

Various techniques have been developed for visualizing time-dependent data, some of which have been extended to deal with multivariate data. For example, Bach et al. [2] developed *Time Curves*, which is a general approach that visualizes time-dependent data. In this approach, data similarity is naturally expressed by folding a timeline. *ThemeRiver*, which was proposed by Havre et al. [9], depicts thematic variation of documents over time using a smooth stacked-graph layout. *Storyflow*, which was developed by Liu et al. [13], improved ThemeRiver by enabling it to visualize storylines legibly.

In addition, 3D visualization techniques have been developed for visualizing time-dependent multivariate data. The *Great Wall*, which was proposed by Tominski and Schulz [18], visualizes spatial-temporal data with reference to 2D geographical space and 1D linear time. To express time variation, Gruend et al. [7] expanded parallel coordinates into 3D space.

Though these methods treat multivariate data, they do not provide an optimal way to explore datasets in an astrophysics context.

2.2 Uncertainty visualization

Uncertainty visualization remains one of the major scientific visualization research problems, as noted by Johnson [11] and Fujishiro et al. [5].

Error bars are commonly used to express uncertainty caused by errors in statistical datasets [14]. Li et al. [12] visualized uncertainty in astrophysical data, using an elliptical metaphor to handle uncertainty in a way similar to TimeTubes. Moreover, glyph- and ribbon-based uncertainty visualizations were presented by Sanyal et al. [15]. Feng et al. [4] used density plots to visualize uncertain multivariate data.

2.3 Visual data fusion

Various approaches to data fusion have been developed mainly in the database [3] and the multisensor domain [8].

A few approaches to data fusion have been developed in the visualization domain, but composite visualization techniques can be expanded to visual data fusion. Senay and Ignatius [17] proposed a set of rules for forming composite visualization techniques from primitives to display multidimensional data. We introduced the rule *composition by union* into the present version of TimeTubes.

Table 1: Representative time-varying variables for observed blazars.

Variable	Description
$Flx(V)$	Observed intensity of blazar
Q/I	Linear polarization component (0 or 90 degrees)
E_Q/I	Error on Q/I
U/I	Linear polarization component (+45 or -45 degrees)
E_U/I	Error on U/I
$V-J$	Observed color of blazar

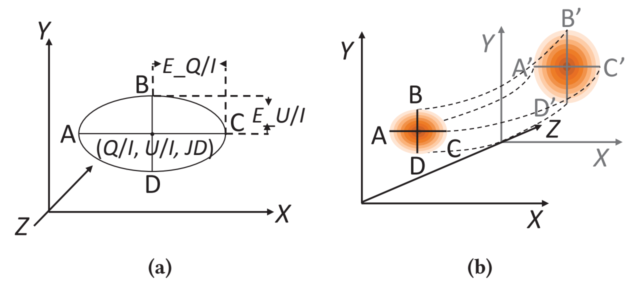


Figure 2: Spatial mapping of TimeTubes: (a) One data sample with each time stamp is shown as an ellipse. (b) The neighboring ellipses are connected by Catmul-Rom splines.

3 DESIGN OF TIMETUBES

In this section, we briefly describe the target blazar datasets and spatial mapping of TimeTubes proposed in the previous work [20]. As tabulated in Table 1, TimeTubes visualizes six representative variables from eight variables in the original blazar dataset to facilitate effective blazar classification. Each variable is measured in Julian day (JD). Instead of animating 2D plots, TimeTubes relies on 3D geometry and shows the multiple variables with each time stamp as an ellipse, whose central coordinate is given as $(x, y, z) = (Q/I, U/I, JD)$ and whose major and minor axes are given as $2E\_Q/I$ and $2E\_U/I$, respectively, as shown in Figure 2 (a). The neighboring ellipses are connected to each other by centripetal

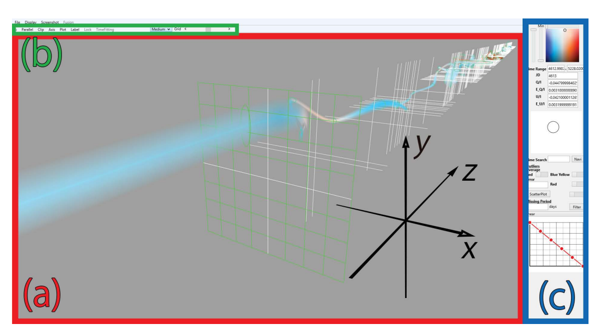


Figure 3: User interface of TimeTubes: (a) Visualization window, (b) menu, and (c) operation panel.

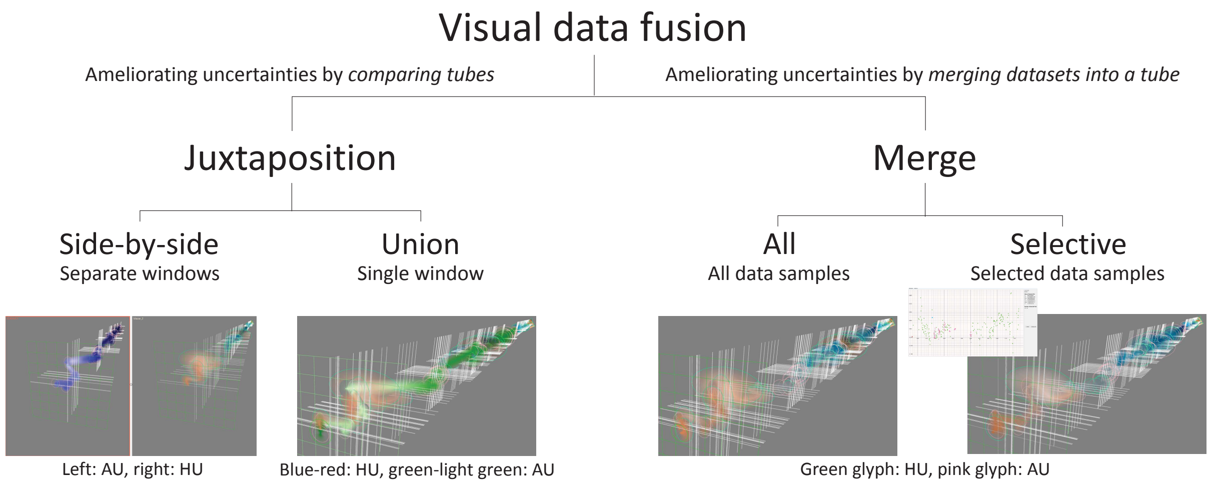


Figure 4: Categorized functions of visual data fusion with TimeTubes. Two visual fusion modes and two options for each are provided. Results of visualizing the datasets for body 3C 454.3 around $JD = 4,742.73$ are shown.

Catmull-Rom splines to form a 3D volumetric tube, as shown in Figure 2 (b). To reflect the reliability of observations, the translucency of the outer tube is larger than that of the inner. Small errors result in a sharply rendered tube, whereas a tube associated with a large range of errors has a vague appearance. Astronomers can see the time variation of these six time-varying variables simultaneously.

The current user interface of TimeTubes, in which the method proposed here has been installed, is shown in Figure 3. Figure 3 (a) shows the visualization result of a dataset, in which users are allowed to manipulate the tube interactively. The menu shown in Figure 3 (b) allows for camera control, switching the display of the cruciform axes and placing a glyph that expresses the contour of the tube at each data sample, which has been introduced newly to clarify the missing periods of observation. The operation panel shown in Figure 3 (c) enables users to perform their visual analysis through overviewing, filtering, details-on-demand, and relating with scatterplots. See the accompanying video for the actual look and feel of the interface.

4 BASIC VISUAL DATA FUSION OPERATIONS

The proposed method is designed to fuse two observed datasets: one from Hiroshima University (HU) [10] and the other from the University of Arizona (AU) (http://james.as.arizona.edu/~psmith/Fermi/). Some differences can be found between HU and AU datasets. The astronomical telescope at HU allows us to observe six time-dependent variables simultaneously, as seen in Table 1, whereas the one at AU does not provide polarization or intensity simultaneously, and thus the observation time stamps of polarization and intensity in the dataset do not match. Therefore, we need to interpolate each of these variables respectively in order to treat the AU datasets in the same way we treat the HU datasets. Though the AU datasets do not have intensity data with the same observation time stamps of polarization, TimeTubes interpolates those intensity values to pretend as if there were intensity data observed with the time stamp. To visually identify whether there exist data samples or not and whether the shape of the tube is formed by observed values or interpolated values, TimeTubes places white crosses with all observation time stamps and glyphs with time stamps when polarization was observed. Moreover, to clarify whether the current focused JD in TimeTubes has observed data or not, the colors of the grid, cross, and glyph will be changed when the current focused JD coincides with an observation time in the dataset. Note that the color of the tube generated from the AU dataset is determined in an ad hoc manner; this is because the color data is not available from the same data source.

We will introduce two modes of visual data fusion and two options for each mode, as summarized in Figure 4. Note that the *Merge* mode corresponds to visual data fusion at the filtering stage of the conventional visualization pipeline: fusing them *numerically* to ameliorate both data- and mapping-inherent uncertainties by increasing the amount of observed data used to form a single tube. In contrast, the *Juxtaposition* mode corresponds to the mapping stage: fusing the datasets *optically* to ameliorate data-inherent uncertainty by comparing the datasets from two observatories.

In addition, the up-to-date TimeTubes system shown in Figure 3 provides a federated view with traditional scatterplots, with which astronomers have been familiar.

4.1 Visual data fusion

4.1.1 Juxtaposition. The *Juxtaposition* mode is the most straightforward way in the visual data fusion, and it would be best to begin with this essential mode. The observation values are not completely reliable due to their errors like $E\_Q/I, E\_U/I$, but we can increase their reliability by using datasets from two different observatories in a comparative manner. Moreover, users can identify differences between multiple datasets with Juxtaposition, which may lead to the estimation of the true observed value.

With the *Side-by-side* option, users can compare two observed datasets in separate windows. This option can be used for datasets not only for the same blazar but also for different blazars. With the *Union* option, users can overlap multiple tubes in the same window. The color of the tubes can be defined separately. This option is suitable for comparing datasets for the same blazar, where arbitrarily focused time of the datasets in the visualization space fits automatically.

If the values of the observed data from different observatories are very close, we can consider these values to be more reliable than those from a single observatory. If they are dissimilar, we can estimate a true value by allowing for errors and observation conditions.

Because of the difference between the observation conditions, the global centers of observed datasets may not coincide with each other. We can get a hint for proper calibration by comparing multiple observed datasets from different observatories with the Juxtaposition mode.

4.1.2 Merge. The number of data samples will increase by joining datasets from two observatories with the *Merge* mode. As a result, the missing period of observation can be shortened virtually and uncertainties by the missing periods can be ameliorated.

In the Merge mode, data samples from the AU and HU datasets have been merged into a single dataset in chronological order before the resultant tube is rendered. If there are multiple data samples with the same observation time stamp, TimeTubes chooses the one with smaller errors. The color hue of the glyph expressing the tube contour distinguishes data sources: Green indicates HU and pink indicates AU. For the analysis of blazars, denser observation is required because blazars fluctuate very rapidly. Merging the two observed datasets, we can densify information rather than visualizing them separately. Using this mode, new features of the blazars are expected to be found.

With the *All* option, which is selected by default, all the data samples from the two observatories are merged into a single tube. This option leads to the densest information. The *Selective* option allows users to select arbitrary portions of the datasets with scatterplots. Outliers and/or unexpected values may be included in the dataset for various reasons. Visualizing the dataset without those values, users can analyze more correct visualization results. Moreover, when both HU and AU have data samples at an equal JD, users can choose to visualize either of them with this option, which allows users to validate the observed data visually.

Note that the current Merge mode does not take the gaps between the center of the observed datasets into account, which may give rise to improper visualization, as will be discussed in detail in Section 5.3. Users can ascertain whether what is visualized is proper or not by using the Merge mode in combination with the Juxtaposition mode.

4.2 Linking with traditional scatterplots

In its current version, TimeTubes can be mutually linked with scatterplots between two arbitrary variables, as shown in Figure 5. This function is available in both visual data fusion modes. Plots in this scatterplots are colored differently between HU and AU as glyphs around the tube: Green plots indicates HU and pink plots indicates AU. Note that the focused data sample in TimeTubes is shown as a blue plot in the scatterplots. Moreover, users can jump to specific JD in TimeTubes easily by selecting a plot in the scatterplots. This function serves a substantial role because we need to consider the fact that astronomers have thus far relied primarily on scatterplots, as shown in Figure 1. Users can reconfirm what was found in the tube representation in the traditional view as well. Please take a look at the accompanying video for more details.

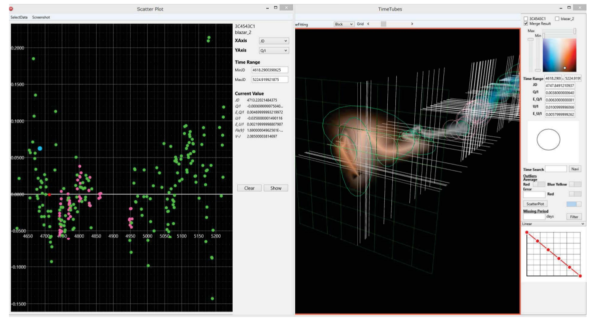


Figure 5: Linking with traditional scatterplots. Left window: scatterplots, right window: TimeTubes.

5 VISUAL ANALYSIS RESULTS

We present three kinds of findings that we were able to obtain from conducting a visual analysis of the actual blazar datasets from HU and AU. Note that several black-background images will be used for visibility below.

5.1 Juxtaposition

We took full advantage of the Juxtaposition mode to observe the HU and AU datasets for the same blazar. Figure 6 juxtaposes the orthogonally projected visualizations of the datasets for body **3C 454.3** around $JD = 5,124$. The AU dataset is visualized in the left window and the HU dataset in the right. The red and green lines in the resulting image show the centerline of the tubes. Even though the datasets for the same blazar were chosen for the same period, it turned out that the values in the vertical-axis direction (U/I) changed differently.

Using Juxtaposition, users can identify the global differences between the datasets easily and analyze them more carefully.

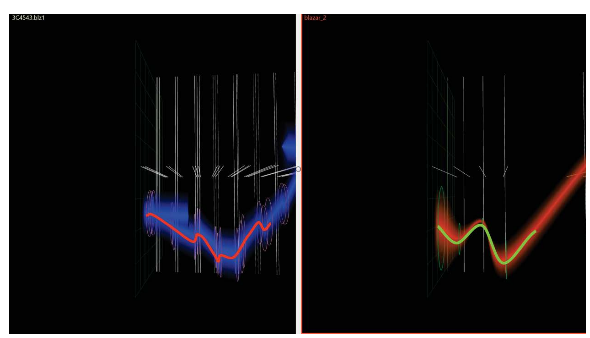
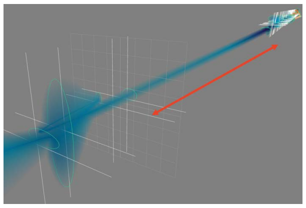
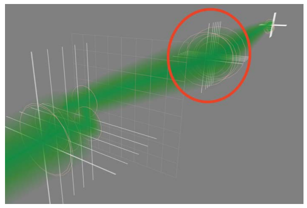


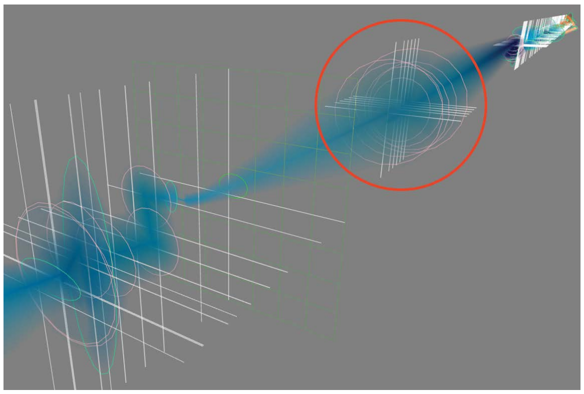
Figure 6: Juxtaposition: Side-by-side. Left: AU, right: HU. The red and green lines show the centerline of the tubes.



(a) Before Merge: HU.

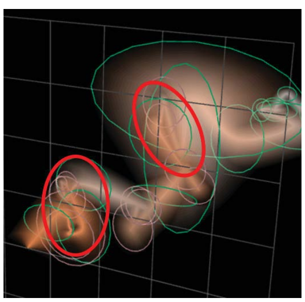


(b) Before Merge: AU.

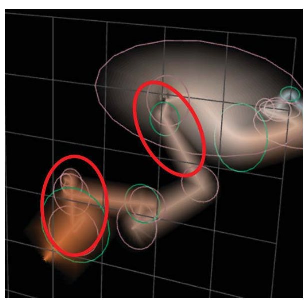


(c) Merged result. Filling up missing periods in a red circle.

Figure 7: Filling in the missing period.



(a) All option.



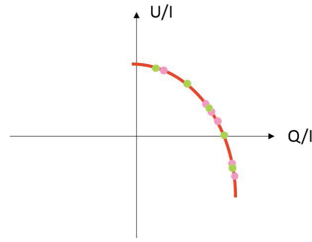
(b) Selective Option.

Figure 8: Effect of data selection in the Merge mode.

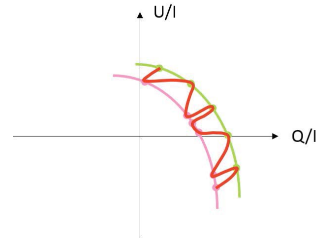
5.2 Merge

We merged the observed datasets from HU and AU for the same blazar (that is, **3C 454.3** around $JD = 4,856$) using the All option. Figures 7 (a) and (b) visualize the two datasets separately. The HU dataset does not have data samples for the period indicated by the red arrow in Figure 7 (a), whereas the AU dataset does have data samples for the same period, as indicated by the red circle in Figure 7 (b). We relied on Merge to fill in the missing period in the HU dataset with the data samples from the AU dataset. Contrasting the result shown in Figure 7 (c) with the original shown in Figure 7 (a) indicates that the uncertainty caused by the missing period is ameliorated and astronomers can get more information from one view than the result of visualizing a single dataset.

Figure 8 visualizes the dataset for body **3C 454.3** around $JD = 4,742.73$ using the Selective option. In Figure 8 (a), all data samples were merged to render a single tube. In contrast, as shown in Figure 8 (b), we selected data samples from AU in periods when AU observes the blazar intensively and from HU in the remaining periods. We can see that the tube shape in the areas that appear in the red circle in Figure 8 (b) is different from the corresponding shape in Figure 8 (a). If the gap between the datasets is large, the visualization result may be improper, as will be explained in Section 5.3. By choosing between HU and AU for every period, information will be provided that is denser than what could be provided by the tube from an individual dataset with less influence by the gap.



(a)



(b)

Figure 9: Unexpected visualization: (a) Expected result by increasing the number of data samples. (b) Improper visualization caused by the gap between the datasets. Red lines show the centerline of the tube after Merge.

5.3 Negative effect caused by the gap between the datasets

Current TimeTubes merges the datasets from different observatories without any consideration of their gap. Though we expect that increasing the number of data samples will result in a more detailed and accurate visualization of the behavior of blazars, as shown in Figure 9 (a), the gap between the datasets can cause an improper and misleading visualization of the behavior, as shown in Figure 9 (b). The datasets cannot be calibrated automatically, but users are allowed to estimate the gap using the Juxtaposition mode.

6 CONCLUSION

Our new method can ameliorate two types of uncertainty, each of which may arise at the data input/filtering stages and the mapping stage in the visualization pipeline. The new TimeTubes functions can utilize multiple datasets to represent the behavior of the observed blazars more accurately. According to Gleicher et al. [6], visual designs for comparison are grouped into three basic categories: juxtaposition, superposition and explicit encodings. We have already implemented juxtaposition and superposition as the Side-by-side option and Union option, respectively. Our next challenge is to think about explicit encodings (for example, by showing the difference between two datasets).

For a more effective analysis of blazars, we need to introduce more sophisticated functions to handle uncertainty, including auto/manual calibration of datasets, filtering of missing periods, and feature extraction. Moreover, implementing visual data fusion at the rendering stage still constitutes a challenge.

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