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Publication Date
2002

Peer reviewed

ISpace: Interactive Volume Data Classification Techniques Using Independent Component Analysis

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Abstract

This paper introduces an interactive classification technique for volume data, called ISpace, which uses Independent Component Analysis (ICA) and a multi-dimensional histogram of the volume data in a transformed space. Essentially, classification in the volume domain becomes equivalent to interactive clipping in the ICA space, which as demonstrated using several examples is more intuitive and direct for the user to classify data. The result is an opacity transfer function defined for rendering multivariate scalar volume data.

Keywords: *Histogram, image processing, independent component analysis, medical imaging, multivariate data analysis, multimodality data, scientific visualization, segmentation, volume rendering*

1 Introduction

In scientific and medical investigations, often the goal is to identify unique features, trends, or structures in some sampled data domain. Segmentation is the core problem for many applications in medical imaging. Fully automatic segmentation methods are generally unavailable. Instead, interactive, supervised segmentation is often done with thresholding followed by binary mathematical morphology and connected component labeling [7]. For color images, interactive classification is often done in a color space, e.g., RGB [17], YIQ [19], or others.

With parallel supercomputers, scientists are able to model physical phenomena at sufficient accuracy and complexity. Visualizing the resulting simulation data fully and directly can be a challenge. A general practice is to extract a subset of the data through either interactive exploration or a batch-mode feature extraction process. For example, for aerodynamic applications, scientists are interested in vortices, shocks, and boundary layers. Many of the existing techniques either have been designed for a particular application problem or are labor-intensive. Several techniques have been suggested for generating good transfer functions for classifying volume data [1, 5, 18]. These techniques work quite well for single-value scalar volume.

More recently research has been devoted toward the development of transfer functions appropriate for multivariate data sets [13, 21] and time-varying data sets [9]. Kniss et al. describe the use of graphical widgets for multi-dimensional transfer function specification [12], where opacity is set based on several values such as the original scalar value, gradient magnitude and second derivative. Although this type of technique is effective for producing better classification, methods for the intuitive specification of higher dimensional transfer functions remains an open problem. In particular, the specification the three-dimensional transfer functions is complicated by the two-dimensional display typically found in visualization systems, with the specification of transfer functions beyond three dimensions becoming even more difficult. It is becoming increasingly necessary, however, to specify transfer functions with high dimensionality. Take for example a data set containing pressure and vorticity magnitude for each volumetric sample. If first and second derivative magnitudes are incorporated in classification, it becomes necessary to specify a sixth dimensional transfer function.

In this paper, we introduces an intuitive interactive classification technique for multivariate volume data, in particular, multi-channel color data generated from different image modalities. We call the technique "ISpace," which uses Independent Component Analysis(ICA) [14] to transform the original data space into a space better facilitating classification. The different variables in a data set, such as the RGB colors in a cryosection slice, are typically highly cor-

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related with one another. Using ICA, however, it is possible to convert the data into a set of statistically (usually also physically) independent components[16]. Since ICA can separate the statistically independent components, we can apply ICA to a data set to classify the material in a volume based on statistically meaningful differences. Even if a volume has similar characteristics (e.g., brain tissues), ICA can be used to separate materials. Therefore we use ICA to transform these data sets into ICA space to facilitate interactive classification based on a volume's physical characteristics. The advantages of using ISpace are two fold. First, ICA can be used to transform a volume's histogram into a coordinate system that is better suited for segmentation via clipping along axis aligned plains, thus making transfer function specification more intuitive. Second, ICA is effective in reducing transfer function dimensionality, simplifying the multi-variable transfer function specification problem. Dimensionality is reduced since the transformed axis in ISpace are effective in separating statistically independent components, thus requiring fewer axis (dimensions) along which clipping must occur.

We demonstrate the effectiveness of ISpace using the Visible Human data set, a cryosliced human brain data set, and a multi-modality MRI/CT mouse brain data set. The rest of the paper is organized as follows. Section 2 introduces ICA. Section 3 describes the interactive classification followed by case studies using data sets with different characteristics. Finally, we conclude our study and suggest directions for further research.

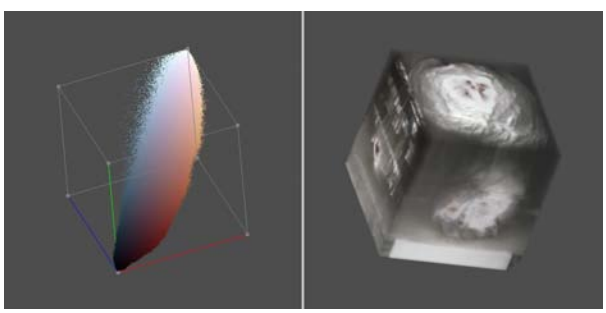

Figure 1. Left: the 3D histogram for an RGB, cryosliced human brain data set. Right: volume rendering of the same data set using a constant opacity map.

2 Independent Component Analysis

Multivariate data analysis has been an active research area. Generally, the data are preprocessed to derive relevant relationships between the variables or to reduce the dimensionality before we can better understand different aspects of the data. Many statistical methods have been developed and can be coupled with visualization techniques to help analyze multivariate data. For example, principal component analysis (PCA) is a statistical technique for data reduction. Independent component analysis (ICA) [14], on the other hand, allows us to reveal interesting information in a multivariate data set by giving access to its independent components. If the variables are independent, they are uncorrelated. ICA has many application in data analysis, source separation, and feature extraction. For example, Muraki et al. [16] use ICA to color multichannel MRI data.

We can also think of ICA as representing arbitrary multivariate data in terms of a linear combination of non-Gaussian random variables that are as independent as possible. Non-Gaussian means that the data distribution is not symmetric. Let's assume that an L-dimensional multivariate vector $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_L]^T$ is observed in an M-dimensional space $\mathbf{S} = [\mathbf{s}_1, \ldots, \mathbf{s}_M]^T$ spanned by M statistically independent parameters as a linear combination $\mathbf{X} = \mathbf{A}S$ where $M \leq L$ and $\mathbf{A}$ is an $L \times M$ matrix. By assuming that $\mathbf{X}$ is a zero-mean vector, ICA is considered to be the problem of finding the $L \times M$ matrix $\mathbf{A}$ and the component vector $\mathbf{S}$ by making each element of $\mathbf{S}$ as independent as possible.

Assuming $L = M$, we can compute the inverse of $\mathbf{A}$, say $\mathbf{W}$, and obtain the independent component simply by $\mathbf{S} = \mathbf{W}X$. A (stochastic) gradient decent method may be used to modify $\mathbf{W}$ interactively so that each element of $\mathbf{S}$ becomes as independent as possible. There are several ways to make each element of $\mathbf{S}$ independent, including mutual information minimization [2, 22] and the nonlinear PCA [10].

The gradient descent method can be very expensive due to its slow convergence. Hyvärinen proposed a fixed-point algorithm, called FastICA, for performing the estimation of ICA [8]. Instead of modifying $\mathbf{W}$, FastICA finds independent component one by one as $\mathbf{s}_i = \mathbf{w}^T\mathbf{X}$, where the vector $\mathbf{w}$ is one of the rows of matrix $\mathbf{W}$. Furthermore, instead of using every data point immediately, FastICA uses sample averages of the data in a single step. Consequently, the convergence speed of FastICA is much faster than that of the gradient descent method. Various experiments show that FastICA is about 10-100 times faster than the conventional gradient descent methods. In this research, we thus use the FastICA package for MatLab [4]

Although both ICA and PCA can be used for reducing data dimensionality, they have several differences worth noting. ICA and PCA can decorrelate components, and thus allows the user to extract specific features more easily. PCA decorrelates the data based on the magnitude of the distribution and the perpendicularity, while ICA finds the statistically independent components without regard to those properties (the magnitude of the distribution and the perpendicularity) so that it can be used to classify features even if its distribution is small.

Since PCA assumes a Gaussian distribution (in many cases, mixed signal) and maximizes this distribution, the features of the multi-dimensional data are only found in the first component. With ICA a non-Gaussian distribution is assumed (in many cases, independent signal), and thus can be used to classify statistically independent components, according to the deflection of the data characteristics. Therefore ICA can enhance the small differences in voxel values depending on the data by taking advantage of the characteristics of the factors of the multi-dimensional data.

3 An Interactive Classification Technique

In direct volume rendering, classification is equivalent to the problem of finding an appropriate opacity transfer function. Considerable research has looked into the generation of transfer functions for volume visualization. Recently, Fujishiro, Azuma, and Takeshima [5] use topological information from a hyper-Reed graph to generate color and opacity transfer functions. Kindlmann and Durkin [11] use information from first- and second-order directional derivatives to generate a volume of derivative histograms for generating opacity maps emphasizing boundary surfaces. Bajaj et al. [1] discuss using other volume function information to find isovalues of interest; these include the volume enclosed by an isosurface, the isosurface area, and the isosurface gradient. Isovalues chosen by this method can be emphasized in a corresponding opacity map. For color transfer functions, Bergman et al. [3] lay out procedural rules for informative color choices. Both He et al. [18] and Marks et al. [15] describe systems for color and opacity parameter generation. In [18], genetic algorithms are used to breed transfer functions. The user can either select functions from generated images or allow the system to be fully automated; in the later case, images are evaluated using statistical qualities such as their entropy and variance. The Design Galleries system [15] addresses parameter manipulation in general by rendering a multidimensional space of those parameters. The user then navigates this space to discover a parameter setting.

A transfer function is often specified and displayed as a 2D curve. When making a transfer function, it is helpful to also see the histogram of the volume data since the shape of the histogram shows the distribution of data values and gives hints about how to segment the data into parts. Given a single-value scalar volume V, let $f(i)$ denote the relative frequency with which intensity level i occurs in V, for all i in the overall intensity level range $[i_{min}, i_{max}]$ of V. The graph of $f(i)$ as a function of i is called the histogram. If f is quantized, and has intensity levels $i_1, \ldots, i_k$, its histogram can be represented as a bar graph having k bars. For a multivariate scale volume data set M, such as a RGB volume data set, a three-dimensional histogram can be made

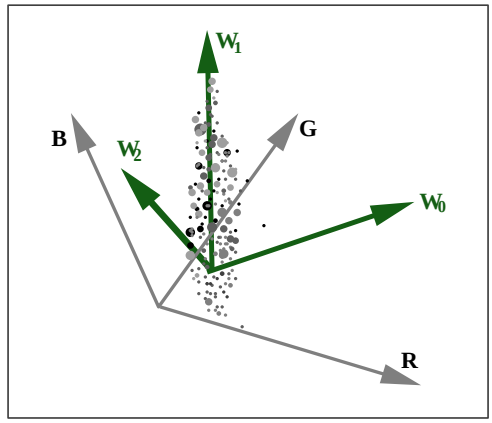

Figure 2. A sketch of a 3D histogram with both RGB and ICA coordinate axes shown.

by plotting f as a function of (R, G, B). Figure 1 shows the three-dimensional histogram of an RGB brain data set. The three main axes (R, G, and B) are colored accordingly. One way to segment such a data set is to derive threshold RGB values by operating directly on this three-dimensional histogram. The other way is to first convert the data from the RGB space to a different color space, e.g., YIQ, and then look for good threshold values [19]. We have developed an interactive technique based on ICA, permitting more intuitive classification of multivariate scalar volume data.

3.1 The classification procedure

The proposed classification procedure starts by applying ICA to the volume data. Assume we are classifying an RGB volume data set. The operation can be characterized by:

$$\begin{bmatrix} s_0 \\ s_1 \\ s_2 \end{bmatrix} = \begin{bmatrix} w_{0,0} & w_{1,0} & w_{2,0} \\ w_{0,1} & w_{1,1} & w_{2,1} \\ w_{0,2} & w_{1,2} & w_{2,2} \end{bmatrix} \begin{bmatrix} r_i \\ g_i \\ b_i \end{bmatrix}$$

for every voxel. $[s_0, s_1, s_2]^T$ is the resulting three independent components. The three vectors $[w_{0,0}, w_{1,0}, w_{2,0}]^T$, $[w_{0,1}, w_{1,1}, w_{2,1}]^T$, and $[w_{0,2}, w_{1,2}, w_{2,2}]^T$ are essentially the three coordinate axes of the new space, i.e. the ICA space. A three-dimensional histogram of the RGB volume is constructed and displayed. Often, the distribution of voxels in the RGB space is an ellipsoid, as also shown in Figure 1. Figure 2 sketches such a histogram with both the RGB and ICA coordinate axes drawn. Typically, the long side of the ellipsoid is aligned with a particular coordinate axis of the ICA space. Each point is colored by using the RGB values, and transparency may be used to show the number of voxels has the corresponding RGB values. When transparency

is used, this three-dimensional histogram should be volume rendered.

Classification is then performed by the user moving clipping planes along the main axes. Interactive rendering permits the user to almost immediately see the resulting classified volume to quickly fine tune the positions of these planes. Note that the clipping becomes intuitive exactly because the three coordinate axes are oriented in space in a way such that each of them is independently aligned with the shape of the histogram. The transfer function used for rendering can be defined in several different ways. The simplest approach is to map all values of the voxels in the unclipped region to the same opacity, and make those voxels in the clipped region transparent (i.e. invisible).

The histogram clipping technique has the advantage of being visually intuitive, but is limited to transfer function specification of three or fewer dimensions. As an alternative approach that avoids this limitation, we have also developed a second ISpace approach where a transfer function is specified as several 1D transfer functions, one for each ICA axis. The resulting opacity of each voxel is the product of the opacity specified along different axes. By showing the histogram along each axis, the user is also able to see value distributions to aid in classification. The dimension reducing properties ICA typically means that fewer curves need to be specified than there are dimensions, simplifying the specification process. Thus users can use a few relatively simple 1D transfer functions that effectively traverse the entire data space.

4 Test Results

To evaluate the effectiveness of ISpace, we have experimented with three different data sets. Since ISpace must be integrated with interactive rendering to work well, we have utilized multi-texture graphics hardware to accelerate volume rendering. With an AMD 1.2 GHz Athlon with 768MB of main memory and a 64MB Nvidia GeForce 3 video card, we use 3D texture mapping [6] and can render up to $256\times256\times256$ volume interactively. It is particularly important for the user to be able interactively modify transfer functions and to immediately see the resulting changes in the rendered images. This is accomplished using the multi-texturing, where each ICA component is stored in a separate paletted texture. Changes to the classification function simply require the changing of texture palettes, rather that the computationally expensive manipulation of volume itself.

Using the three data sets, we are able to show that operating in the ICA space with interactive rendering capability can greatly simplify the segmentation tasks. However, in this study, we had to downsize two of the data sets due to the limited video memory size.

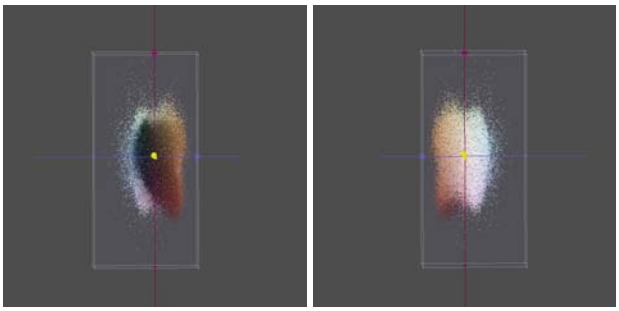

Figure 3. Two different views of the histogram of the human brain data set in ICA space.

4.1 A cryosliced human brain data set

A brain data set provided by the UCLA Brain Research Institute consists of 753 cryosections of a human brain. Each slice has a resolution of 1472×1152 pixels, and each pixel stores real-color RGB information with 16 bits per channel. The size of each slice is 7 MB. The cryoslice process used to create this data set consisted of taking photographs of the human brain after removing successive thin slices from the top to the bottom. Photos were taken of the unsliced portion of the brain rather than the removed slice itself. This results in a number of unique segmentation challenges not present in MRI or CT data since each image can contain data that is part of the deeper slices. In particular cavities or gaps in the brain reveal structures that are actually located in "deeper" layers. These parts of the image need to be eliminated. The brain must also be separated from the surrounding matter, i.e., from the ice and the background.

Figure 3 shows two different views of the 3D histogram of the brain data in ICA space. The white-color region represents the ice, reddish region the brain, and the dark-color region the tray. In contrast to in the RGB space as shown in Figure 1, note that clipping now becomes straightforward to do in the ICA space since the three coordinate axes is independently aligned with the color distribution and the shape of the histogram. Figure 4 display two views of the clipped histogram to extract the only the brain from the whole volume. Figure 5 shows the corresponding volume rendering of the segmented data. The cut-away rendering shows that the cavity corresponding to the lateral ventricle, near the center of a brain, has been correctly removed.

As a comparison, Figure 6 shows that clipping can be very difficult, if not impossible, in the RGB space. In order to obtain a good segmentation, the clipping must be done from oblique angles and separately for different regions. As shown in Figure 6, orthogonal clipping results in bad segmentation.

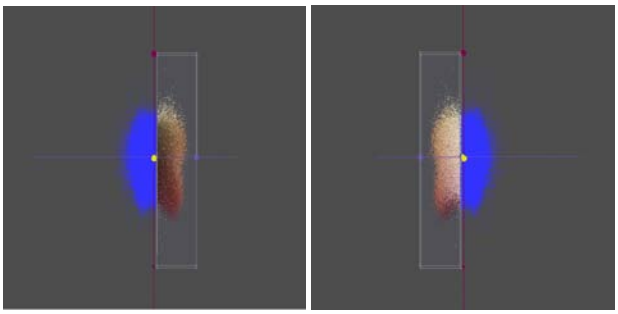

Figure 4. Two different views to show clipping of the histogram in ICA space to extract the brain.

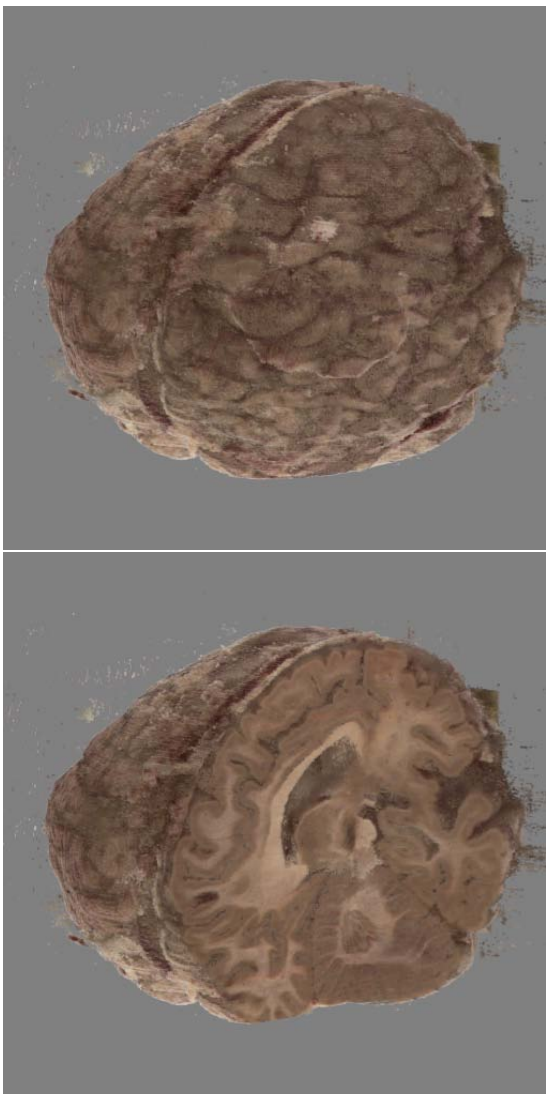

Figure 5. Rendering of the segmented result. Left: full brain; right: cut away to see inside.

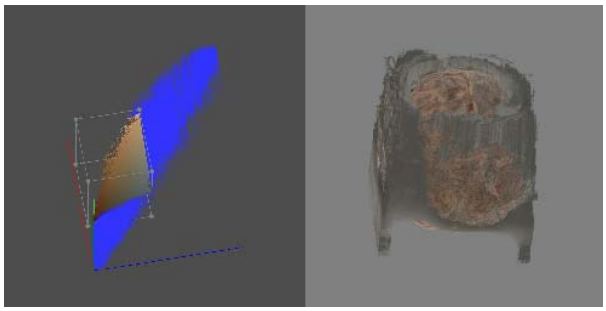

Figure 6. Segmentation of the brain volume in RGB space. Left: clipping the histogram; right: the corresponding volume rendered image.

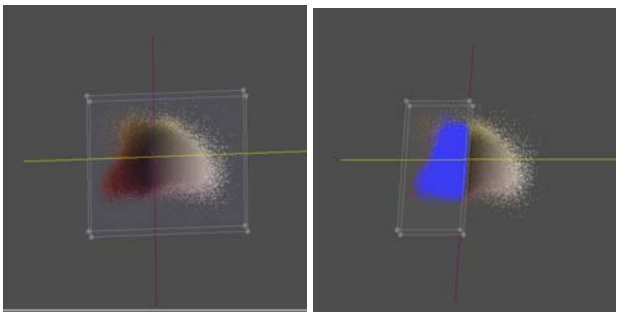

Figure 7. Left: histogram of extracted brain volume data as a result of repeating ICA; right: clipped to remove the gray matter (dark brown color).

Further segmentation may be done to the extracted brain data by applying ICA multiple times. Figure 7 shows the histogram of the extracted brain volume data as a result of applying ICA the second time. This new histogram in the ICA space allows us to easily remove the darker brown color material representing the gray matter of the brain. The corresponding rendered result is displayed in Figure 8.

We are able to segment the brain in ISpace by using our second technique that requires the specification of multiple 1D transfer functions which specifying an opacity distribution along each transformed ICA axis. The left side of Figure 9 shows the segmented brain that results from using the set of transfer functions shown on the right of the figure. For each transfer function, the histogram along that ICA axis is shown in beige while the opacity map is shown in blue. Notice that for the third axis the transfer function is constant across the distribution, demonstrating the dimension reducing properties found when working with ISpace; only two axis require transfer functions to segment the volume.

Figure 8. Volume rendered image of the segmented human brain using ICA twice.

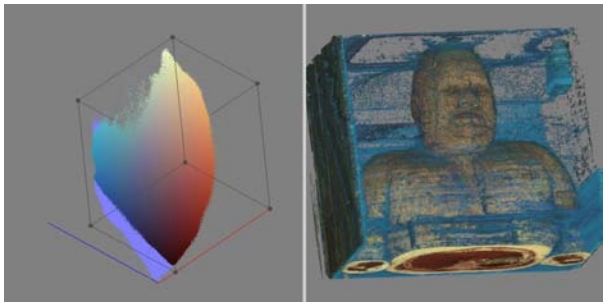

Figure 10. Segmentation of the Visible Female data is not effective using clipping in RGB space. Left: clipped histogram in RGB space; right: a volume rendered image.

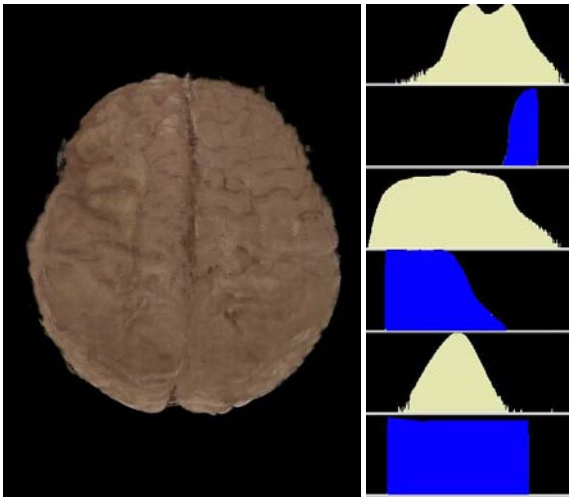

Figure 9. The segmented brain on the left was rendered using the three 1D transfer functions shown in blue on the right.

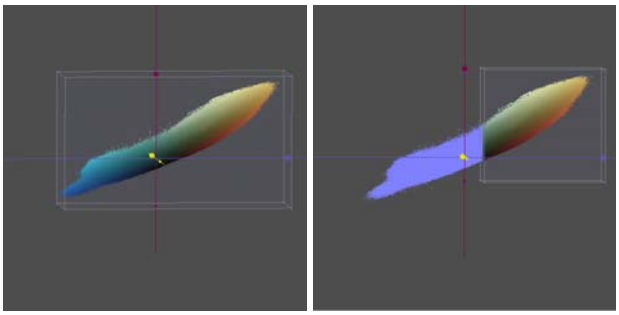

Figure 11. Histogram of the Visible Female data in ICA space. Left: the complete histogram; right: clipped histogram.

4.2 The Visible Female data set

The Visible Female data set has a resolution of $488 \times 1700 \times 900$. Figure 10 shows its three-dimensional histogram in RGB space, and a volume rendered image of the data. The histogram was clipped to reveal the body. As shown in the right image of Figure 10, the body cannot be cleanly segmented in the RGB Space without also removing some portions inside the body. Figure 11(a) shows the 3D histogram in ICA space and Figure 11(b) shows a clipped histogram, in which the clipped part is colored in purple. Images of the corresponding segmented results are displayed in Figure 12, in which the right image reveals the internal of the body to show all parts are retained.

4.3 A mouse brain data set

ISpace may be used for visualizing multivolume data; that is data from multiple imaging modalities. A mouse data set [20] consisting of two volumes, one from MRI (Magnetic Resonance Images) and one from PET (Positron Emission Tomography) of a mouse brain are used. Each volume consists of 47 slices at 256×256 pixels per slice. Prior to visualization, the data was cropped to remove the significant amount of empty space, and resampled to 100 slices at 256×256. The MRI data provides a structural information of the brain, and the PET volume contains functional data about the mouse brain.

In the past, volumes from different modalities have been mainly visualized individually or side by side. It is beneficial to visualize them simultaneously by superimposing the volumes and rendering them into a single image. In this way, it is possible to relate the functional data to particular anatomical structures.

However, we found it is very difficult to directly specify individual transfer functions for the PET and MRI volumes in order to derive desirable images. We thus treated the PET and MRI volumes as a bivariate volume and applied ICA to it. Transfer functions were made for the resulting first and second ICA components instead. The key advantage of this approach is that the user can explore the data set as a single entity rather than as two or three separate volumes (i.e. MRI, PET, CT, etc.) In some sense, a combined transfer function can be interactively defined with ease to reveal dominant features in the PET and MRI volumes. Figure 13 contrasts segmenting in the PET/MRI space (left) and the ICA space (right). As shown in two different views, some isolated features revealed in the ICA are almost impossible to capture in the PET/MRI space.

The volume can also be rendered using two one-dimensional transfer functions as shown in Figure 14. This methods provides the advantages of working in ISpace, while permitting the specification semi-transparent PET/MRI voxels. Although some of the intuition provided by the unified 2D histogram and clipping planes is lost, the user is able to work with the more familiar 1D histogram and transfer function user interface.

5 Conclusions

We have introduced a new intuitive interactive technique for the often tedious classification problem. While we have demonstrated the effectiveness of ISpace using medical data sets, we believe it is possible to generalize ISpace for multivariate data visualization. Further work is also needed to improve multimodality volume visualization. Our segmentation of the mouse data set shows promising results. We will integrate this interface with a parallel volume renderer running on a PC cluster such that we are able to segment large data set at the original resolution. We will also investigate if visualization of the I-components (i.e. s_0, s_1, s_2) would offer other hints for classification.

The shape of each of the 3D histograms we have seen so far are usually ellipsoids. If the shapes were spherical (i.e. Gaussian), then ICA would not be applicable. However, the histogram of physical data sets appear to almost always have these non-spherical shapes.

We are currently implementing a VR interface for ISpace which we believe will make interactive clipping even more intuitive. Finally, we plan to conduct more studies using other types of data sets.

Acknowledgments

This work was supported by NSF (CAREER Awards: ACI 9624034, ACI 9983641, LSSDSV: ACI 9982251, NPACI). The authors are grateful to Dr. Juan Jose Vaquero and Dr. Michael Green at the National Institutes of Health, Dr. Arthur Toga of UCLA Brain Research Institute, and the Visible Human Project for providing the test data sets.

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Figure 12. Volume rendered images of the segmented Visible Female data using ICA. Left: external view; right: cut-way view.

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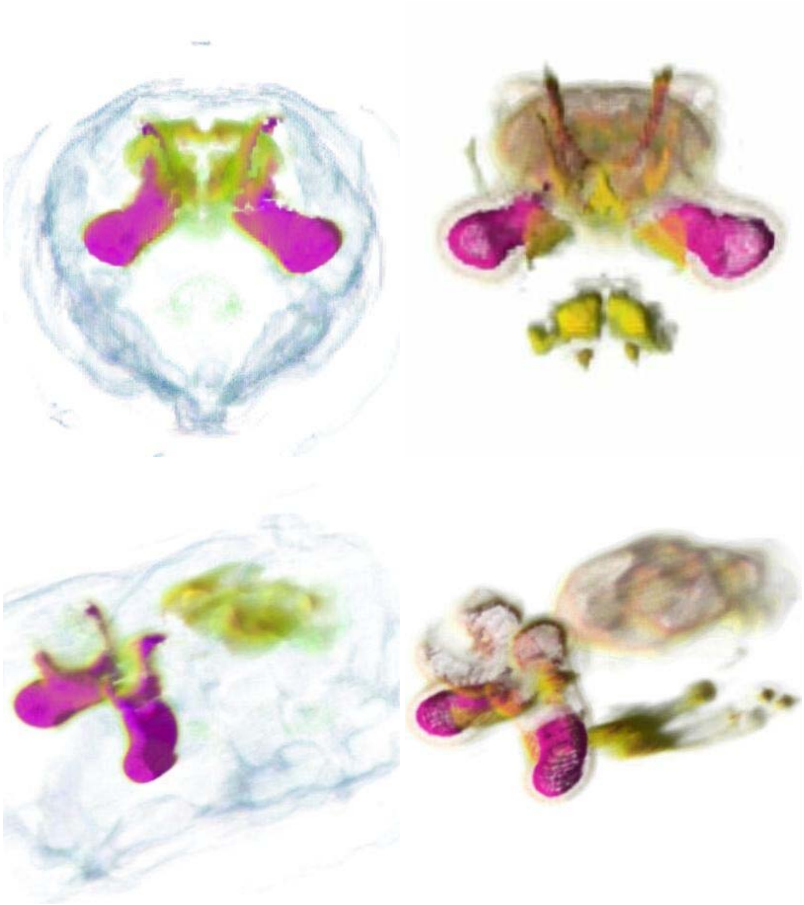

Figure 13. Left: segmented mouse brain in PET&MRI space; right: segmented mouse brain in ICA space.

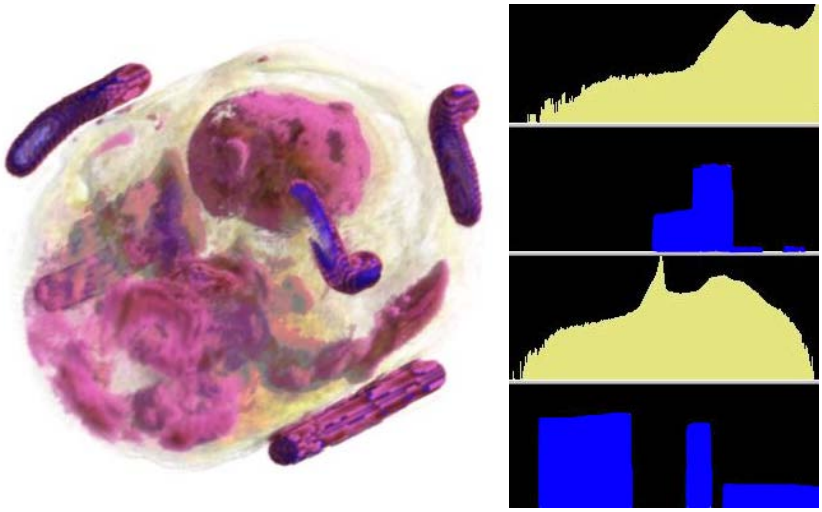

Figure 14. The fusion of MRI and PET data shown on the left was rendered using the pair of ISpace aligned 1D transfer functions appearing on the right.