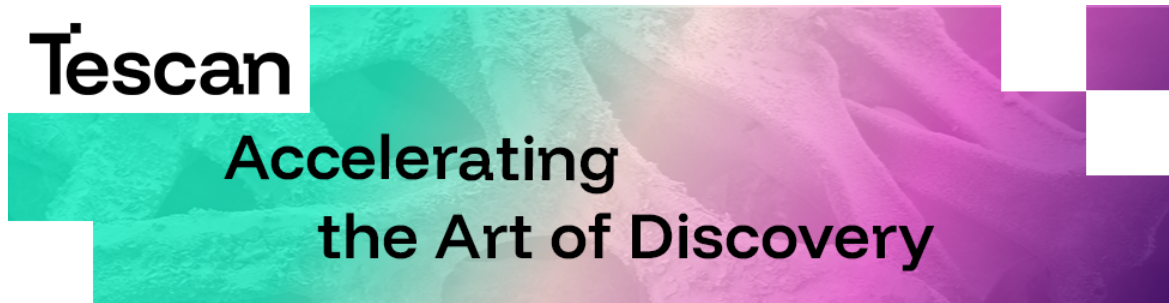


Multivariate Volume Data: Advances in Visualization and Analysis Techniques

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Multivariate Volume Data: Advances in Visualization and Analysis Techniques

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Nanoscale imaging techniques employed at DOE's modern X-ray facilities are important in guiding future experiments, enabling successful scientific discoveries, and bringing products to market. However, the increasing size and complexity of nanoscale imaging data have made the analysis process more difficult and, in some situations, infeasible. Nanoscale imaging techniques commonly produce multivariate volumetric data, which contains more than one channel per voxel and has become increasingly prevalent in important industries such as battery technology, manufacturing, and medical imaging. Due to its multidimensional nature, multivariate data is complex and usually requires substantial human effort to analyze. Often, each channel is visualized separately and individually. Such an approach, however, does not readily reveal the complex yet frequently important cross-channel interactions.

Based upon *RadVolViz* [1], a novel research application for direct multivariate volume rendering and exploration, the open source prototype *MultivariateView* [2] was recently developed to enable intuitive and highly interactive exploration of multivariate volume datasets. *MultivariateView* utilizes the widely used open source frameworks *frame* [3] and *VTK* [4] in order to create a powerful, interactive web application. Fig. 1 provides an overview of the rendering and radial colormap features. We anticipate that the full integration of these features into the visualization library *VTK* will provide access to even more tools and filters within *VTK*'s ecosystem to greatly improve the power and capabilities of multivariate volume rendering.

A lens feature within the prototype enables interactive exploration of different regions of the radial colormap, which translates to different phases/composites within the volume. As shown in Fig. 2, the four phases of the MIEC dataset [5] were successfully visualized by moving the lens around the radial colormap. This was also confirmed by the authors of the paper. Multimodal visualization and analysis techniques were successfully demonstrated through studying a medical dataset (a knee containing a sarcoma) containing four unique modalities per voxel: CT, PET, MRI-T1, and MRI-T2.

Voxel similarity maps were likewise explored and were found to correctly separate voxels belonging to different phases, as demonstrated in Fig. 3. In particular, the t-SNE method appeared to be quite successful at separating voxels belonging to different phases within the MIEC dataset [5]. The t-SNE method was similarly able to segment out the sarcoma and other interesting features (such as the patient's bone) within the medical dataset.

A novel segmentation method in which SLIC superpixels [6] of the multivariate voxels are generated and subsequently merged through several steps of progressive agglomerative clustering was found to accurately segment multivariate phases/composites, as demonstrated in Fig. 4. Global consideration of similarity allows the algorithm to label similar disconnected regions of phases/composites as belonging to the same phase/composite.

Many example datasets from several scientific disciplines have been successfully analyzed through the techniques discovered in this work. Future plans include integrating the newly discovered visualization and analysis techniques within the widely used open source visualization applications *ParaView* [7] and *Tomviz* [8]. All software produced for this research will be open source and freely available [9].

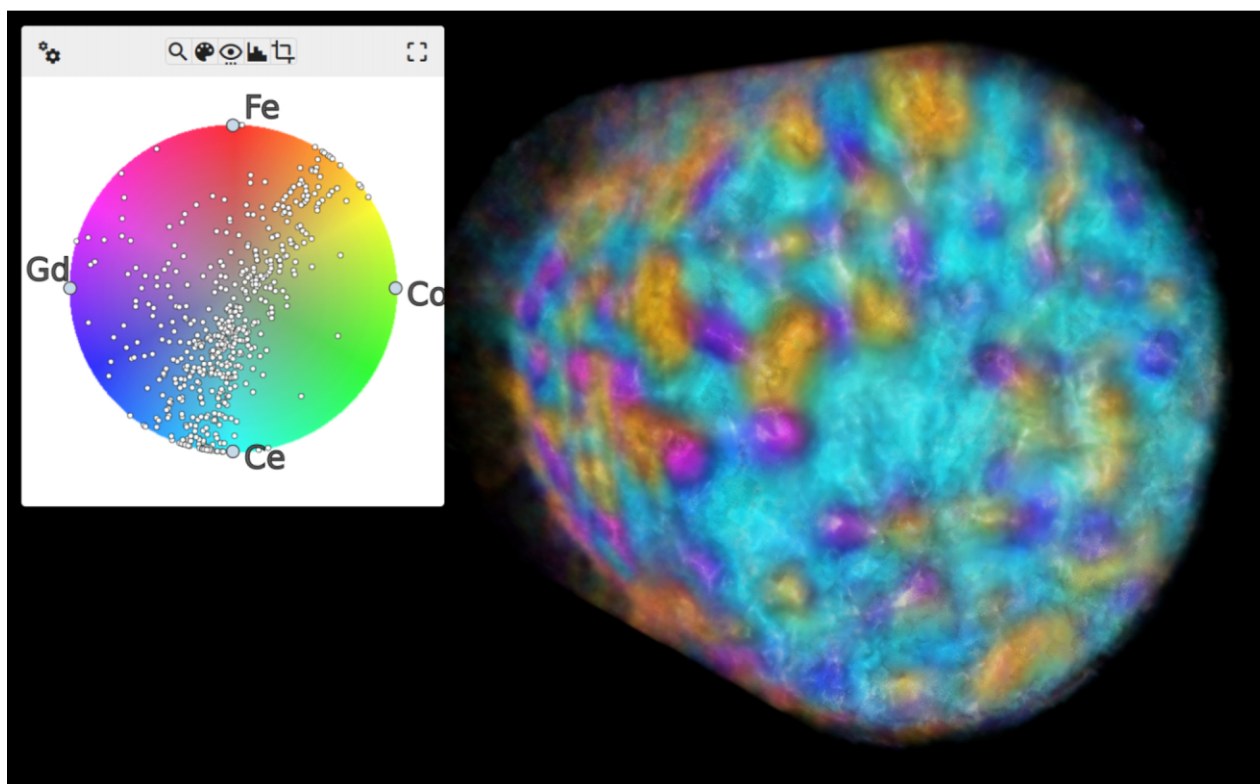


Fig. 1. MultivariateView [2] overview, visualizing an MIEC dataset [5]. The radial multivariate transfer function editor on the left matches that described in the *RadVolViz* application [1], where voxels are mapped to the radial colormap according to the values of their channels (a voxel high in Ce, for instance, will appear close to the Ce node. A voxel high in Gd, will appear close to the Gd node. And a voxel that contains a mixture of each will appear in between). A subsampled distribution of voxels is plotted within the display to provide a general idea of the voxel distribution.

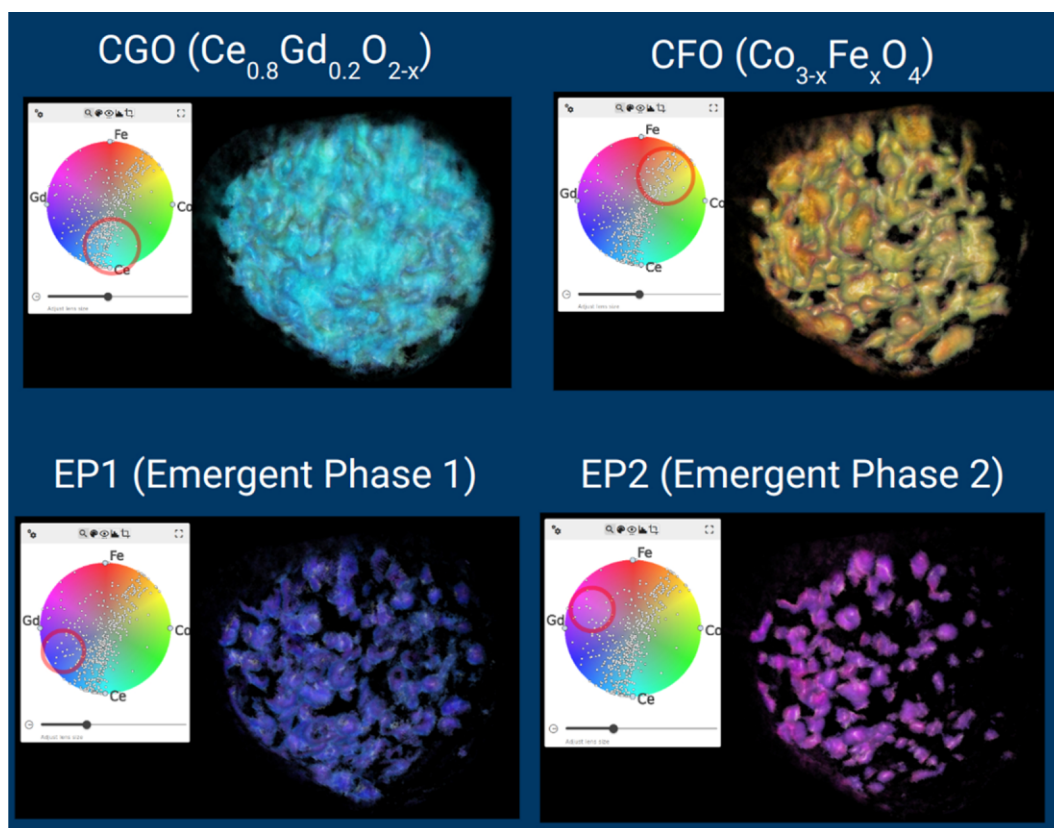


Fig. 2. Visualization of the four phases identified in the MIEC paper [5] by using the interactive lens exploration of MultivariateView [2]. The authors of the MIEC paper confirmed that the phases were correctly identified in these visualizations.

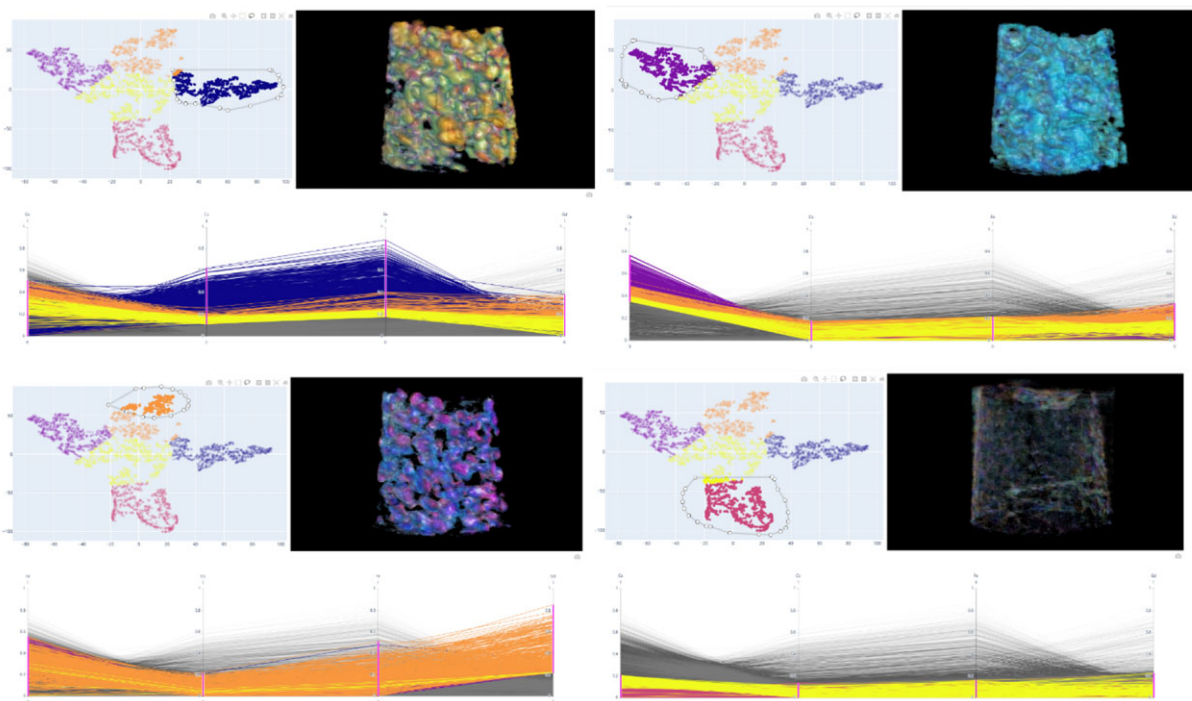


Fig. 3. t-SNE mapping of voxels demonstrated noticeable separation between the phases of the MIEC dataset [5]. In each of the above subfigures, the upper left region is a unitless 2D similarity plot of the voxels colored by k-means clustering, the upper right region is a rendering of the selected voxels using the same coloring from MultivariateView [2], and the bottom region shows parallel coordinates of the selected voxels (selected voxels are colored and unselected voxels are gray). The top-left and top-right subfigures show the CFO and CGO phases, respectively, as identified in the paper. The bottom

left subfigure shows the two emergent phases. And the bottom right subfigure shows miasma (noise). It was a very interesting finding to see that the clustering separated out the noise into its own region.

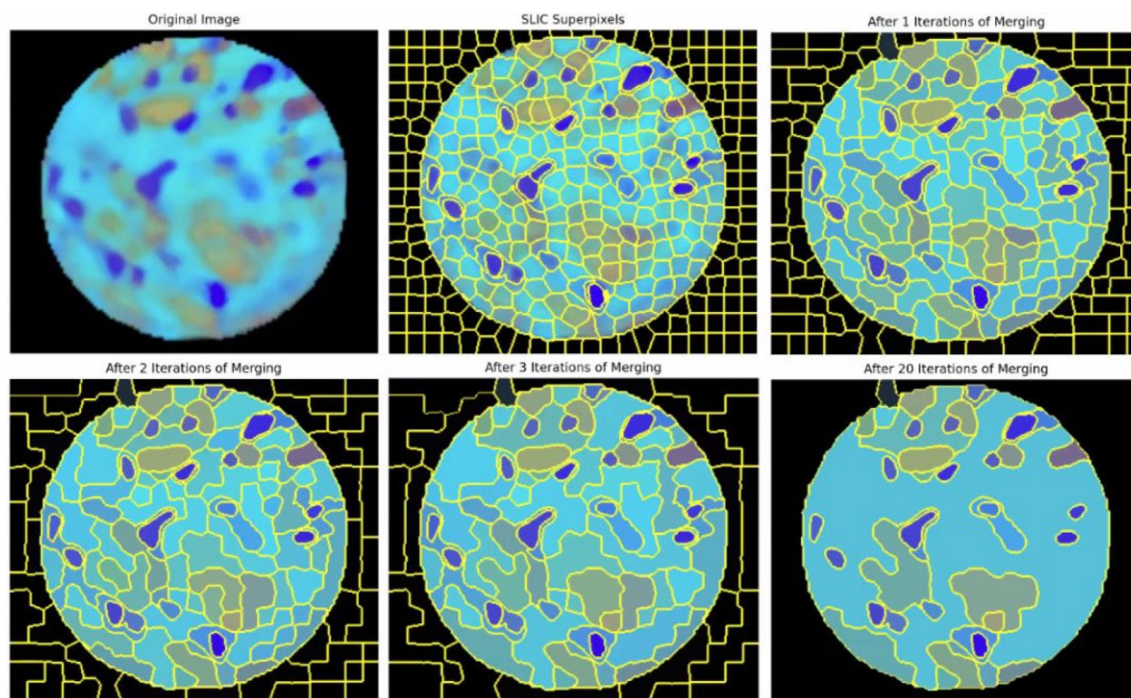


Fig. 4. Segmentation by generating SLIC superpixels [6] followed by several iterations of merging. On the top left is the slice RGB-colored by *RadVo/Viz* [1]. The next image (top center) shows the initial SLIC segmentation. The other slices show the results obtained after progressive agglomerative clustering (merging) of the initial superpixels. Note that, due to global consideration of similarity, the merging algorithm has the ability to label similar disconnected regions of phases/composites as belonging to the same phase/composite.

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