Exploring Ensemble Visualization

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ABSTRACT

An ensemble is a collection of related datasets. Each dataset, or *member*, of an ensemble is normally large, multidimensional, and spatio-temporal. Ensembles are used extensively by scientists and mathematicians, for example, by executing a simulation repeatedly with slightly different input parameters and saving the results in an ensemble to see how parameter choices affect the simulation. To draw inferences from an ensemble, scientists need to compare data both within and between ensemble members. We propose two techniques to support ensemble exploration and comparison: a *pairwise sequential animation* method that visualizes locally neighboring members simultaneously, and a *screen door tinting* method that visualizes subsets of members using screen space subdivision. We demonstrate the capabilities of both techniques, first using synthetic data, then with simulation data of heavy ion collisions in high-energy physics. Results show that both techniques are capable of supporting meaningful comparisons of ensemble data.

Keywords: Ensemble, high-energy physics, perception, heavy ion collision, visualization

1. INTRODUCTION

Advances in computational speed and storage have made it possible to study the development of complex, dynamic systems. For example, researchers in astrophysics are currently investigating the formation of our galaxy based on subtle structural clues about smaller galaxies that were long ago absorbed into the Milky Way. Simulation models are used to test the validity of competing hypotheses, and to study how different assumptions about the system's initial state affect its behavior. A common approach to investigate a simulation's parameter sensitivity is to produce an *ensemble:* a collection of datasets representing independent runs of the simulation, each with slightly different initial parameters or execution conditions. Visualization has been proposed as one promising approach to analyzing an ensemble. To succeed, visualization techniques must summarize the data, highlight noteworthy features, and enable rapid and accurate value comparison, pattern detection, and pattern matching.

We are collaborating with a group of colleagues in mathematics, high-energy physics, astrophysics, and meteorology to study the problem of ensemble visualization. Based on discussions with our colleagues and a study of their existing workflows, we identified the following needs for ensemble visualization:

1. **Attribute value exploration.** The ability to identify values and their distributions across both space and time.
2. **Shape comprehension.** The ability to locate and explore surface contours.
3. **Outlier detection.** The ability to highlight values that vary from the norm.
4. **Member comparison.** The ability to compare values, shapes, and outliers across multiple members.

To address these needs, we designed and implemented two prototype ensemble visualization tools. The first approach, *pairwise sequential animation*, orders n members in an ensemble, then combines subsets of the members and presents them as an animated visualization using hue and texture. The second approach, *screen door tinting*, uses screen space subdivision to superimpose similarities and differences between m members and a reference member using hue and luminance.

We tested our methods on two sets of ensembles. The first contains simulated volumes with predefined data patterns, allowing us to evaluate each method's strengths and weaknesses in a known context. The second contained volumes from a simulation of quark–gluon plasma during heavy ion collisions, to test our techniques on real-world data.

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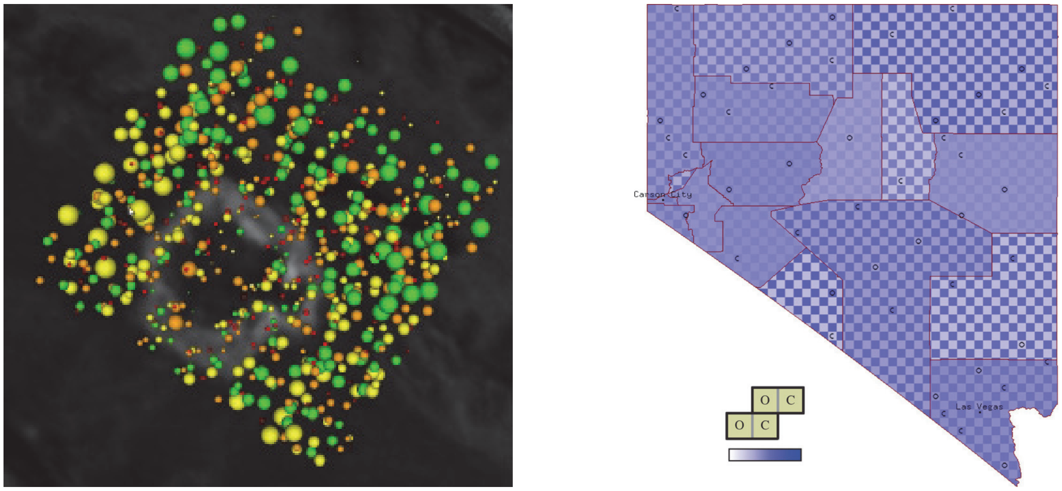


(a)

(b)

Figure 1: Multidimensional visualization examples: (a) SDDS visualization of an MRS scan of a brain, red spheres represent cholin, orange represents creatin, yellow represents glutamine, green represents n-acetylaspartate, low levels of all four metabolites (small spheres) are seen within a grey tumor region; (b) attribute block visualization of Nevada vote totals for Clinton and Obama during the 2008 Democratic presidential primary election, showing counties with a near-even split of votes (near-constant color), and counties where one candidate was favored over the other (a checkerboard pattern)

2. RELATED WORK

Existing visualization techniques could conceivably be used to visualize ensembles. Since our ensembles contain volumetric data, some extension of direct volume rendering might be appropriate. An ensemble could be viewed as a multidimensional dataset, with each member representing one dimension. Finally, a number of methods for visualizing ensembles have been previously proposed. We focus here on techniques that motivated our pairwise sequential animation and screen door tinting designs.

2.1 Direct Volume Rendering

Volume rendering has been applied to many fields, including our domains of astrophysics, meteorology, and high-energy physics. Direct volume rendering is one approach that maps volume data to 3D volumetric elements, called voxels, using transfer functions.[1] Rendering techniques have been proposed to visualize multiple overlapping volumes.[2,3] Unfortunately, it is challenging to accurately represent properties like interpenetration or surface order, even for two volumes. Applying these approaches to an ensemble with numerous members would produce significant occlusion and on-screen clutter, making it difficult or impossible to identify and compare properties of individual members.

2.2 Multidimensional Visualization

Another approach is to treat an ensemble as a multidimensional dataset, where each member represents one or more data attributes. Existing visualization techniques could then be used to visualize the ensemble as a multidimensional image.

Glyphs. A common approach to multidimensional visualization is to represent data elements with geometric shapes, or glyphs. The visual properties of a glyph are varied to visualize its data element's attribute values. For example, a meteorological dataset could use squares to represent weather readings, with a square's hue and size varied to show temperature and pressure values. Many multidimensional visualization techniques use glyphs. Early examples include Chernoff faces, where faces represent data elements and a face's expression represents attribute values,[4] or starfields, where rectangular glyphs are arrayed in 2D to visualize multidimensional data in a scatterplot-like fashion.[5] More recent approaches apply perceptual guidelines on the use of color and texture to general highly salient glyph patterns.[6]

Scaled Data Driven Spheres. An alternative visualization method called scaled data driven spheres (SDDS) samples each data attribute to produce a single, combined image. A set of non-overlapping spheres are randomly positioned within a volume containing the data elements. For n attributes, $\frac{1}{n}$ spheres are assigned to each attribute. The subset of spheres is drawn with a unique color, to identify the attribute it represents. The size of a sphere is varied to visualize its underlying attribute value. Figure 1a shows an example of visualizing the levels of four metabolites captured with an MRS scan: the amounts of cholin, creatin, glutamine, and n-acetylaspartate are shown by the size of the red, orange, yellow, and green spheres, respectively.[7] Low levels of all four metabolites, seen as small spheres, highlight a region containing a tumor.

Attribute Blocks. Attribute blocks use screen-space subdivision to visualize multiple attributes.[8] The screen is subdivided into a regular grid, and cells are assigned to visualize one of the n attributes. For example, for $n = 4$ attributes, the cells are combined into 2×2 blocks. The same cell in each block is used to visualize a specific attribute's values using color. Attribute blocks were originally designed to show areas of similarity and difference. To do this, each cell uses the same color scale to represent its attribute values. When all n values are similar, the block is drawn with a constant color. If the n values are different, the block shows different colors in each cell, producing a checkerboard-like pattern. Figure 1b shows an example of visualizing vote totals for Hillary Clinton and Barack Obama during the 2008 Nevada Democratic presidential primary election. Counties with a near-constant color show similar vote totals. Counties with strong checkerboard patterns show a significant win by one candidate over the other. Small `C` and `O` symbols are used to identify which cells represent Clinton, and which represent Obama.

2.3 Ensemble Visualization

Various techniques and systems have been proposed to visualize ensembles. One common approach is to use side-by-side visualizations, one for each member, often augmented with linking or brushing to allow viewers to highlight data in a common spatial region within each member.[9] Statistical summaries like average and standard deviation over all the members are also used to compress and visualize an ensemble as a single, derived dataset. This capability is provided through summary views and trend charts in Ensemble-Vis, an ensemble visualization framework developed jointly by Sandia National Laboratory, Lawrence Livermore National Laboratory, and the University of Utah.[10]

Another approach, used for visualizing weather model ensemble uncertainty, builds isocontour "spaghetti plots" to highlight similarities and differences across members.[11] For n members, n isocontours for a user chosen attribute and value are constructed. The isocontours are assigned unique colors, then visualized. If the contours cluster together into a bundle, the given attribute value follows a similar spatial distribution across the members. If the contours diverge, the attribute value distributions differ.

Although it is tempting to try to select an existing multidimensional or ensemble visualization technique for our data, certain shortcomings of these approaches and specific requirements of our users makes this difficult. For example, glyph-based multidimensional visualizations begin to break down when n increases beyond even a small number. Identifying a sufficient number of visual features, and combining them in effective ways, is a significant challenge. SDDS and attribute blocks also suffer as n grows. More attributes means more spheres are needed to capture each attribute's distribution of values, increasing occlusion and on-screen clutter. Attribute blocks need to increase in size, reducing the total number of data elements that are displayed, and significantly increasing the difficulty in matching an individual cell to its parent attribute. These issues suggests that the techniques are best applied to ensembles with only a small number of members.

Ensemble visualization systems are specifically designed to handle large number of members. Unfortunately, this is normally done by compressing the data, for example, by visualizing statistical summaries, or by focusing on only a specific value of a specific attribute. Our scientists need to compare individual data elements both within and between members, so approaches that hide this level of detail cannot be used.

Given these challenges, we were faced with two alternatives: to try to modify and extend existing techniques to visualize our data in ways that support our users' needs, or to design a completely new ensemble visualization technique. In the end, we decided on a combination these two approaches. Specifically, we used SDDS and attribute blocks as a motivation and a starting point for two new methods to visualize ensembles in ways that support data and member-level comparisons.

3. PAIRWISE SEQUENTIAL ANIMATION

We made two initial decisions to simplify our visualization designs. First, we assume each member encodes a single attribute value. Although there are ways to support multidimensional members, we have not addressed this problem in our initial prototypes. Second, each member's data elements are represented using glyphs that vary their visual appearance to represent parent members and attribute values.

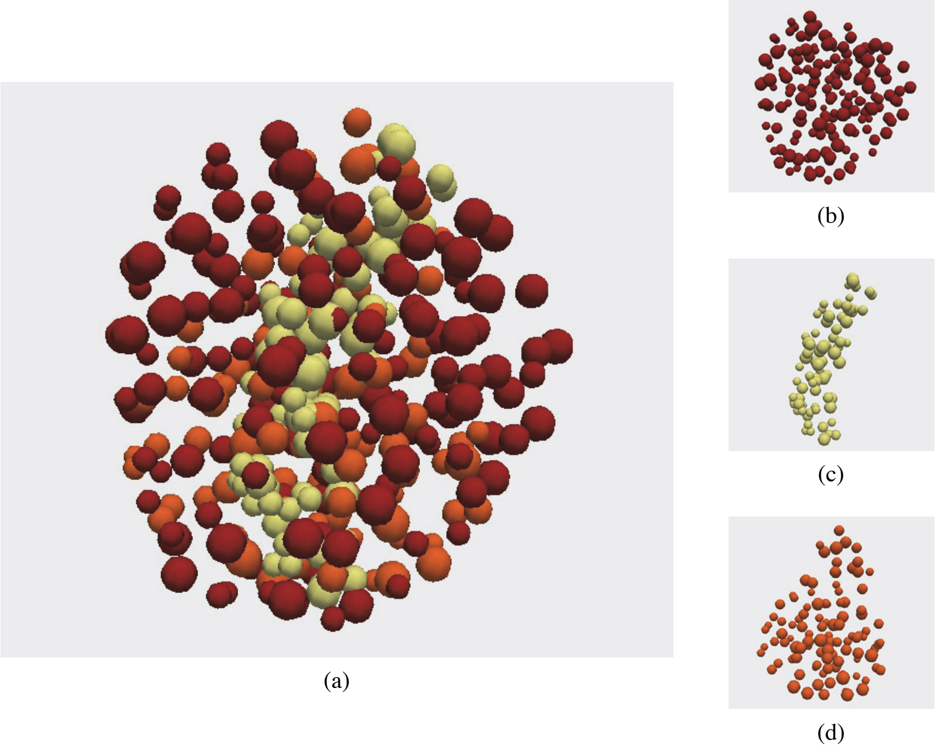


Figure 2: Three simulated ensemble members whose volumes represent an apple, a banana, and a pear, combined into a single ensemble visualization: (a) ensemble visualization; (b) apple volume; (c) banana volume; (d) pear volume

Our first technique builds on SDDS by visualizing a subset of an ensemble's members as a collection of samples from each member. Each sample is visualized with a glyph. One visual property of the glyph (e.g., color or shape) is used to identify the member it represents. A second visual property (e.g., size or color) is used to visualize the attribute value at the glyph's spatial position in the parent member. Based on this initial idea, we divided our design problem into three steps: (1) visualizing one ensemble member; (2) combining individual visualizations to produce a display containing all the members; and (3) managing occlusion in the combined visualization.

3.1 Visualizing One Ensemble Member

Since our technique is based on SDDS, visualizing a single ensemble member is simple. Each sample point is represented by a sphere, with the size of the sphere visualizing the sample point's attribute value. All the spheres are colored a single, unique color to identify the common member they belong to.

A second issue that must be addressed is the number of sample points in the member. Although it is possible to visualize every sample point, this can lead to occlusion due to over-populated volumes. The problem becomes even more acute when we visualize multiple members simultaneously. To address this, we implemented a sampling technique that allows a user to specify a sample size m. A cluster-based algorithm is then used to select m sample points that match the spatial distribution of the attribute values in the member.

3.2 Visualizing Multiple Ensemble Members

Given visualizations for each ensemble member, the simplest way to combine them is to display them simultaneously. Not surprisingly, this produces poor results, even for a small number of members. Figure 2 shows an example of combining three simulated members representing an apple volume, a banana volume, and a pear volume into a single visualization ensemble (Figure 2a). Because the combined result contains numerous overlapping spheres, it is difficult to make out the shape of any of the individual volumes.

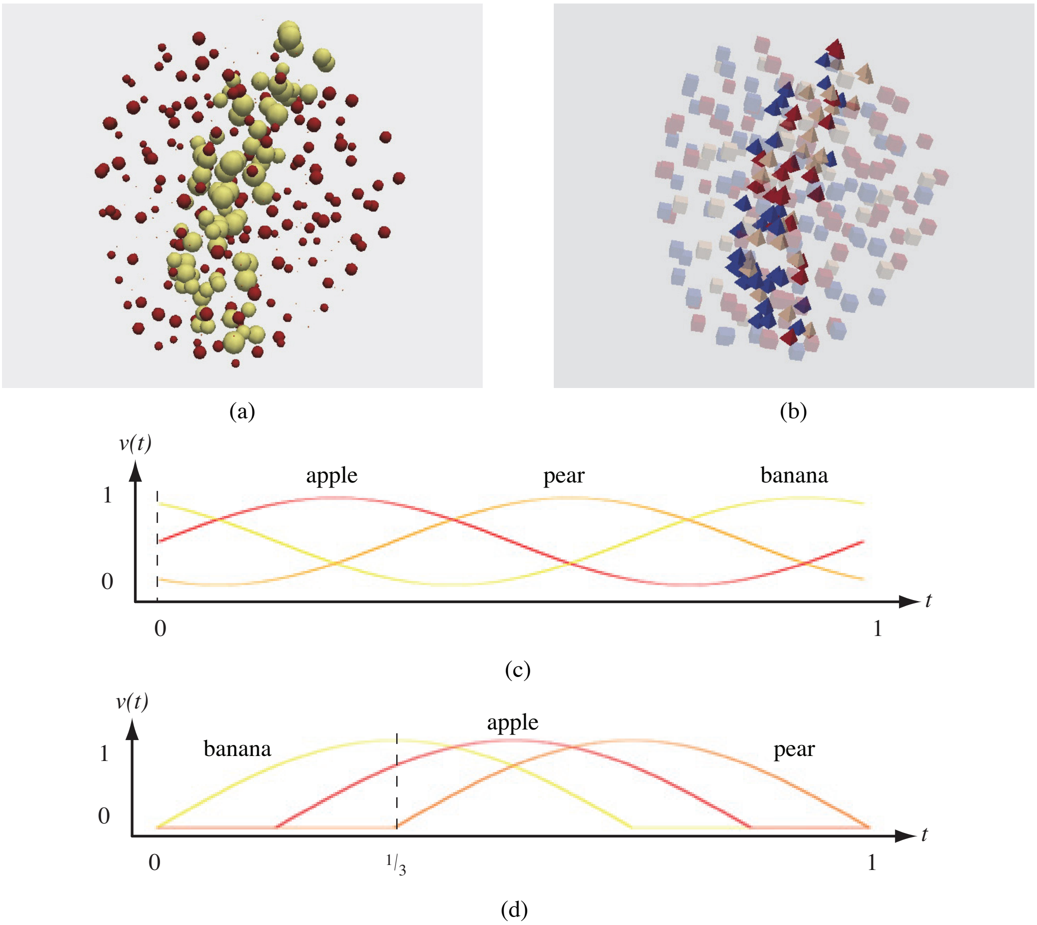


Figure 3: The same three volumes as in Figure 2, but with visibility controlled using a sinusoid visibility function: (a) ensemble visualization with size visibility; (b) ensemble visualization with opacity visibility; (c) sinusoid visibility functions, ensemble in (a) shown at $t = 0$; (d) sequential visibility function, ensemble in (b) shown at $t = \frac{1}{3}$

Although we can reduce the clutter by reducing the number of samples in the individual member visualizations, this will not work well for ensembles with a larger number of members. Moreover, fewer samples will produce visualizations that do not properly represent the members' attribute value distributions.

3.3 Managing Occlusion

To manage the problem of occlusion when many member visualizations overlap, we provide a mechanism to vary the *visibility* of each member. We add a time axis to our visualization, converting it into an animation. Each member is then assigned a visibility function $v(t)$ to define its visibility at time t. We use a sinusoid function for $v(t)$ to generate smooth increases and decreases in visibility. $v(t)$ for different members are offset so that their full visibility peaks occur at different times. This ensures that when one member is fully visible, the others will be partially visible or hidden. $v(t)$ is mapped to a glyph's size: when $v(t) = 0$ the size is set to 0 to hide the glyph, and when $v(t) = 1$ the size is set to the glyph's maximum size—that is, the size used to visualize the glyph's attribute value.

Figure 3a shows the same three volumes as in Figure 2, but with visibility control enabled. Time is set to $t = 0$, producing $v(t)$ of 1 for the yellow banana volume, $\frac{1}{2}$ for the red apple volume, and close to 0 for the orange pear volume (Figure 3c). This produces a fully visible banana, a partially visible apple, and small orange dots to indicate the presence of another member, in this case, a pear.

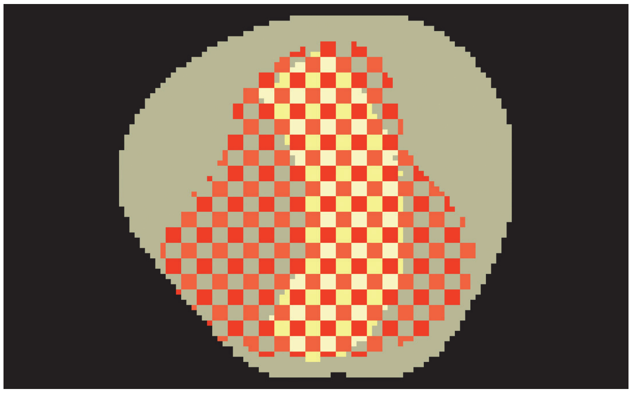


Figure 4: The same three simulated ensemble members—apple, banana, and pear—as in Figure 2, with an apple reference member and differences between members visualized using a yellow tint for banana, an orange tint for pear, and grey for regions in the apple that do not overlap either comparison member

3.4 Opacity-Based Visibility

Our sequential animation method was designed to mimic SDDS as closely as possible, to try to ensure that the advantages of SDDS extended to our ensemble visualizations. This decision made intuitive sense, and initial results from the technique were promising. There are potential drawbacks to our choices, however. The most obvious issue is that size is used for two different purposes: to control visibility, and to visualize attribute values. This can cause ambiguities to arise, for example, if a set of spheres are small, is it because they represent small attribute values, or because their visibility $v(t)$ is low? A second, more subtle issue, is that our visual system is less accurate at distinguishing differences in size, versus differences in other visual properties like color.[6] This may make it harder to see differences in attribute values.

To address these issues, we made a number of changes to how visibility is controlled, how attribute values are visualized, and how a glyph's parent member is represented. Visibility is varied using opacity rather than size. Attribute values are represented with color rather than size. Glyph membership is represented with shape rather than color. Finally, visibility curves are truncated to ensure at most two overlapping curves at any given t.

These changes remove the use of size entirely, ensure that no visual feature dual-encodes information, and reduce the number of members visualized simultaneously to two. Figure 3b shows the same volumes as in Figure 3a, but visualized using our modified design. Now, a glyph's member is represented with shape: cubes for the apple volume, tetrahedrons for the banana, and spheres for the pear. Time is set to $t = \frac{1}{3}$ (Figure 3d), producing a fully opaque banana volume, a partially transparent apple volume, and a fully transparent pear volume. The different colors show the attribute values associated with each glyph.

4. SCREEN DOOR TINTING

Rather than comparing subsets of neighboring members using visibility, we decided to pursue a technique that did not use animation, but still offered flexibility in the number of ensemble members it presents for comparison. The result was screen door tinting, an approach motivated by attribute block visualizations of multivariate data. Here, one ensemble member acts as a *reference* member, and an additional m members act as *comparison* members. The projected screen area of the reference member's surface is subdivided into blocks of $r \times s$ cells, $m = r\,s$. Each cell is assigned a unique hue, and is bound to a specific comparison member.

During visualization, the volume of space that projects onto a cell is identified in both the reference and the comparison member. Sample points in the reference member's volume are compared to corresponding points in the comparison volume. The attribute value difference between the points is used to vary the saturation of the reference member's point: the larger the attribute value difference, the stronger the "tint" applied to the point. Reference member sample points that have no corresponding comparison point are shaded grey. As the reference member's points are projected, they tint the cell to show both the distribution of individual differences, seen as the spatial frequency of the saturation pattern in the cell, and the overall difference between attribute values for the given cell, seen as the average saturation across the cell.

Figure 4 shows an example of screen door tinting applied to the three-member ensemble containing an apple, a banana, and a pear (Figures 2 and 3). The apple member is selected as the reference member. Since screen door tinting visualizes comparisons on the reference member's projected surface, Figure 4 shows an apple shape.

Each attribute block contains a 1×2 array of cells for two comparison members: the left cell is assigned to the banana member, and the right cell is assigned to the pear member. A yellow color scale is used to tint differences between the apple and the banana, and an orange scale is used for differences between the apple and the pear. The yellow and orange checkerboard patterns show large differences in attribute values between the apple and the two comparison members. Since attribute values differ at almost all locations between the members, the outlines of the yellow and orange regions show the silhouettes of the two comparison volumes. A viewer could use this visualization to see the shape of the reference member, to see where the reference member and each comparison member differ in attribute values, and in this case, to see the projected outlines of the comparison members' volumes.

5. RESULTS

We tested our techniques in two stages. First, we generated synthetic data with pre-defined shapes and attribute value distributions. Visualizing synthetic data allowed us to evaluate how well our techniques represent known shapes and data patterns. Next, we visualized an ensemble generated by our physics collaborators that models quark-gluon plasma flow during heavy ion collisions.

5.1 Synthetic Data

Our synthetic volumes approximate fruit shapes: an apple, a banana, and a pear. We used fruits because they come in a variety of shapes, and because they should be recognizable to most viewers. The sample points that make up each fruit volume are systematically assigned attribute values to produce a desired data distribution.

Same shape, different attribute values. Our first test ensemble contained two apple members, each with their own attribute value distribution. The first apple has large attribute values in the upper-left and low attribute values in the lower-right. The second apple reverses the distribution, with low values in the upper-left and high values in the lower-right. A small diagonal strip through the center of both apples contains low attribute values. Figures 5a–d show frames from an animation that uses the size for visibility control, while figures 5e–h use opacity for visibility control.

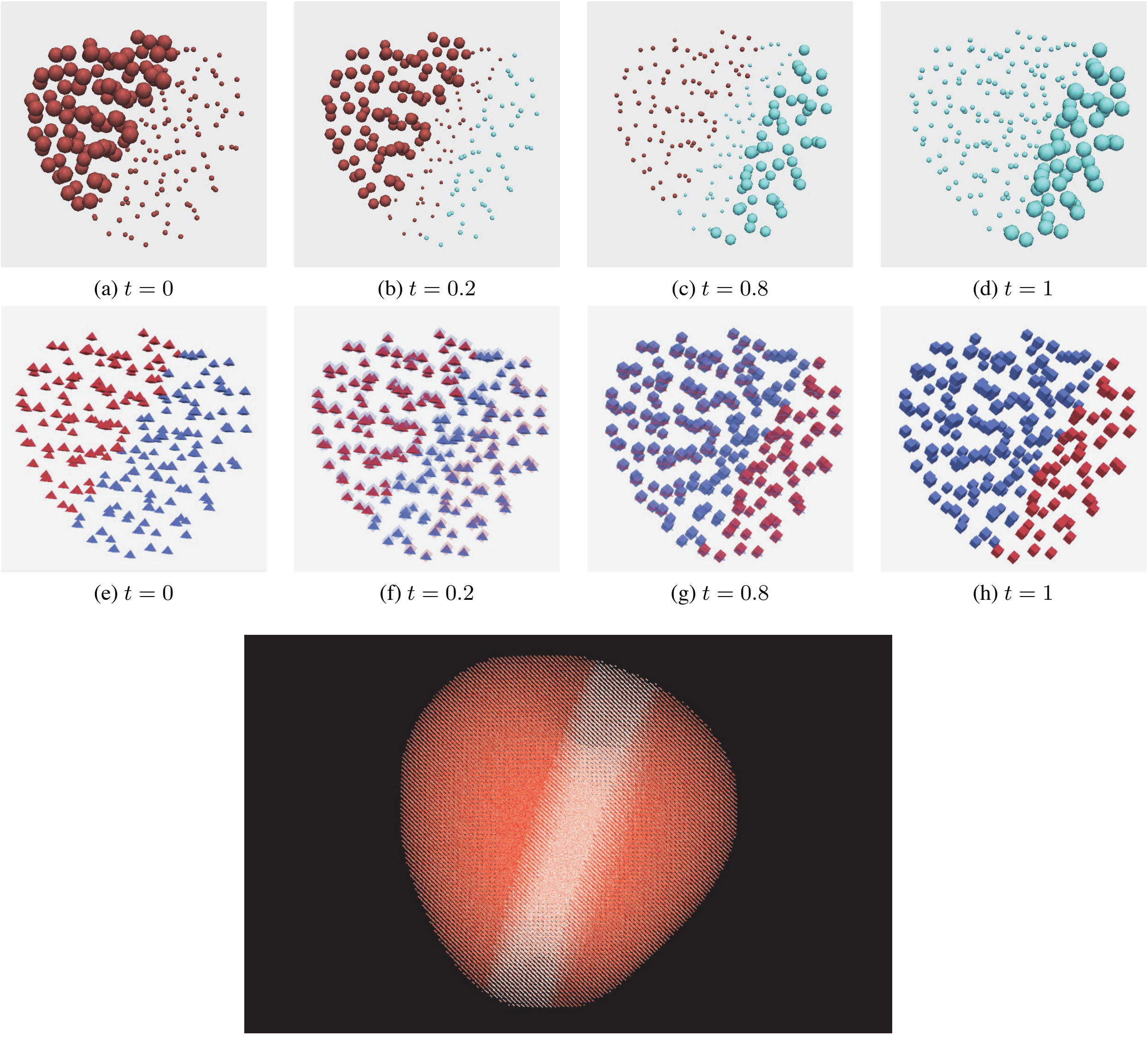
The distribution of attribute values in the two members is clearly visible as a pattern of large and small spheres in Figures 5a and 5d, and as a pattern of red and blue glyphs in Figures 5e and 5h. The diagonal strip of low attribute values in both volumes can be seen, for example, as a set of small red and small blue spheres in the same location in Figures 5b and 5c, or as overlapping blue tetrahedrons and cubes in Figures 5f and 5g.

Figure 5i shows a screen door tinting visualization of the two members, with the first apple member acting as the reference member. This image is rendered to allow gaps between the projected sample points, producing a visualization with a pointillism-like style. Since there is only one member to compare to, the visualization is equivalent to a heat map, showing high attribute value differences in red everywhere except along the diagonal strip of common values.

Different shape, same attribute values. The second test ensemble contains two members, a pear volume and an apple volume, with different shapes but the same attribute values where they overlap. The pear has medium attribute values where it overlaps with the apple, and high attribute values where its sample points are unique. The apple has medium attribute values where it overlaps with the pear, and low attribute values where its sample points are unique. Figures 6a–d use size for visibility control, and Figures 6e–h use opacity.

The differences in the members' shapes is clearly visible when each member is fully visible (e.g., Figures 6a and 6d, or Figures 6e and 6h). Both visualizations show the common attribute values in the overlap region between the members, shown as medium-sized spheres in Figure 6d, and as tan-colored spheres in Figure 6h. Using color to represent attribute values better highlights the pear's large attribute values at unique sample positions, however. This is seen as a set of red tetrahedrons in Figure 6e, versus larger spheres in Figure 6a when size represents attribute values.

Figure 6i shows a screen door tinting visualization of the two members, with the apple member acting as the reference member. As in Figure 5, there is only one member to compare to, producing a the visualization that looks like a heat map, Here, values within the overlap between the apple and the pear are identical, so the overlapping shape of the pear appears within the apple, drawn in fully unsaturated white. Parts of the apple that do not overlap the pear have no comparison sample points, and are therefore shown in grey.



(a) $t = 0$

(b) $t = 0.2$

(c) $t = 0.8$

(d) $t = 1$

(e) $t = 0$

(f) $t = 0.2$

(g) $t = 0.8$

(h) $t = 1$

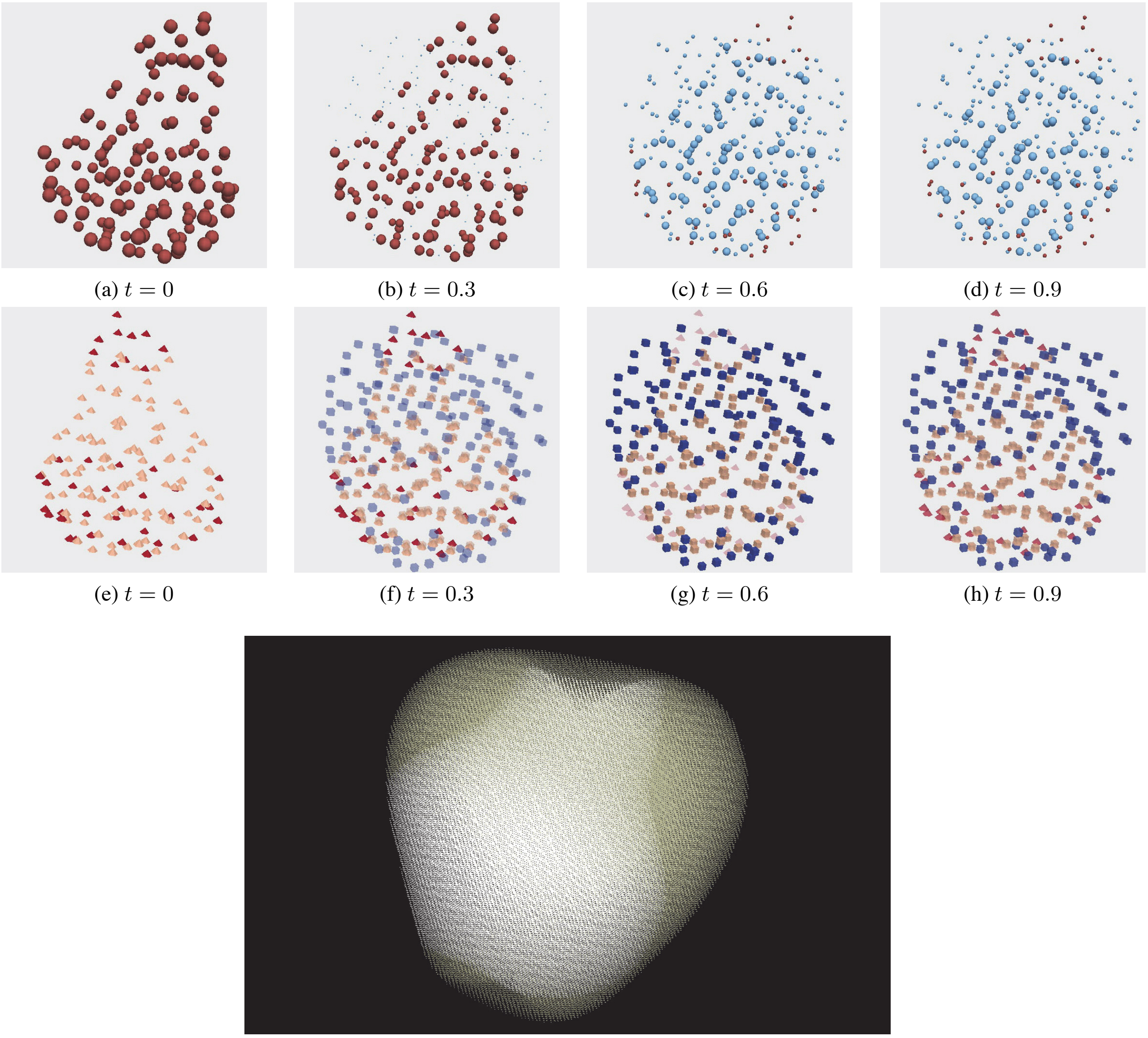
(i)

Figure 5: Two apple member volumes with different attribute value distributions: (a–d) visualized with size controlling visibility, color identifying a glyph's parent member, and size representing attribute values; (e–h) visualized with opacity controlling visibility, shape identifying a glyph's parent member, and color representing attribute values; (i) visualized using screen door tinting, differences between the two members are seen as red regions, and similarities as white regions

5.2 RHIC Ensemble

We conclude our results with visualizations of an ensemble created by our physics colleagues at Duke University. This ensemble contains four members, representing four simulation results from a hydrodynamic calculation of the quark-gluon plasma created in gold–gold collisions at the Relativistic Heavy Ion Collider (RHIC) at Brookhaven National Laboratory.[12] Figure 7a–d visualizes the surfaces of the four members, and Figure 7e–h visualizes temperatures in a vertical slice through each member. These visualizations show that the members have different shapes, and different distributions of temperature values throughout their volumes.

We started by visualizing the ensemble using the pairwise sequential animation technique with visibility controlled by size. The four members were drawn with green, yellow, red, and blue spheres, respectively, with a sphere's size



(a) $t = 0$ (b) $t = 0.3$ (c) $t = 0.6$ (d) $t = 0.9$

(e) $t = 0$ (f) $t = 0.3$ (g) $t = 0.6$ (h) $t = 0.9$

(i)

Figure 6: A pear and an apple member volumes containing common attribute values within their overlap: (a–d) visualized with size controlling visibility, color identifying a glyph's parent member, and size representing attribute values; (e–h) visualized with opacity controlling visibility, shape identifying a glyph's parent member, and color representing attribute values; (i) visualized using screen door tinting, similarities between the two members are seen as white regions, areas in the apple that do not overlap the pear are seen as grey regions

representing temperature. Figure 8 shows eight frames from the resulting animation. The following observations can be made from these frames:

- The first two members—with green and yellow spheres—have a similar volumetric shape, as seen in Figures 8a–c.
- The presence of green spheres and the absence of yellow spheres in the uppermost region of Figure 8b shows a difference between the first and second members: either the surface does not extend as high in the second member, or the temperature values in this region of the second member are very small.
- The large red spheres in Figures 8d–e show regions of high temperature values.

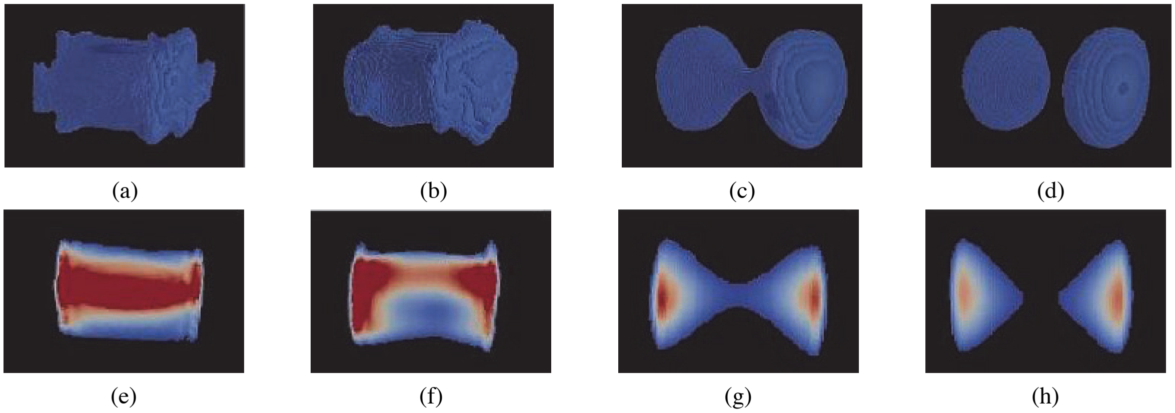


Figure 7: RHIC simulation ensemble with four members: (a–d) isosurface visualizations of the members' surfaces; (e–h) visualization of temperatures in a slice through the center of each member, blue for cold to red for hot

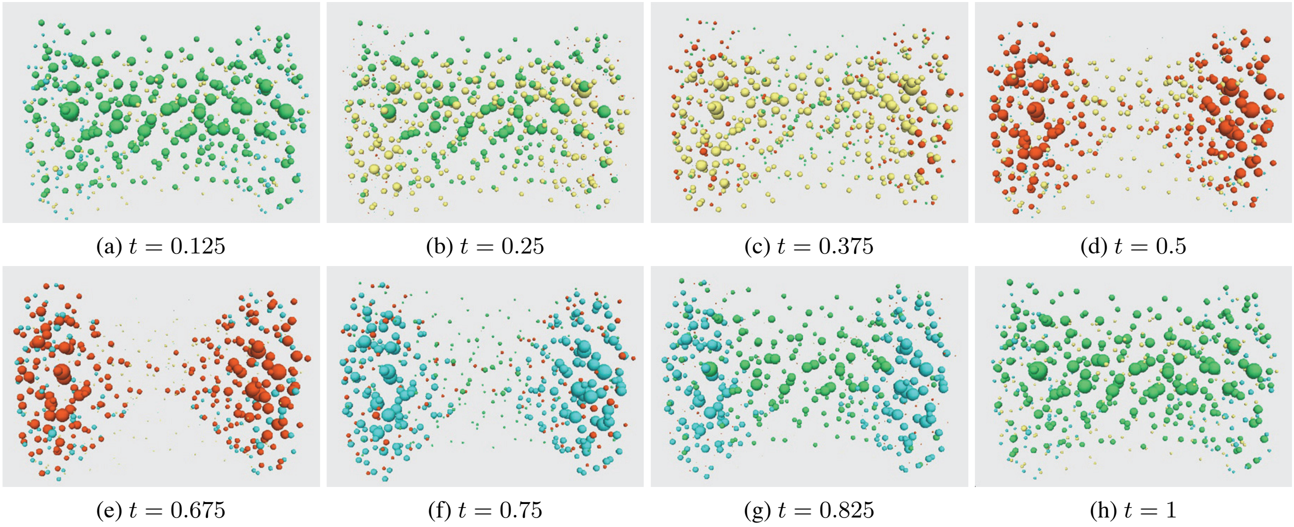
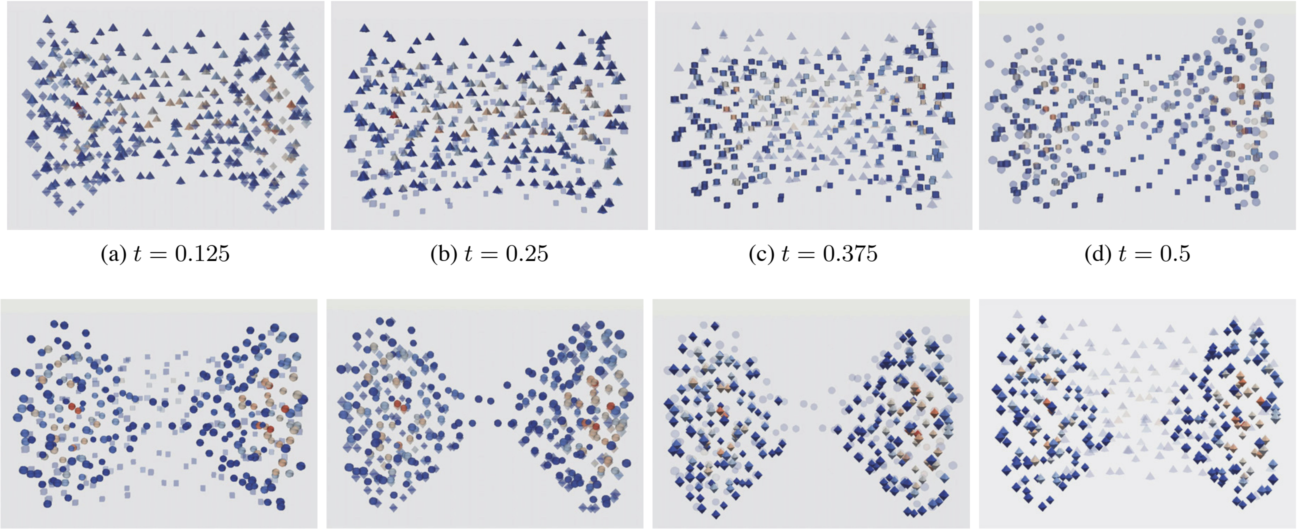

(a) $t = 0.125$
(b) $t = 0.25$
(c) $t = 0.375$
(d) $t = 0.5$
(e) $t = 0.675$
(f) $t = 0.75$
(g) $t = 0.825$
(h) $t = 1$

Figure 8: Eight frames from the RHIC ensemble, size controls visibility, color identifies a glyph's parent member, and size represents temperature values

- The distribution of large red spheres in Figure 8d gives an idea of the temperature distributions in the third member.
- The third and fourth members—with red and blue spheres—have a shape that is clearly different from the first two members, highlighted by the appearance of small green spheres in Figure 8f where no red or blue spheres exist.

Next, we switched to the pairwise sequential animation that uses opacity for visibility control. The four members are drawn with tetrahedrons, cubes, spheres, and octahedrons, respectively. Color ranges from blue for low temperatures to red for high temperatures. Figure 9 shows the same eight frames as in Figure 8. The following additional observations can be made in these frames:

- Red tetrahedrons seen in the left of Figures 9a–b highlight a small region of high temperatures in the first member.
- A shape difference between the second and third members—shown with cubes and spheres—is seen in Figure 9e, where semi-transparent cubes with no corresponding spheres highlight a narrowing in the middle of the third member.
- The narrow middle region in the third member disappears completely in the fourth member, shown in Figure 9g as semi-transparent spheres with no corresponding octahedrons.


(a) $t = 0.125$ (b) $t = 0.25$ (c) $t = 0.375$ (d) $t = 0.5$

(e) $t = 0.675$ (f) $t = 0.75$ (g) $t = 0.825$ (h) $t = 1$

Figure 9: Eight frames from the RHIC ensemble, opacity controls visibility, shape identifies a glyph's parent member, and color represents temperature values

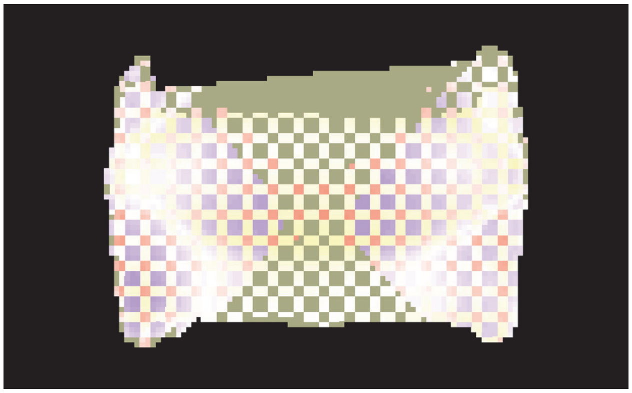


Figure 10: RHIC ensemble visualized with screen door tinting, the first member is the reference member, blue tint shows differences with the second member, green tint shows differences with the third member, and red tint shows differences with the fourth member

Finally, we used the screen door tinting algorithm to visualize all four members simultaneously. The first member acted as the reference member, with yellow, red, and blue tinting used to compare against the second, third, and fourth members, respectively. Similar volume and data attribute properties can be seen:

- The grey region at the top of the visualization shows that the base volume extends higher than any of the other volumes.
- The narrowing in the centers of the third and fourth volumes are shown as an absence of red and blue cells in the center of the visualization.
- There are regions of small temperature difference between all four members, shown as curved paths of fully unsaturated white on both the left and the right of the reference member.

6. CONCLUSIONS AND FUTURE WORK

This paper proposes two new methods for visualizing ensembles that contain numerous member datasets: a pairwise sequential animation technique that combines subsets of members using visibility control, and a screen door tinting technique that presents differences between members using screen space subdivision and saturation tinting.

We have investigated the capabilities of these approaches using both synthetic data with known attribute value patterns, and simulated data of quark-gluon plasma flow caused by heavy ion collisions in the Relativistic Heavy Ion Collider. Each technique supports comparing attribute values both within and between ensemble members.

Our techniques are still limited to comparing only a small number of members at any given time. The pairwise sequential animation technique begins to suffer when more than three members are shown. The screen door tinting algorithm can handle more members, but as the number of members increases, so too does the block size, which reduces the total number of blocks—that is, the number of comparison points—that can be shown. If blocks become too large, the underlying attribute value distributions become distorted, or lost entirely.

Future work will focus mainly on handling ensembles with larger number of members. We plan to investigate the use of mathematical or statistical approaches to reduce the number of members in an ensemble, for example, to combine subsets of highly similar members in ways that preserve only the areas of significant difference between them. We are also interested in determining intelligent ways to order the members, for example, to ensure that the subsets being visualized by the pairwise sequential animation technique present comparisons that are "most interesting" to our domain users.

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