Abstract Feature Space Representation for Volumetric Transfer Function Exploration

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Abstract

The application of n-dimensional transfer functions for feature segmentation has become increasingly popular in volume rendering. Recent work has focused on the utilization of higher order dimensional transfer functions incorporating spatial dimensions (x, y, and z) along with traditional feature space dimensions (value and value gradient). However, as the dimensionality increases, it becomes exceedingly difficult to abstract the transfer function into an intuitive and interactive workspace. In this work we focus on populating the traditional two-dimensional histogram with a set of derived metrics from the spatial (x, y and z) and feature space (value, value gradient, etc.) domain to create a set of abstract feature space transfer function domains. Current two-dimensional transfer function widgets typically consist of a two-dimensional histogram where each entry in the histogram represents the number of voxels that maps to that entry. In the case of an abstract transfer function design, the amount of spatial variance at that histogram coordinate is mapped instead, thereby relating additional information about the data abstraction in the projected space. Finally, a non-parametric kernel density estimation approach for feature space clustering is applied in the abstracted space, and the resultant transfer functions are discussed with respect to the space abstraction.

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1 Introduction

A common method for direct volume rendering is to employ the use of interactive transfer functions as a means of assigning color and opacity to the voxel data. One of the most popular transfer function design tools is the interactive 2D histogram widget introduced by Kniss et al. [8]. In this widget, the user is presented with a 2D histogram (the axes of which represent a feature space of the data) and various selection tools are used to assign color and opacity to the voxels through an interactive brushing of the feature space. This widget typically displays each entry in the histogram as a gray scale color with white representing the entry that maps to the largest number of voxels within a given data set, Figure 1 (a). While such a tool has been shown to be extremely effective at advanced transfer function

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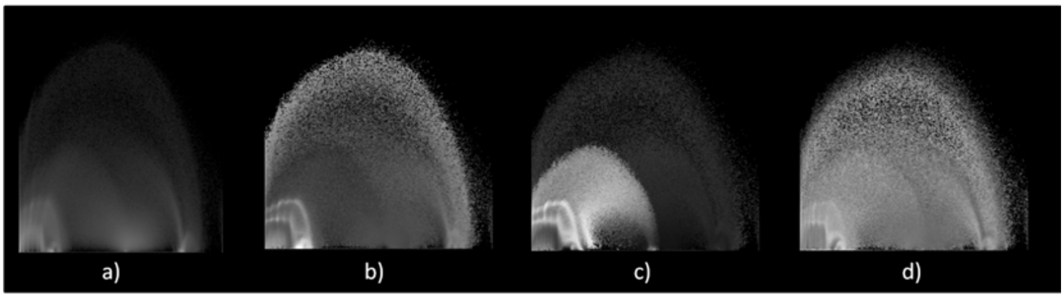

Figure 1 The value vs. value gradient magnitude feature space with the intensity as a function of a) the number of voxels, b) the magnitude of spatial variance of x, c) the magnitude of spatial variance of y, and d) the magnitude of spatial variance of z for the CT bonsai dataset.

creation, this type of histogram provides no information about the spatial relationships between the voxels at the histogram entry.

In this work we propose to enhance the conventional 2D histogram transfer function by mapping the entries of the histogram to statistical properties related to the spatial locations of the voxels, specifically, the magnitude of the spatial variance, Figure 1 (b-d). By doing so, this new abstracted feature space now illustrates the areas in which the voxels have a higher spatial relationship as opposed to simply providing the user with a view of where in the feature space the majority of their voxels lie. Users are able to toggle between the *conventional transfer function view*, Figure 1 (a), (in which the entries in the 2D histogram are colored by the number of voxels that map to a location) and the *abstracted transfer function views*, Figure 1 (b-d), (in which the entries are colored by the spatial variance in the voxels that map to a location).

Traditionally, the appropriate selection of features in multi-dimensional transfer functions is a difficult task, often requiring the user to have an underlying knowledge of the data set under exploration. By providing users with information about the spatial domain (x, y, and z) of their data in an abstracted feature space (e.g., value versus value gradient magnitude) we are able to enhance the exploration, allowing users to better discover features within their dataset. Finally, we utilize the non-parametric transfer function design method proposed by Maciejewski et al. [12] clustering the feature space in both the conventional and abstracted transfer function views. In this manner, we explore the usefulness of abstracting statistical properties into the transfer function widget and illustrate the effects on the exploration of the feature space.

2 Related Work

Interactive transfer function design has been addressed with many different approaches, ranging from simple (yet intuitive) one-dimensional (1D) transfer functions (e.g., [5, 13]) in which a scalar data value is mapped to color and opacity, to more complex multi-dimensional transfer functions in which color and opacity are mapped across multiple variables. Early work by Kindlmann et al. [6] and Kniss et al. [8] applied the idea of a multi-dimensional transfer function [9] to volume rendering. This work identified key problems in transfer function design, noting that many interactive transfer function widgets lack the information needed to guide users to appropriate selections, making the creation of an appropriate transfer function essentially trial-and-error which is further complicated by the large degrees of freedom available in transfer function editing. While many volume rendering systems have

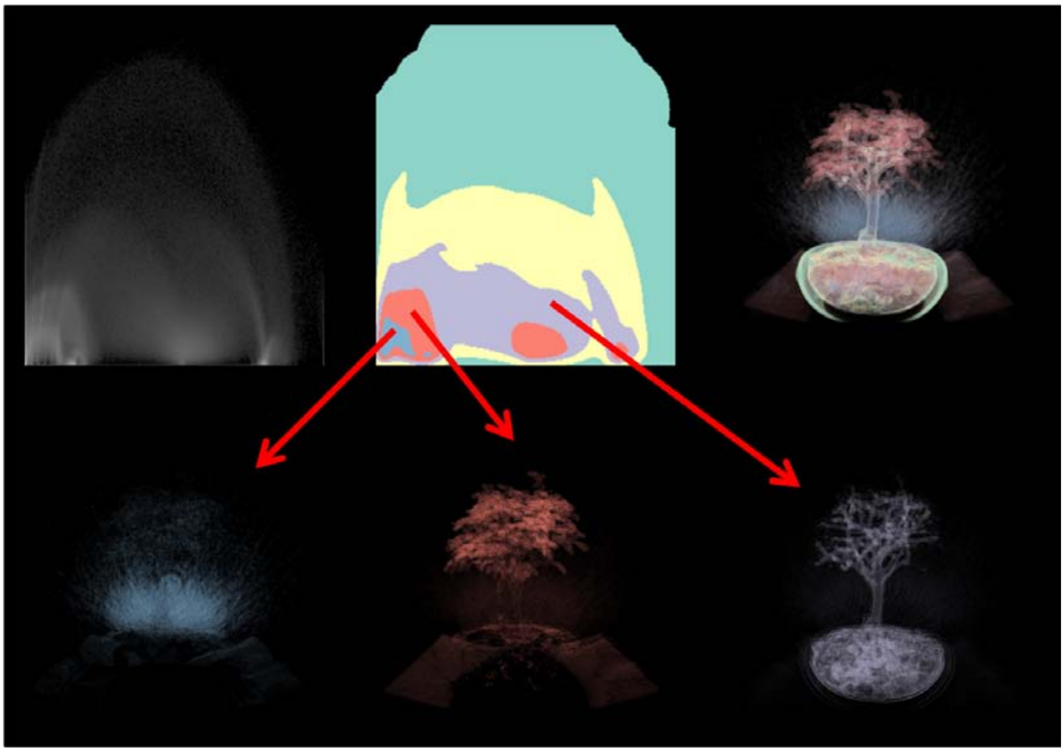

Figure 2 The value vs. value gradient magnitude feature space as a function of the number of voxels and the rendering from the denoted segments of the transfer function for the CT bonsai dataset.

adopted multi-dimensional transfer function editing tools, the creation of an appropriate transfer function is still difficult as the user must understand the dimensionalities of the feature space that they are interacting with.

Recent works on transfer function design have proposed higher-dimensional transfer functions based on mathematical properties of the volume. Examples include work by Kindlmann et al. [7], which employed the use of curvature information to enhance multi-dimensional transfer functions, and Tzeng et al. [18], which focused on higher dimensional transfer functions which use a voxel's scalar value, gradient magnitude, neighborhood information and the voxel's spatial location. Work by Potts et. al [15] suggested visualizing transfer functions on a log scale in order to better enhance feature visibility. Lundstrom et al. introduced the partial range histogram [10] and the α-histogram [11] as means for incorporating spatial relations into the transfer function design. Correa et al. introduced size based transfer functions [3] which incorporate the magnitude of spatial extents of volume features into the color and opacity channels and visibility based transfer functions [4] where the opacity transfer function is modified to provide better visibility of features.

While such extensions enhance the volume rendering and provide a larger separability of volumetric features, they still fail to provide users with information about feature space structures. In fact, the addition of more dimensionality into the transfer function is often automatically incorporated into the rendering parameters, obscuring the relationship between the volumetric properties and the volume rendering. Work by Roettger et al. [16] incorporates similar ideas of using spatial features of the volume to enhance transfer function design. They enable the automatic setup of multi-dimensional transfer functions by adding spatial

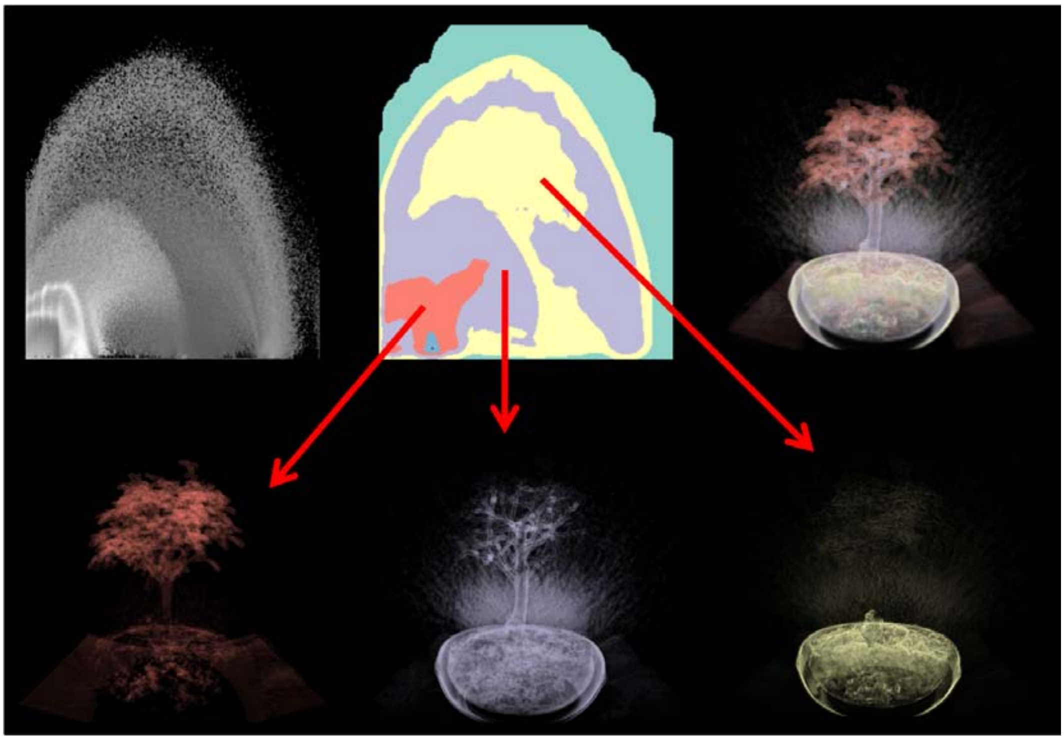

Figure 3 The value vs. value gradient magnitude feature space as a function of the magnitude of the spatial variance and the rendering from the denoted segments of the transfer function for the CT bonsai dataset.

information to the histogram of the underlying dataset, where as our work proposes a means for the direct analysis of spatial properties. Other work focuses on the addition of more dimensions to provide coherency between transfer functions. Recent work by Akiba et al. [1, 2] utilized parallel coordinate plots to create a volume rendering interface for exploring multivariate time-varying datasets. Muelder and Ma [14] proposed a prediction-correction process to aid in creating coherent feature tracking.

In all of these related works, one can note that various statistical properties of the volumes are being used in order to extract features of interest and segment properties of the volume. Unfortunately, as the number of dimensions increases, interaction in n-dimensional space becomes cumbersome to the point that few systems exceed two dimensional transfer functions; instead, the extra dimensionality is incorporated automatically, somewhat limiting the user's control. In order to enhance the information provided in the transfer function histogram widget, our work incorporates some statistical properties of the spatial domain (x, y and z) into the projected feature space domain (e.g., value versus value gradient magnitude).

3 Abstract Feature Space Representation

Given any two-dimensional feature space for a given volume data set, the user is presented with a representation illustrating the number of voxels at a given location within that feature space. In order to enhance this feature space, we propose the use of an *abstract feature space* representation. By this, we mean that the 2D histogram feature space is no longer representing the number of voxels as a given location. Instead, the 2D histogram feature space is representing statistical properties of the volumetric (x, y and z) space with relationship to a particular feature. The key property we have chosen to look at is spatial variance with respect to a given feature set. Thus, given any two feature properties of the volumetric data set (e.g., value vs. value gradient norm, temperature vs. pressure, x vs. pressure) we compute the spatial variance of all the points that map to a given entry in the feature space histogram.

As such, at location (i, j) in the feature space histogram, we have N voxels, V_k, that map to this given feature space pair. For all the N voxels that map to the feature space pair (i, j) we calculate the mean position within the (x, y, z) space of the volume.

$$\bar{V}_{(i,j)} = \frac{1}{N}\sum_{k=1}^{N} V_k \tag{1}$$

Once the mean is calculated, we can then determine the magnitude of the standard deviation within the volumetric space at the feature space pair (i, j).

$$|\sigma_{i,j}| = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(V_k - \bar{V}_{(i,j)})^2} \tag{2}$$

Figure 1 illustrates the difference between the traditional histogram mapping the magnitude of the voxels found at a histogram entry (a) to the magnitude of the spatial variance found at a histogram entry (b-d). Furthermore, we can see that the magnitude of the spatial variance in the z-direction is relatively constant; however, there is an obvious clustering of high spatial variance in the y-direction. The magnitude of the standard deviation vector can also be employed for analyzing the spatial variance found within a given feature space, and the utility of the creation of this abstract feature space is further discussed in Section 5.

4 Non-Parametric Transfer Function Generation

Once the abstract feature space is defined in the 2D histogram, we can use the non-parametric transfer function generation approach described in Maciejewski et al. [12] to provide users with a means to group data in the 2D histogram by areas of similar value (in terms of the number of voxels or in terms of the abstracted standard deviation metric described in Section 3). In order to create these clusters we employ the use of a variable kernel method [17, 19] formed in Equation 3. Furthermore, we utilize an adaptive kernel which scales the parameter of the density estimation by allowing the kernel radius to vary based upon the distance from each point, X_i, to the kth nearest neighbor in the set comprising the $N-1$ data points of the histogram feature space.

$$\hat{f}_h(\mathbf{x}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{d_{i,k}}K\left(\frac{\mathbf{x} - X_i}{d_{i,k}}\right) \tag{3}$$

Here, $\hat{f}_h(\mathbf{x})$ is the probability density estimate of the histogram (h) at a given location, $\mathbf{x}$, in the feature space, $d_{i,k}$ represents the multi-dimensional smoothing parameter and N is the total number of samples in the histogram (i.e., the number of voxels in the volume). The window width of the kernel placed on the point X_i is proportional to $d_{i,k}$ (where $d_{i,k}$ is the distance from the i-th sample to the k-th nearest neighbor) so that data points in regions where the data is sparse will have flatter kernels. We choose $k = \lfloor\sqrt{N}\rfloor$ as this tends to approximate the optimal density estimation fitting (this is a rule of thumb approximation

[17]). Such a method groups the data based on their neighborhood information, allowing us to visualize the underlying structure of the data.

In order to reduce the calculation time, we have chosen to employ the Epanechnikov kernel, Equation 4.

$$K(\mathbf{u}) = \frac{3}{4}(1 - \mathbf{u}^2)1_{(||\mathbf{u}|| \leq 1)} \tag{4}$$

The function $1_{(||\mathbf{u}|| \leq 1)}$ evaluates to 1 if the inequality is true and zero for all other cases.

5 Exploring Abstracted Feature Spaces

The focus of this work is to determine if statistical properties derived from the make-up of a given feature space can be utilized to extract more information and aid in transfer function creation and data exploration. In this section we describe the impact of utilizing the proposed abstract feature space for feature segmentation and data exploration.

5.1 Feature Segmentation

Figure 2 illustrates the application of the non-parametric transfer function generation technique on the conventional transfer function view of the CT bonsai data set, and Figure 3 illustrates the application of the non-parametric transfer function generation technique on the abstracted transfer function. Here we can see which portions of the clustered transfer function map to regions of the volume. Note that the cluster pattern is completely different between Figure 2 and Figure 3. Here we can see that the clustering in the conventional transfer function space winds up with a larger portion of the background noise in each feature segmentation than the abstract transfer function view.

Furthermore, in Figure 2 we see that in segmenting out the leaves (the red cluster), values representing air are still being included with the transfer function; however, by utilizing the spatial variance, those values are not included in the segmentation of the leaves as seen in Figure 3 (again the red cluster). However, other features wind up being combined when using the spatial variance. We can see that the tree trunk and root ball has more separation when utilizing the voxel magnitude for clustering than when using the spatial deviation.

We can further explore the effects of using spatial deviation in transfer function generation by utilizing the x, y and z spatial components separately, thus creating an abstract transfer function space representing the standard deviation . Figure 4 (middle) illustrates the same transfer function generation technique on each of the components of the spatial deviation mapped to the transfer function. What we find in the case of the CT bonsai data is that the area representing air (the red circled area in Figure 4 (middle)) in the feature space is not found as a separate cluster portion in any application of the non-parametric transfer function generation; however, when utilizing the y spatial variance component in the transfer function, the area representing air in the transfer function is associated with another data grouping within the transfer function. This grouping allows us to segment out the air component (as seen in the resultant volume rendering (Figure 4 (bottom)) where as this component is directly related to other important features in the volume when utilizing the x and z spatial components. The segmentation of the air component is also what leads to the noise in Figures 2 and 3

Based on these observations, it seems likely that utilizing information on the spatial variance can help in transfer function design; however, it seems unlikely that this feature alone can create the desired segmentation. Another option for creating abstract feature space

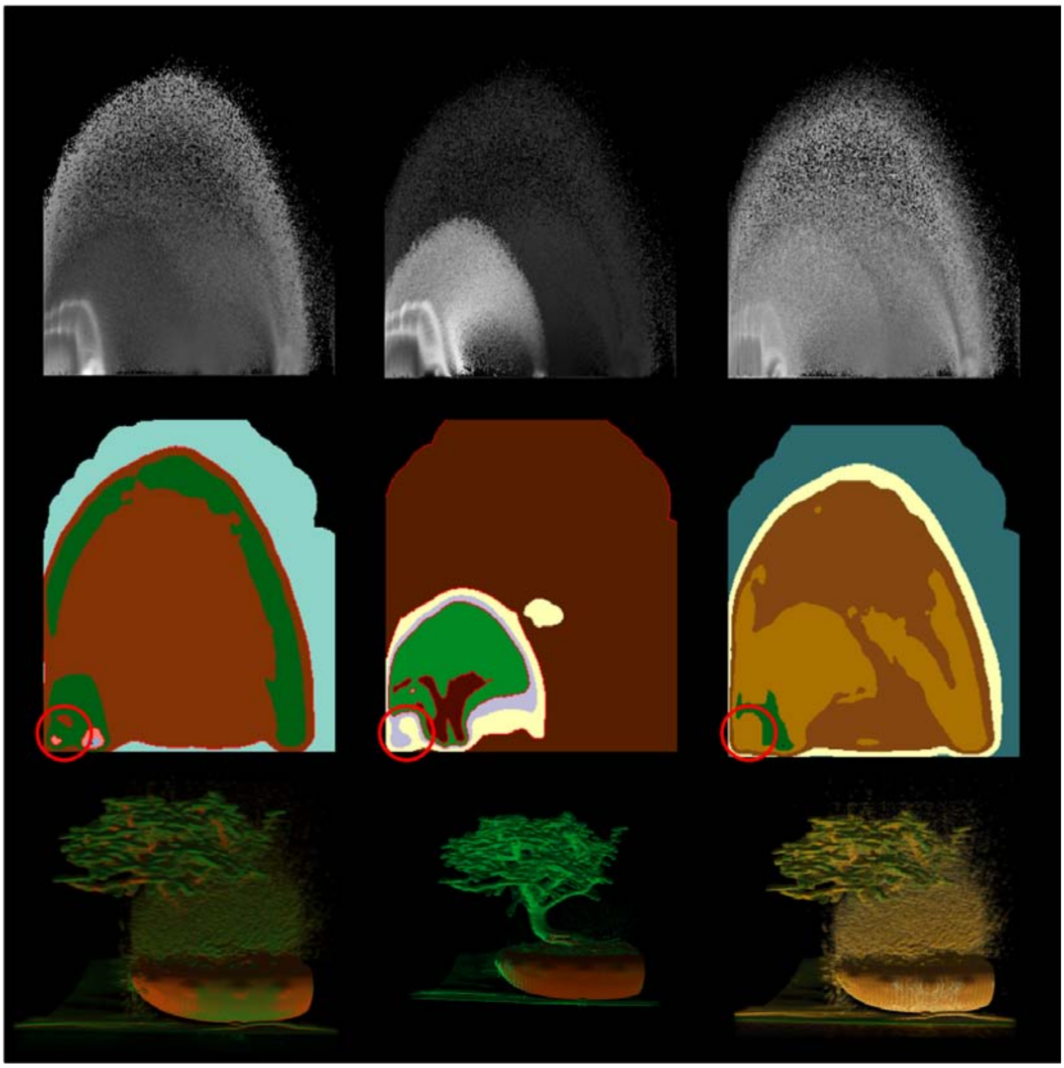

Figure 4 (Top) The value vs. value gradient magnitude feature space as a function of the spatial variance in the x (left), y (middle) and z (right) component direction. (Middle) The resultant non-parametric transfer function. (Bottom) The resultant volume rendering from applying various segments of the transfer function. Note in the x and z spatial variance histograms, segmentation of the noise can not be accomplished.

representations could be utilizing bivariate color mapping schemes to simultaneously relay information about the magnitude of change at a transfer function location and the number of voxels that map to that location.

5.2 Data Exploration

While such tools have their use in traditional volumetric datasets (CT and MRI), the application of these novel analytic methods to more complex simulation data also proves to be very interesting. With the maturation of computational power, simulations are capable of modeling physical phenomena at increasingly more realistic scales. Analysis tools, however, are struggling to keep up with the explosion of data that has resulted from the increase in computational horse-power. This is particularly evident in computational fluid dynamic

(CFD) simulations modeling time-dependent complex flow phenomena. Because the contents of the simulation are not known exactly, and because computational simulations are still evolving and improving their ability to correctly and accurately model physical behavior, the output from these simulations must be analyzed using data mining, feature detection, and feature extraction techniques to provide useful, pertinent information.

Analytical 3D feature detection methods employ well-formed mathematical descriptions of features often unique to a given domain, thus demanding *a priori* knowledge of the nature and location of any potential "areas of interest." This is a cumbersome and tedious task, resulting in a set of methods incapable of scaling with the size of the data. Statistical feature detection tools, on the other hand, provide an automatic way to provide general characteristics.

Flow data sets are ideal candidates for statistically based feature detection techniques because we can leverage physical properties to apply segmentation algorithms. For example, using similarity allows us to segment those regions of the flow data that contain like properties for a given variable. Conversely, using dissimilarity allows us to pinpoint regions in which the flow changes drastically or perhaps discontinuously. This discontinuity is of interest in all flow data sets and often indicates an important region of interest. As such, the utilization of abstract feature space for exploring CFD data should allow researchers to discover interesting regions hidden within their datasets. By utilizing a mapping of the spatial deviation, analysts should be able to quickly explore areas in which flow feature properties (temperature, pressure, velocity, etc.) quickly change from a consistent amount of spatial deviation to a (relatively) larger or smaller amount.

6 Conclusions

From our preliminary work on creating abstract feature space, it seems like utilizing the underlying statistical properties of the spatial volumetric features that map to a given feature space histogram pair will provide analysts with another tool in which to explore data. Based on our exploration of the abstract feature space, it seems likely that enhancing transfer function design through the use of statistical information about the spatial relationships between voxels will aid in feature segmentation and exploration. Future work will focus on utilizing the spatial variation as an uncertainty metric, and looking at other derived data properties (entropy, etc.) as a means for enhancing transfer function exploration and design. Furthermore, we plan to utilize abstracted feature space measures for novel volume rendering parameters in order to reduce the burden of transfer function design on the user. In this manner, we hope to match statistical properties of the data to visual properties thereby being able to semi-automatically create effective transfer functions. Finally, we plan to extend this to the analysis of complex fluid dynamic simulations and map a variety of statistical properties to the transfer function domain, thereby providing researchers with a tools that provide both a fast statistical analysis of data properties and a means in which to filter the data on said properties.

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