Artistic Rendering for 3D Streamtube Visualizations: A User Study

Jian Chen, *Member*, *IEEE*, Liming Xu, Alexander P. Auchus, Guohao Zhang, Keqin Wu, *Member*, *IEEE*, Zhigeng Pan, Mingmin Zhang, James C. Lynch, and David H. Laidlaw, *Senior Member*, *IEEE*

Abstract—We investigate some consequences of choosing realistic versus stylized rendering in order to provide guidelines for visualization designers in creating tractography visualizations for diffusion magnetic resonance imaging (DMRI) studies. Artistic rendering can simulate effects similar to those of high-fidelity lighting with real-time performance through visual abstraction. We conducted a lab-based study with 12 brain scientist participants to determine whether and how rendering style affects how precisely and efficiently brain scientists can perform clinically relevant tasks. We tested three independent variables: shading (Phong, tone, and hatching), shadow (with and without), and halo (with and without). We found that the most abstract tonal shading led to the best task performance in terms of both accuracy and task completion time. However, although hatching led to the least accurate and longest task performance and halo had no impact on task performance, most brain scientists preferred these techniques. We also found that depth-dependent shadows always led to the lowest accuracy and that brain scientists, when using shadow, prefer halos to be present simultaneously. Our findings suggest that people interpret certain shapes very well from abstract shading images and that a simply shaded image can effectively depict spatial structure. Highly-rich cues from hatching do not necessarily lead to better task performance.

色调

Index Terms—Streamtube visualization, rendering style, artistic rendering, depth cues, diffusion MRI tasks.

1 Motivations

Choosing an appropriate rendering style for visualizing complex three-dimensional (3D) tube renderings computed from tensor or vector fields can be challenging. In diffusion magnetic resonance imaging (DMRI), streamtube visualization has been considered a valuable representation of the underlying physical phenomena. However, streamtubes or fiber tracts can easily become cluttered, thus impeding the identification of spatial structures and slowing user interaction. Realistic lighting effects can be useful [1] but are computationally expensive and can produce unacceptably slow interaction [2]. In recent years, powerful artistic rendering techniques have been studied that mimic realistic lighting effects [3] and sometimes fool our eyes by directly weakening or strengthening some visual cues, thus helping us perceive and understand more of our surroundings [4], [5]. However, there is little scientific evidence on whether particular artistic rendering techniques are more effective than others for complex spatial structure interpretation, especially if details are abstracted away in rendering.

论文：全局光照

Here we explore the shading continuum from abstract (tone) to rich-cue depiction (hatching); we link artistic rendering style and problem solving to investigate if mimicking visual lighting cues using abstraction can assist brain scientists in detecting and analyzing, features in complex streamtube visualizations derived from DMRI (Fig. 1). Since this is the first study to compare styled lighting effects and depth cuing for dense tube visualizations, we focus on their real-world uses in an interactive fashion so that our results will be directly applicable to selected clinical tasks. More specifically, we consider: Are there differences in accuracy and efficiency when more or less abstract artistic renderings are used compared to the classical Phong shading models? Can the rendering styles be combined with depth-augmenting cues, e.g., the most influential ones of halo and depth-dependent shadows? Does rendering style influence preferences for increasing brain scientists' confidence in their judgments? Answering these questions will have implications for combining cues in dense tube visualizations.

This paper makes several contributions. It provides evidence that brain scientists interpret these particular rendering styles differently. We provide both statistical and anecdotal evidence on the performance of several stylized rendering and depth cues that is useful in designing future visualization algorithms for brain scientists examining complex spatial structures. To our knowledge, this work is the first to use a formal approach in studying

- *J. Chen, G. Zhang and K. Wu are with the Computer Science and Electrical Engineering Department, University of Maryland Baltimore County, Baltimore, MD 21025, E-mail: {jichen, keqin, guohaozhang}@umbc.edu.*
- *L. Xu is with the Computer Science and Electrical Engineering Department, University of Maryland Baltimore County and Department of Computer Science, Zhejiang University, China, E-mail: limingxu@ umbc.edu.*
- *M. Zhang is with the Department of Computer Science, Zhejiang University, China, E-mail: zmm@cad.zju.edu.cn.*
- *Z. Pan is with the Computer Science Department, Hangzhou Normal University, Hangzhou, Zhejiang, China, E-mail: zgpan@hznu.edu.cn.*
- *A.P. Auchus is with the Neurology Department at the University of Mississippi Medical Center, Jackson, MS 39216, E-mail: aauchus@umc.edu.*
- *J.C. Lynch is with the Neurobiology and Anatomical Sciences at the University of Mississippi Medical Center, Jackson, MS 39216, E-mail: jclynch@umc.edu.*
- *D.H. Laidlaw is with the Computer Science Department, Brown University, Providence, RI 02912, E-mail: dhl@cs.brown.edu.*

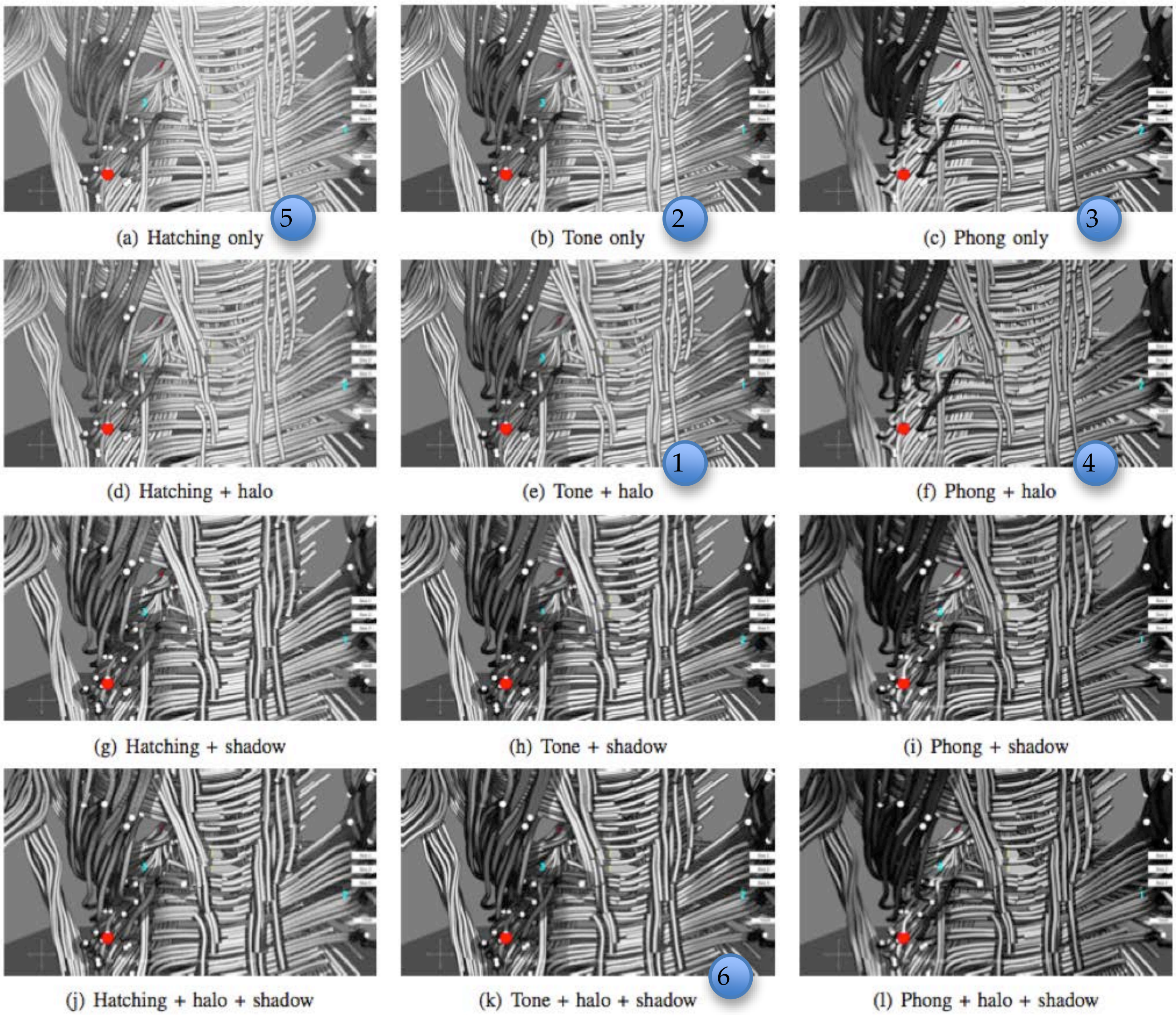


Fig. 1. Twelve renderings styles in our study: three shading (tone, hatching, Phong) × 2 halo × 2 shadow. The blue circles mark the six overall best techniques identified in the present work.

the effects of several shading techniques for complex 3D structure understanding.

2 Background and Related Work

This section first reviews diffusion MRI studies in terms of brain scientists' tasks and then examines the rendering styles used here in terms of shading, shadow, and halos. To simplify the description, we use *shading* to represent an *intrinsic shadow*, or the shadow an object makes on itself; a *shadow* is the *extrinsic shadow*, or the shadows cast between objects in a scene.

2.1 Brain DMRI Studies

Diffusion magnetic resonance imaging (DMRI) is an in-vivo MRI technique that measures water molecules in motion to reveal microscopic details of tissue architecture [6], [7]. In brain DMRI, a common way to interpret the data is to calculate a set of integral curves depicting neural fibers; these techniques are called fiber tracking or tractography [8]. Collective fibers following similar anatomical structures are clustered into fiber bundles that can depict brain connectivity, therefore providing powerful assistance in clinical diagnosis []. Because of the complexity of brain white matter, and because users often sample at many positions to avoid missing important information, the data displays easily become cluttered.

Many tensor field visualizations have improved the display of these dense datasets by: (1) decluttering by clustering fiber bundles for optimal seeding; this can effectively reduce the enormous quantity of individual fibers to a number that can be understood visually and still conveys anatomical meaning; (2) designing interaction techniques either to select regions of interest [9], [10] or to lower the dimensions from three to two through embedding to resolve fiber occlusion [11], [12]; and (3) improving the rendering algorithms. Among these techniques, only recently have powerful artistic rendering approaches such as ambient occlusion effects [13], depth-augmented halos, and photorealistic rendering allowed scientists to depict scenes with greater clarity. But the effect of these rendering styles is little understood: relatively few problem-solving studies have explored whether or not these techniques truly assist data analysis.

2.2 Shading

描绘的明暗处理（暗影）

Shading of rendering style improve interpretation

Shading (intrinsic shadow) is the shadows cast on the object itself. The quality of shading depends to a high degree on accurate modeling of the light interacting with the objects in a scene. For example, global illumination algorithms can render many visual effects to produce realistic visualizations [1]. Zockler designed illuminated lines through texture mapping to replicate specular highlights and thus produce regions of high image intensity to enhance the shapes of a group of lines [14]. Ambient occlusion, which estimates the ambient light distribution in a complex scene to imitate the radiance of light on non-reflective surfaces, not only can increase visual realism but also can augment depth cues [4] and structure from shadows [5] for better structural depiction.

Interestingly and perhaps most relevant to our study, some lighting effects can also be simulated by artistic rendering. First, to depict the cue effect from lighting, Praun et al. used texture-mapping techniques to create hatching that simulates shading and specular highlights [15]. Second, artistic rendering can abstract away unimportant visual features to make information easier to understand [16]. For example, tone shading maps intensity to color; techniques can mimick multi-layer painting techniques can show multivariate tensor attributes [17]. Third, artistic rendering can also be used to emphasize cues. Halos are enhanced to augment depth perception and shadows are added to lines to reduce the occlusion [18]. Interrante and Grosch designed transparent surfaces, textures, and halos to convey shapes [19]. All these techniques, while powerful, may require significant interpretation by viewers [20]. Evaluating these various rendering styles will help visual designers pick the representations that are most intuitively understood under various task conditions.

Perception
相关

While past research on realistic lighting and artistic cue rendering has significantly advanced rendering methods and algorithms for depicting complex tensor fields, empirical studies of 3D dense line- or tube-based visualizations have only began to address visual encoding [18] and display issues [21]. Artistic rendering styles are evaluated mostly in computer graphics and psychophysics domains and remain rare in visualization studies.

Previous work in psychophysics has shown that different regions of the brain are activated when presented with real and virtual stimuli, suggesting that realistic and artistic renderings could differ significantly. Grishick et al. suggested that line direction matters and recommended the use of principal line orientation in designing spatial structures [22]. McDonnel et al. compared 12 techniques and found that observers preferred abstract avatars of self-portraits in graphical renderings [23], and Perani et al. observed that the level of realism had only a limited effect in a positron emission tomography scan study where participants viewed sequences of a real hand, a realistic virtual reproduction, and a low-quality virtual hand [24]. Han et al. measured brain activity using functional magnetic resonance imaging while participants viewed cartoons or live action movies and found more diverse brain activity when interacting with real people than with artificial or cartoon characters [25]. These results suggest that we might expect very different performance when comparing rendering style from either lighting or cues and from cues at different levels of abstraction.

Rendering style has been a core study in computer graphics. It is suggested that high-quality lighting is important for judging whether an image is real [26] but less important in rendering an animated character [23]. Isenberg et al. used questionnaires to evaluate aesthetic issues related to non-photorealistic rendering [27]. Bousseau studied gloss painterly techniques for material perception and found that shiny materials appear more diffuse and diffuse materials appear shinier in cartoon images [28]. Most work in graphics on these issues has studied perception, while we study problem solving in interactive visualization. The present study attempts to understand the effects of rendering style on complex brain streamtube visualizations that demand precise interpretation.

2.3 Shadows

阴影（光照产生的深度信息）

Shadows improve depth-perception and spatial structure

Shadows (extrinsic shadows) are those shadows cast on one object by another, and provide particularly salient cues on relative position, such as depth, distance, and orientations of objects. Often only global illumination produces (extrinsic) shadows between tubes [1]. It is generally agreed that shadows increase reported task accuracy [29]. For example, Thompson et al. studied how shadows affect depth perception and found that shadows "glue" objects to the surfaces they touch and hence improve spatial structure understanding [30]. Hubona et al. found that the effects of shadow were task-dependent: shadows enhanced only the accuracy, not the speed, of object positioning, and they had no effect on object resizing tasks [31]. Shadows can also be subtle enough to distort the perception of 3D shapes [24]. Penny et al. observed the benefits of shadows only for tumor detection tasks where the tubes and fibers were close to each other and did not observe its benefit for global structure understanding [2], which also stated in Ware [32].

In this study, we are more interested in a second approach to using shadow: we assume that viewers can rapidly discriminate and act upon artistic rendering in data elicited by shadows. Ritter et al. made explicit depictions of the distances between parts in vascular structures to create numerous hatching strokes as well as distance-encoded shadows to enhance depth perception, enabling viewers reliably to compare small depth distances [5]. The distances assist the judgment of distance in 3D space in a way similar to the effects of color bleeding in global illumination [1]; without rotating the data, viewers might be able to judge the spatial distance precisely. Inspired by Ritter et al.'s work, we study these depth-dependent shadows and their contributions to spatial structure understanding.

2.4 Halos

adding halos improves visualization?

Halos are frequently employed by artists to enhance depth perception, especially occlusion information, by darkening or brightening the area around the edges of objects. In real-world applications, people usually exploit halos by suitably placing lights, like rim light, to emphasize objects by separating them from the background. More flexible and targeted halos can be generated in computer graphics. Everts et al. introduce depth-dependent halos on dense lines that emphasize tight line bundles and increase depth perception by relating depth cues to halo width [4]. Halos have also been used in numerous volume rendering studies to augment depth [19] and show properties of the original data [33]. Wenger et al. designed a transfer function to add halos in volume renderings of brain datasets [34]. Inspired by these designs, our purpose here is to study whether or not adding halos significantly improves doctors' problem-solving skills in complex DMRI tractography visualizations.

3 Experimental Method

Our work focuses on two factors largely unexplored in complex 3D streamtube visualization. The first is shading methods, specifically Phong, tone, and hatching techniques. The second is depth-augmentation techniques such as halo and depth-dependent shadow effects. We adopted a within-participant design with 12 participants using a 3 (rendering techniques) × 2 (halo) × 2 (depth-dependent shadow) design. Each participant is assigned three tasks and two data types (whole-brain dataset and regions of interest only), leading to three independent variables: rendering technique (Phong shading, tone shading, and hatching), halo (with and without), and shadow (with and without). Figure 1 gives a side-by-side view of the rendering effects exemplified using tone shading.

3.1 Hypotheses

Our three general hypotheses arose from discussions with three brain scientists and from the visualization literature described above:

- More abstract artistic representations such as tone shading will generally produce the best outcome because they abstract away unimportant cues; however, brain scientists may prefer hatching as it is more visually striking;
- Depth-dependent shadows could improve task performance by reducing task completion time and increasing accuracy;
- Halo could lead to better task performance; however, brain scientists may not like it because it increases the clutter of the dense tubes.

3.1 Rendering Style

3.1.1 Choice of Rendering Style

The rendering styles and depth cues have been chosen using three criteria: actual uses in real-world applications, novelty, and the abstract representation they embody. For the last criterion, we want to choose visually different techniques with diverse cues. The artistic rendering techniques are chosen based on one more criterion: the algorithm must be able to generate *time-coherent* and *spatially coherent* strokes and tones that can be interactively changed with viewpoint [15]. Finally, we weight the three criteria based on discussions with two brain scientists.

Artistic rendering

We have carefully chosen and implemented three techniques. We used tone shading and hatching because tone shading abstracts away detailed lighting conditions and uses colors only to represent spatial cues from lighting, while hatching produces relatively high-quality replication of cues produced from real lighting conditions, such as specular highlights and both principal and secondary primary directions given they convey shapes differently [35]. When rendering Phong shading, we carefully adjusted the parameters in the lighting equations. For example, specular highlights are believed to provide powerful sources of information for 3D shape that differ from texture in terms of cues projected in human eyes, since specular highlights follow the principal directions and textures follow the secondary primary directions [36]. We choose halos because of their pervasive nature and high citation counts, and depth-dependent shadow mainly because of its novelty. We also visually measured and compared each technique to select the visual effects used. We carefully tuned the light placement to achieve good visualizations that brain scientists were happy with, using a three-point light scheme in the scene. This lighting scheme is subsequently used in all other renderings.

3.1.2 Tone shading

Tone shading extends the Lambertian shading model by using the computed illumination (dot product of a light vector and the object surface normal) to index into a one-dimensional (1D) texture that describes how the final shading varies from dark to light regions. The techniques can be used to place a bright cast on surfaces facing the light and a dark cast on surfaces not facing the light, generating effects suggestive of illumination by a light source.

To meet the spatial- and temporal-coherence criteria, our view-dependent tone shading mapped the luminance values onto four orders of magnitude, as shown in Fig. 2. It is implemented efficiently via vertex and fragment shaders to preserve lighting effects. The human visual system is capable of perceiving scenes spanning five orders of magnitude, and adapting more gradually to over nine orders of magnitude. We used four levels because experimentally they provide sufficient abstraction. First, visibility is reproduced to clearly show the spatial relationships and the overall brightness, contract, and colors are easy to see. Our tone shading produces sharp boundaries between dark and light regions. Second, viewing the visualization abstracts away some details that correlate well with the Phong shading model. Here shades and highlights appeared like blocks of color, rather than mixed, in a smooth way similar to cartoon renderings.

亮度

four levels of luminance values

Only grayscale tone is used to depict shading, so as to avoid confounding factors from colors. Our brain scientist collaborators also did not like the popular cold-warm (blue-

Toonshading Lake等人和Lander同时提出了一种方法:首先计算每一个顶点的漫反射项着色点乘N#L(N法线向量,L光照向量),然后将计算结果作为纹理坐标来访问一维纹理图。由于纹理图像本身只包含两种明暗效果,即:亮与暗。因此当N#L >0 时,表面朝向光源,只需要读取纹理中比较亮的着色部分。当N#L <0,可以断定物体表面背向光源,处于阴影中,则读取纹理中较暗的部分。
还有一种是Gooch等人的2-toon shading

orange) tone shadings and thought they looked fake, a response that reduced their trust in the data, despite its higher contrast.

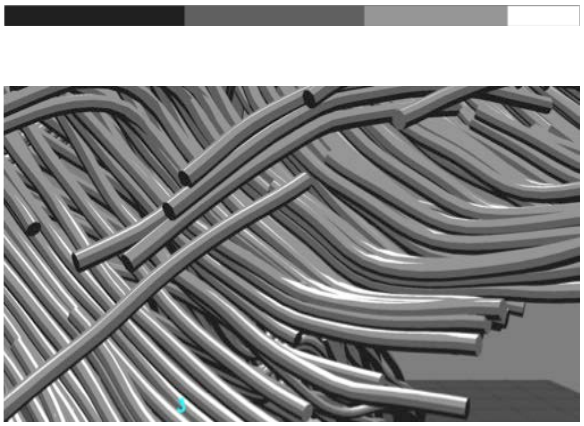


Fig. 2. Tone shading texture map and shading result.

3.1.3 Hatching

Fig. 3 shows the tonal art map (TAM) used to produce the hatching in Fig. 4, adapted from the algorithm in Praun et al. The hatching can simultaneously convey lighting, suggest material properties, and reveal tube shape by multitexture blending of the hatch images over the rendered faces to maintain spatial, temporal, and tone coherence. The tone, lighting effects, and temporal coherence are simulated by updating the underlying hatching strokes and can be implemented simply by texture mapping that is independent of the geometric space. The advantage of this method is that we need not compute the curvature to obtain the direction of the hatching lines.

We did find that our thin-tube geometries affect the choice of TAM that defined a mipmap image set containing a set of pre-rendered hatch strokes corresponding to different tones (Fig. 3). ~~Praun et al.'s implementation suggested a 4 × 6 mipmap [15]~~. We used a 1 × 6 mipmap only and found adding other levels introduced salt-and-pepper-type image noise. The 1 × 6 mipmap creates the most visually satisfying effects for our thin tubes. Tone continuity is implemented by nesting properties, i.e., strokes in lighter images are subsets of those in darker ones.

We further used smooth transitions of a six-way blending scheme to ensure the coherence rules. The darker texture in the darker areas was assigned the crossing texture (Fig. 3 second row), similar to the methods used by artists. We aligned the stroke direction to the secondary principal curvature directions to reveal the spatial geometry structures.

3.2 Distance-Dependent Shadows

Fig. 1(j)-(l) show the shadows from our implementation that represent the distances between two tubes: the closer the tubes, the smaller the shadow between them. We implemented a distance-dependent shadow algorithm similar to that used in Ritter et al. [5] to show small distances between vascular structures. One implementation challenge is that the DMRI streamtubes are much denser than the vascular structure in Ritter et al.'s work, despite their

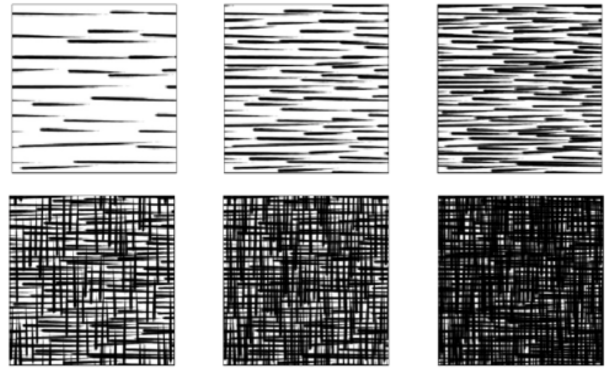


Fig. 3. The tonal art map: strokes in the left or top image appear in all the images to its right or bottom.

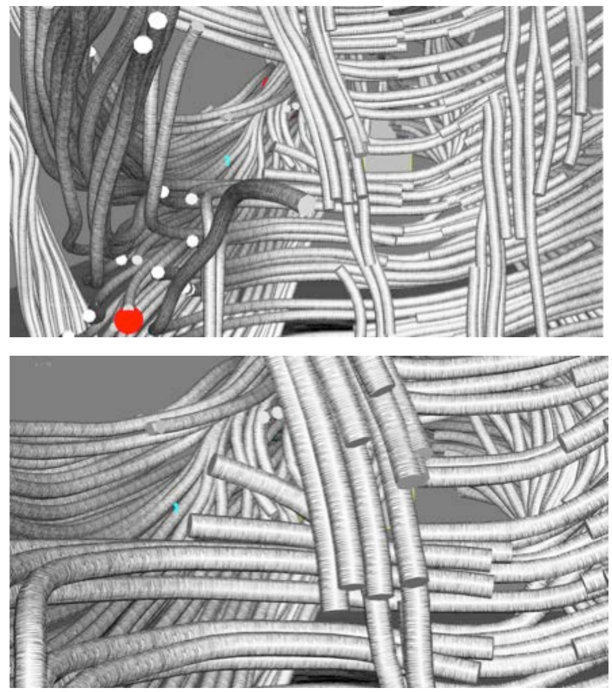


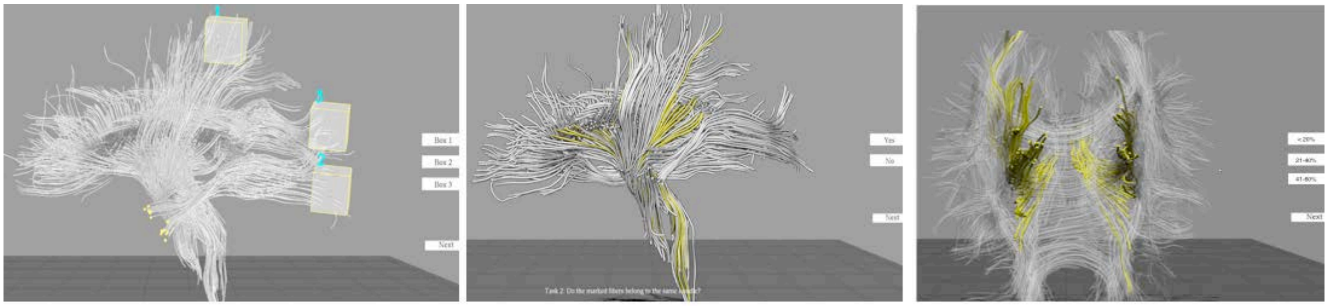
Fig. 4. Hatching result.

spatial similarity. Therefore, we expanded Ritter's line algorithms to depict the shadows because the tubes are densely distributed and parallel lines would produce many shadows and thus increase the occlusion in the scene. We therefore used the depth-dependent halo approach in Everts et al. [4] because the result resembled halos in adding darker lines to the regions when two lines overlap. The first step is to paint twice to generate a depth-difference map drawing of the object at the correct depth; the second step is to draw an enlarged object along the normal direction.

To estimate the distances between maps, we take Ritter et al.'s approach using the equation

$$D = (D_m ax + 1)^{(T+\delta)/T_m ax} - 1,$$

where T_{max} is the maximum shadow width or the maximum scale of the object, D_{max} is the maximum distance between tubes, and δ is the shadow step size. We use $T + \delta$ to scale the shadow width to a suitable distance between tubes, because there are N different kinds of depth-difference maps, and every map must have a different T.



(a) Tracing **(b) SameBundle** **(c) SizeComp**

Fig. 5. Three example tasks used in our study.

When rendering the images, we first render the tubes and subtract the value from the maximum T values in all depth-difference maps to calculate the possible depth distance. Based on this distance, we redraw the shadow areas and add texture and transparency to the shadows in such a way that the wider the shadow or the further away the two tubes, the greater the transparency.

3.3 Halos

Algorithms for depicting halos vary. Because our dataset is dense, adding halos could introduce occlusion or interfere with the depth-dependent shadows described above. We used a simple implementation to first draw the halos and then turn off the backface culling so as to render the backfaces.

3.4 Tasks

Chen et al. provide a detailed discussion of brain scientists' workflow and lay out seven task types that can be used as benchmarks for rendering techniques [21]: (1) certain numerical measurement metrics, (2) spatial relationships of fiber bundles (e.g., for resolving brain connectivity), (3) pathological condition search and manipulation (e.g., is there a lesion? How can fibers be cut to remove a tumor?), (4) comparisons (e.g., how different are two bundle volumes in two hemispheres? Are two brain tractographies the same? Are they normal?), (5) categorical (e.g., to which anatomical structure does a bundle belong?), (6) tube tracking (e.g., where does a tube bundle go?), and (7) understanding of functional or structural images. Among the seven task types, we chose three related to spatial structure understanding, based on discussions with and suggestions from brain scientists.

Fig. 5(a) (*Tracing*) shows a sample interface for the fiber-tracing task in the DMRI streamtube visualizations; the yellow spheres mark the starting points and the three boxes show possible ending positions. Participants were asked to find the box in which the ending points lay. They were told that the marked fibers belonging to the same bundle followed the same orientation; they were also told that the three boxes were placed at the end of bundles, each belonging to one of the three anatomical orientations (anterior-posterior, dorsal-ventral, and left-right), and that no two enclosed the bundles on the same orientation. For example, box 1 in Fig. 5(a) covers cranial-caudal fibers, box 2 (the correct answer) encloses anterior to posterior fibers, and box 3 is at the end of the only inter-hemispheric fibers.

Fig. 5(b) (*SameBundle*) shows an example of task 2, in which participants were asked whether the fibers in yellow all belonged to the same bundle. 50% of the data were in the same bundle and 50% were not. The choice of distracting fibers was based on fiber orientations; often fibers from the closest perpendicular bundles were selected. The example in Fig. 5(b) includes the highlighted fibers that belong to the same bundle, with a set from the CST (corticospinal tract, cranial-caudal oriented). In the not-the-same-bundle condition, we would add noisy fibers from the CC (corpus callosum, inter-hemispheric) bundles and ask the participants to make a judgment.

Fig. 5 (c) (*SizeComp*) illustrates the situation where participants were asked to judge if two highlighted fiber bundles have about the same numbers of fibers and, if they differ, by how much. All tubes except for two fiber bundles were rendered transparently, and participants were ask to compare how different the sizes of the two fiber bundles were. Three choices were provided to the participants: similar (<20%), 20-40%, and 41-60% differences.

All tasks have either right or wrong answers and there is only one correct answer for each question. Participants must make a choice before moving on to the next task.

3.5 Diffusion MRI Datasets

When choosing the density, we follow a previous study in which optimal sampling density is measured rather than sampled at every voxel in the brain. We sample at every other voxel in each dimension by following the optimal $2 \times 2 \times 2$ sampling rates that sample at every other voxel in each direction [37]. Tractography data were computed from the source MRI images captured from a normal human brain at resolution $0.9375 \times 0.9375 \times 4.52$ mm^3. Diffusion tensors of each seeding resolution are calculated with tricubic B-spline interpolation and then fiber tracts are approximated using the second-order Runge-Kutta solver.

Not only the number of tubes but also the size of the fibers affect the angular legibility. In the Chen et al. study [21], the tube radius was 0.2 mm, generating relatively thin tubes that could successfully convey both the orientation cues without necessarily cluttering the scene. In this study, we doubled the tube size to 0.4 mm. Otherwise the hatches would be too subtle to be noticeable, which is an inherent characteristic of the hatching algorithm. Our study used the same radius in all rendering styles to avoid confounding factors.

We further reused the datasets from the previous study in Chen et al. [21] because those data were carefully chosen by computer scientists and brain scientists, and also reflect the complexity of the scientists' data analysis workflow. In the first step, the initial global examination of the data, the full brain is examined, since this can facilitate the identification of related measurement metrics that can provide robust markers of white-matter structural integrity [9]. The second step is a deeper analysis in which some fiber tracts are removed from the whole brain in such a way that some contexts are preserved. This partial brain study is an intermediate data-exploration stage in which users remove some irrelevant blocking fibers and focus on the study at hand before approaching the region of interest (ROI). The final step is to investigate a certain ROI that is associated with task-relevant bundles, so as to make a more precise pathological assessment without visual occlusion after the surrounding fibers are sufficiently understood. With this workflow, we used fibers from the half-hemispherical partial volume to reduce the complexity of the full volume while preserving some context information.

3.6 Experimental Design

3.6.1 Participants

Twelve participants (nine medical residents and three medical doctors) in the Neurology Department at the University of Mississippi Medical Center volunteered for the study. We chose this expert group because we observed in a pilot study the significant main impact of expertise on both task accuracy and timing. We thus recruited only neuroscientists in the formal study to avoid the confounding factor of participant expertise. All participants had normal or corrected-to-normal vision.

3.6.2 Design and Interaction

We used a within-participant design by an orthogonal Latin square, with each participant examining all three rendering styles, two halos, and two depth-dependent shadow conditions. We prepared four data groups adopted from Chen et al. [21] in order to cover different anatomical structures of the brain: CC (inter-hemispheric fibers), CST (cranial-caudal oriented), ILF (interior longitudinal occipitotemporal fasciculus, anterior to posterior), and IFO (inferior frontal-occipital fasciculus, anterior to posterior to lateral). Two neurologists confirmed the clinical validity of these data and visualization conditions.

All tasks allowed participants to rotate the data by left-mouse dragging and to zoom in and out using the z button on the keyboard or right-mouse dragging. Allowing the participant to interact with the data can activate motion or binocular disparity, which significantly improved participants' accuracy in our previous studies [2]. Participants were shown the total number of tasks in the session and the number completed so far on the upper-left corner of the screen. The accuracy achieved in each task is defined by the percentage of correct answers. Task completion time and all actions such as rotation and zooming are recorded. The experiment was conducted in a lighted room. All images were rendered on a 24-inch LCD display at 1600 × 1050 resolution.

In summary, our experiment had twelve participants, three shading techniques, two halo conditions, two distance-dependent shadows, two levels of data complexity, and three tasks, for a total of 864 data points.

3.6.3 Experimental Procedure

Upon arrival, participants filled in a background survey form and then read and listened to an experiment manual with detailed instructions on the DMRI data-capture technique, the three task conditions, the visualization techniques, and the procedures. Participants were told that all tasks were related to the four fiber bundles only and were given detailed descriptions of the fiber shapes. They were also instructed to interact with the datasets.

Each participant worked through all three tasks (fiber tracing, same bundle, similarity comparison in order) in a practice session. During training, answers were given and the wrong answers were explained to ensure they understand each condition fully. A formal measure was performed right after the training session and participants were allowed to take a break between two runs. They were free to stop the experiment. Finally, they completed a post-experiment questionnaire containing seven-point Likert scales about their levels of preference and perceived usefulness of each rendering conditions. Participants were interviewed for comments relevant to their experiences. The experiment lasted about 1.5 hours.

4 Results and Analysis

We collected 864 data points with 12 participants while performing three tasks using two datasets, three shading techniques, and with and without halo and shadow conditions. Before conducting a statistical analysis, we used a quantile-quantile plot (QQ plot), a graphical method, to test normality. We removed outliers if they lay more than three standard deviations of the mean in each experimental condition. Overall, we removed 10 outliers from the 864 samples. All error bars in all graphs in this result section represent one standard error from the mean.

We first evaluated the overall main effects by performing two types of factorial analyses: four-way (shading, halo, shadow, and task) and two-way (rendering and task). We called the combined shading, halo, and shadow conditions "rendering", and examining this factor allowed us to understand individual rendering techniques. We then performed the Tukey post-hoc analysis on the cues and rendering techniques when there was significant main effect. Table 1 summarizes overall performance measurement results and test statistics and Table 2 and Fig. 6 illustrate the performance by tasks. We omit the F and p values in the main text if the values appear in the figures or tables.

Table 1. Main Effect of Shading, Halo, Shadow, and Their Combinations (Rendering Style) on Accuracy and Task Completion Time (">" means *significantly better than*).

	Accuracy	Task time
Shading	***F(2, 563)=4.22*** ***p=0.0152*** tone > hatching	F(2, 563)=0.31 p=0.74
Halo	F(1, 564)=0.38 p=0.563	F(1, 564)=0.05 p=0.82
Shadow	***F(1, 564)=10.55*** ***p=0.001*** without > with	**F(1, 564)=6.01** **p=0.015** without > with
Task	***F(1, 564)=41.4*** ***p<0.001***	***F(1, 564)=111.8*** ***p<0.001***
Rendering	***F(11,842)=2.2*** ***p=0.013***	F(11, 842)=1.66 p=0.077

4.1 Performance Summary

The top six visualization choices that led to the most accurate answers are marked in Fig. 1. Table 1 shows the main effect on **accuracy** and **task completion time**. For the accuracy we observed significant main effect of shading approaches (tone is better than Phong, which is better than hatching) and shadow (mean = 54% vs. 66% with and without shadow), with no-shadow being significantly more accurate. *Halo* was not a significant main effect, though with-halo produced slightly more accurate answers (mean = 61% vs. 59% with and without halo). The only significant two-way interaction is between halo and shadow (F = 4.8, p = 0.03). No other two-way or three-way interactions are significant, suggesting that the overall effect of the renderings on accuracy was consistent across tasks. A posthoc analysis using Tukey's Studentized Range (HSD) test revealed that the significant difference was caused by the differences in mean between hatching and tone shading, which produced the least and the most accurate answers accordingly (difference between means 0.11, with 95% confidence interval of [0.003, 0.21]).

Accuracy

For the task completion time, *shadow* is again the significant main effect and without-shadow is more efficient than shadow. Not surprisingly, *task* is a significant main effect, suggesting that the tasks are very different. The following analyses are performed by tasks.

Completion time

4.2 Performance by Task

4.2.1 Accuracy

We first examined for which tasks we could observe the significant main effect of shadow on accuracy and task completion time. Because the application domain is neurology, we are more interested in accuracy than task completion time. Table 2 shows the F and p values and Fig. 6 shows the values of the accuracy and task completion time; significant main effects are shown in purple boxes.

We observed that tone shading led to the most accurate answer, followed by *Phong* and then *hatching*. For the Tracing tasks, this shading effect was significant. Posthoc analysis revealed that the difference arose from tone and hatching. The low accuracy in the *SizeComp* suggested that, as in the two-dimensional reading tasks, people have trouble comparing numbers. This would suggest that in many medical-imaging visualization techniques where brain scientists must interpret numerosity, it is better to show the numbers by other means than to count on human visual perception to make the judgment. Interestingly, we observed the same trend in all tasks, even when participants were guessing when performing the *SizeComp* tasks.

We did not observe any significant main effect of halo. The lack of statistical differences is perhaps due to the small sample size (12 participants), especially for the *Tracing* tasks (Fig. 6a). Shadow had significant impact on task completion time and accuracy of *all three tasks*, with no shadow leading to most accurate answers. Therefore, our third hypothesis was not supported, suggesting that brain scientists had trouble interpreting the depth-encoded shadows.

Table 2. Main Effect of Shading, Halo, Shadow, and Their Combinations (Rendering Style) on Accuracy and Task Completion Time by Tasks.

	Tracing	SameBundle	SizeComp
Accuracy			
Shading	**F(2,277)=3.0** **p=0.049**	F(2, 283)=2.0 p=0.14	F(2, 285)=0.3 p=0.76
Halo	F(1,278)=1.5 p=0.22	F(1, 284)=0.4 p=0.55	F(1, 286)=0.4 P=0.54
Shadow	**F(1,278)=7.4** **p=0.006**	**F(1, 284)=3.8** **p=0.049**	**F(1, 286)=4.3** **p=0.038**
Rendering	F(11,268)=1.7 p=0.077	F(11,274)=1.8 p=0.057	F(11,276)=1.4 p=0.20
Task Completion Time			
Shading	F(2,277)=0.4 P=0.71	**F(2, 283)=4.7** **p=0.01** tone > hatching	F(2, 285)=0.3 p=0.76
Halo	F(1,278)=0.00 4 p=0.95	F(1, 284)=0.1 p=0.72	F(1, 286)=0.2 p=0.64
Shadow	**F(1,278)=3.9** **p=0.04**	**F(1,284)=4.2** **p=0.04**	**F(1, 286)=4.2** **p=0.04**
Rendering	F(11,268)=1.3 p=0.2	**F(11,274)=2.5** **p=0.004**	F(11,276)=1.3 p=0.24

4.2.2 Task Completion Time

We observed significant main effect of *shading* for the *SameBundle* tasks, and again *tone* shading was significantly faster than *hatching*. However, this result must be interpreted carefully, because *hatching* generally slowed down the frame rate though the program could run in real time; also, among the three tasks, the *SameBundle* task could require the most interaction in order to detect the bundle identity. Shadows again had significant effect on time for all three tasks, and no shadow was better than the shadow conditions. When considering all techniques together as a rendering style, we observed significant effect in the *SameBundle* task.

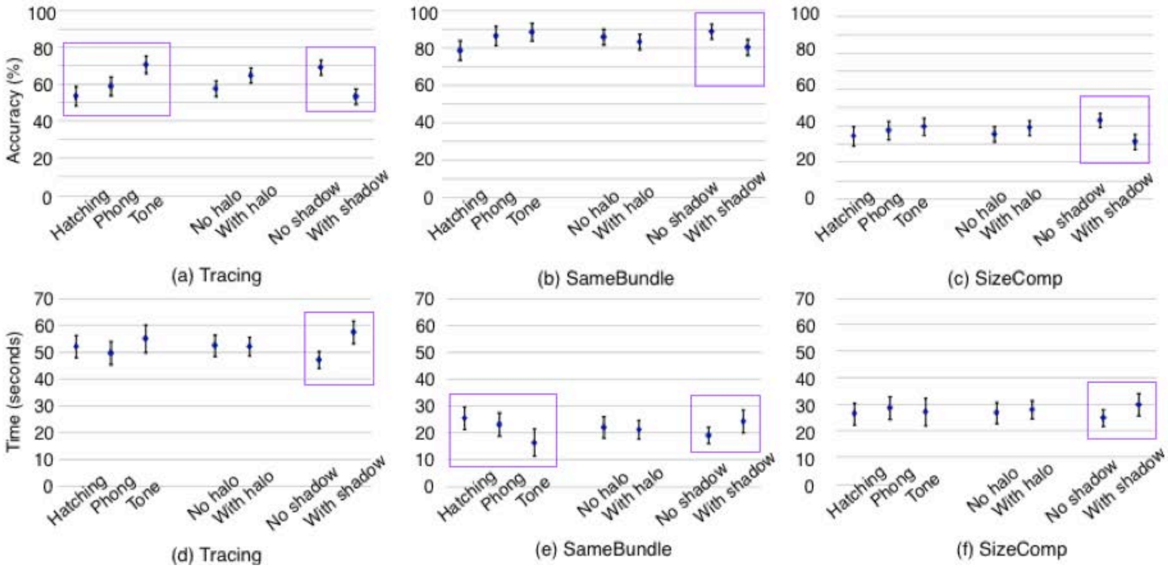


Fig. 6. Accuracy and task completion time by tasks.

4.2.3 Correlation Analysis

A correlation analysis of accuracy and task completion time supports a statistically significant negative correlation: the longer participants took to perform the task, the more accurate their answers were ($p=-0.05$, $r=0.38$). Task completion time and accuracy had no correlation with the shading, halo, or shadow effects.

4.3 Subjective Ratings and Comments

We collected subjective self-evaluation data using a post-questionnaire asking about the effectiveness (a method's ability to meet requirements) for the three cueing conditions (shading, halo, and shadow) on a scale of 1 to 7, with 1 the worst and 7 the best. Participants were given the pictures to ensure there was no ambiguity or misunderstanding. Because the participants are medical professionals, we are especially interested in their preferences. To our surprise, of all the depth cues, participants liked the halo and shadow combination the most.

Among the three shading methods of Phong, hatching, and tone, again to our surprise, hatching had the highest average score, with two participants giving it a full score of 7. These two participants also suggested that hatching helped in assessing similarity, could clearly delineate fibers or group them together, and was easier to follow. When asked about their choice of halos, 11 of the 12 participants selected with-halo.

The preferences on shadow were divided: participants either liked it or disliked it. Half of the participants gave higher ratings to the shadowed than without-shadow conditions. Those who liked shadows commented that shadow was especially useful to help identify the hidden fibers and determine the depth and structures in the data. Those who dislike shadows felt that adding shadow made the tubes and the shadows blend together so that the real data became hard to perceive. Four participants suggested that they could appreciate shadows only when halos are present as well. One participant suggested rendering lighter shadows. We noticed the drawback of using black shadows when we designed the techniques and used gray color instead to reduce the dramatic color changes. This result may suggest that any "unnatural" cues can make interpretation difficult. One participant also pointed out that adding more cues would slow down interaction, especially with complex scenes of hatching and shadow. This participant preferred any techniques that would facilitate interaction.

5 DISCUSSION

Our expectations were that (1) the *tone* would outperform the *hatching* and *Phong* shading, since it assembles necessary visual cues for our experimental tasks, but that brain scientists would prefer *hatching* due to its expressiveness, (2) *shadows* could improve task performance, and (3) *halo* could improve task performance but may not be preferred by brain scientists. Our data did not fully confirm these expectations. The first hypothesis was supported: that tone generally led to the best performance and *hatching* would be preferred. The second and the third hypotheses were not supported. *Shadow* improved neither accuracy nor task completion time. Brain scientists had mixed feelings about *shadows*. They overwhelmingly preferred *halo*, though we saw no significant performance gain.

5.1 Cuing Differences

We found that *hatching* was the least and *tone* the most accurate shading approach for all tasks. This effect on accuracy was significant only in *Tracing*, not in *SameBundle* and *SizeComp*. The effect on time was significant only for *SameBundle*, but not for the *Tracing* and *SizeComp* tasks. Note that the *Tracing* tasks are structural, requiring participants to interpret the spatial structure of the fiber tracts, while the *SameBundle* tasks are more categorical, requiring participants to recognize the tracts. This result may suggest that the *tone* shading, at least in our implementation, would provide sufficient cues for interpreting the spatial structures because it generates sharper colors so that edges are easier to perceive.

The three shading techniques of *tone*, *Phong*, and *hatching* differ in their representation of the following cues: (1) specular highlights (perceived brightness associated with the specular reflection from a surface), (2) contrast (perceived relative brightness of specularly and diffusely reflecting areas), (3) distinctness of visualization (perceived sharpness of images reflected on a surface), (4) sheen (perceived shininess at grazing angles in otherwise matte surfaces), and (5) absence-of-texture gloss (perceived surface smoothness and uniformity). All three techniques can produce about the same specular highlight.

Tone shading abstracts away details and seems to be able to produces images of higher contrast and distinctness and even of greater surface uniformity. The *hatching* model, on the other hand, produces much richer cues; based on traditional artistic practice, the lighting model uses both luminance and changes in hue to indicate surface orientation, reserving extreme lights and darks for edge lines and highlights. Perhaps for the tasks we studied, these richer cues are not needed. *Phong* shading does not provide geometric information of the same richness as the *hatching* techniques, but is a bit more than the tone shading without any abstraction. This might suggest that contrast and distinctness (cues (2) and (3) above) are the most useful visual cues for spatial data interpretation.

Brain scientists preferred *hatching* mainly due to its richness and the high-quality rendering produced by the algorithms. Our results demonstrate that it might be interesting to distinguish the cuing effects produced by the glossy surface from the *Phong* shading and the texture images from the hatching, though somehow the hatching replicates many shading cues appeared in *Phong* shading. We observed no significant differences between the two. Such a distinction may influence our sense of material quality. *Phong* shading clearly depicts the textures, depending primarily on the first derivative of the surface, while the compression of specularities depends on the second derivative of the surface [39]. This means that subtle shapes generally lead to different preferences in the visualization depending on whether it is rendered or coated with texture.

5.2 Shadow

Perhaps one most interesting aspect of our results is the finding that casting data-encoded *shadows* can retard spatial structure perception. When *shadows* were presented, brain scientists often had trouble understanding the data, even though they preferred including *shadow* in the scene. This result can be explained from the perspective of human visual information processing for the data-encoded shadows. Two processes are often involved in shadow recognition: *automatic* and *controlled* shadow understanding [40]. For automatic shadow perception with shadows produced by natural lighting, rapid discrimination can perceive the shadows per se, but controlled shadow understanding requires the discrimination of structures and thus takes much longer to perform.

There could be a conflict between the way our vision works (e.g., automatic shadow perception) and the data encoded by the shadow (controlled shadow perception). Rensink and Cavanagh suggested that natural shadows (e.g., those from lighting) may be rapidly discounted by the visual system in automatic shadow detection [39]. Our visual system can identify natural shadows rapidly and in parallel across the visual field; once identified, however, the properties of these shadows are made less readily accessible to the visual system, as if shadows were nuisance variables to be filtered out early in visual processing. In our system, shadow is used to encode distance information, thus leads to controlled instead of automatic perception. Performing the tasks might require the participants to read the shadows, yet our visual system attempts to discount them, creating a visual conflict. A viewer might wish to notice them so as to infer the locations, shapes, and identities of objects around her, but she would not want to confuse them with real objects, nor would she want to distract her attention from the material objects of interest in the scene. The ambivalent role of shadows in perception may partly explain why the shadows led to worse timed performance but participants still preferred having it there.

Another explanation for the detrimental effect of shadow could be that it is a function of scene complexity. Perceptual literature often has found the benefits of shadows in "gluing" objects together and therefore conveying spatial relationships. But those scenes are relatively simple, containing only a few objects. Our scene contains thousands of tubes in the full-brain conditions, making it hard to discriminate the shadow and the object in the environment. Participants suggested that shadows block the views of the real objects. Further comparison of the results from the ROI and the whole- brain cases shows that the data-encoded shadows had detrimental effects only in the whole-brain condition. These results suggest that shadow may help in distance reading, especially in visualizations with relatively fewer occlusions, but its benefits in complex scenes still need further validation.

In the future, it might be interesting to explore whether our eyes are sensitive to depth-dependent shadows. Tufte in his well-known book suggests "*making all visual distinctions as subtle as possible, but still clear and effective*." [40]. Though we have adjusted the shadow color to make it distinguishable without being very dark, there might be a way to optimize the depth-dependent shadows that would introduce better distinctiveness and clarity, as shown in Section 5.1. Other interesting questions concern which properties of shadows are most useful in making inferences about a scene and the underlying dataset. Illumination in natural scenes is extremely complex, owing to the presence of multiple light sources of various geometries and significant inter-reflection. While many studies suggest that shadows are helpful in scene estimation (as discussed in the related work section above), these studies mostly looked at the extrinsic shadow objects together for depth, size, or orientation judgment, rather than at shadows that encode data.

5.3 Halo

We did not observe differences when halos were absent or present, even though halos were preferred by almost all brain scientist participants. We think the human eye can integrate halos very well and interpret them as part of the scene. When brain scientists looked at the image of an entire object, they would see not only the internal structure of the fiber tracts, but also the occluding contour of the boundary of tracts where the surface curves were out of view. This contour also carries information about 3D shape.

Our failure to observe a significant performance gain is probably caused by the presence of motion cues. Our results may also suggest that shading fields carry more information about 3D shape than the halos alone. Perhaps halos are most useful in still images, when kinetic cues are absent and halos can provide extremely useful boundary conditions for the interpretation of orientation fields. This statement can be validated in the future by comparing halo-only depiction of 3D shapes (removing the shading completely) and cases when both shading and halos are absent.

5.4 Nuances in Our Implementation

We felt that many nuances are present in our study that might impact the preferences and results and might be inherent in the empirical comparison of visualization techniques. For example, nuances in implementation could lead to an overwhelming preference for the halo conditions. In a pilot study we asked three experts for their opinions of the halos; two of them disliked them and thought they occluded the scene, in part because when they zoomed in, they saw thicker halos that did not match what rim lights would produce in a realistic rendering. In the current implementation, we kept the size of the halos consistent to the eye so that when the users zoomed in, the halo size scaled down to give subtle boundary effects and reduce occlusion. This might have led to the overwhelming preferences for the halos.

We carefully optimized each method in our implementation to ensure the validity of our study. For hatching, we increased the size of the tubes to make the textures more legible. When thin tubes are used, the texture size becomes so small (partially because of texture aliasing) that it is similar to salt-and-pepper noise, reducing the texture legibility. Increasing screen resolution can partially solve this problem by reducing the aliasing. The tubes must be at a certain size in order to make the features legible, at least at 2 mm (p. 178, [41]). New algorithms will be needed for thin-tube hatching that would produce legible shading effects, as in the thin tubes from the tone and Phong shading.

6 Conclusions

Our results offer substantial evidence that artistic rendering can accurately depict shapes for showing complex spatial structures, at least for the algorithms we have used. Not all visualizations are equally effective in this regard.

Our work also is the first to study the usefulness of distance-based shadow approaches to visualization. In Section 1 we discussed a number of open questions concerning rendering styles and some depth effects such as halos and shadows. Using experimental methods, we have attempted to answer all these questions, at least in part. As a result, we can provide the following visualization design preferences:

- Use simple abstract visual representation of tone shading whenever possible, because it is sufficient to generate compelling perceptions of spatial structure.
- Combine cues with caution, especially when depth-dependent shadow is integrated. In general, a shading method of Phong or hatching or tone works reasonably well.
- Combine halo with shading methods. Though this does not improve the accuracy of spatial visual data analysis tasks, halo is preferred by brain scientists.
- Represent data such as distance with shadow. This approach is compelling to viewers, yet the placement in complex scenes could have an impact on accuracy and task completion time.
- Perhaps when the scene is interactive and kinetic cues are available, shadows could be removed totally to avoid low accuracy and extended task completion time.

We show that brain scientists interpreted the artistic style rendering much as they interpreted the popular Phong-shaded tube bundles. We demonstrate that tone shading improves task accuracy significantly as compared to line-based hatching techniques. We provide new evidence and expand our understanding of shading algorithms that are data-dependent. Although the precise nature of the artistic rendering is yet to be elaborated, the remarkable performance of participants in the present experiment suggests that the visual abstraction may well be a fruitful area for future research.

Acknowledgments

The authors thank the participants in the Mississippi Medical Center for their time and effort, Dr. Ryan D. Darling, Steven R. Gomez, and Marc Olano for their insightful comments on the shading approaches, Blossom Metevier for her voice-over training, and Katrina Avery for her editorial support. This work was supported in part by NSF IIS-1302755, IIS-1016623, IIS-1017921, DUE-0817106, ABI-1260795, OCI-0923393, EPS-0903234, DBI-1062057, and CCF-1785542, and NIH (RO1-EB004155-01A1).

Jian Chen and Zhigeng Pan are the corresponding authors.

References

[1] D. Banks and C.-F. Westin, Global illumination of white matter fibers from DT-MRI data, in Visualization in Medicine and Life Sciences, (Mathematics and Visualization), Hagen, H, Linsen, L, and Hamann, B. (*eds*), Springer, pp. 173-184, 2008.

[2] D. Penney, J. Chen, and D. H. Laidlaw, "Effects of illumination, texture, and motion on task performance in 3D tensor field streamtube visualizations," in IEEE Pacific Visualization Symposium (PacificVis), pp. 97–

104, 2012. Doi>10.1109/PacificVis.2012.6183579.

[3] T. Strothotte and S. Schlechtweg, Non-photorealistic computer graphics: modeling, rendering, and animation. Morgan Kaufmann, 2002.

[4] M. H. Everts, H. Bekker, J. B. T. M. Roerdink, and T. Isenberg, "Depth-dependent halos: Illustrative rendering of dense line data," IEEE Transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1299–1306, 2009. Doi>10.1109/TVCG.2009.138.

[5] F. Ritter, C. Hansen, V. Dicken, O. Konrad, B. Preim, and H.-O. Peitgen, "Real-time illustration of vascular structures," IEEE Transactions on Visualization and Computer Graphics, vol. 12, no. 5, pp. 877–884, 2006. Doi>10.1109/TVCG.2006.172.

[6] P. J. Basser, S. Pajevic, C. Pierpaoli, J. Duda, and A. Aldroubi, "*In-vivo* fiber tractography using DT-MRI data," Magnetic resonance in medicine, vol. 44, no. 4, pp. 625–632, 2000.

[7] S. Mori and P. van Zijl, "Fiber tracking: principles and strategies – a technical review," NMR in Biomedicine, vol. 15, no. 7-8, pp. 468–480, 2002. Doi>10.1002/nbm.781/full.

[8] A. Vilanova, S. Zhang, G. Kindlmann, and D. H. Laidlaw, "An introduction to visualization of diffusion tensor imaging and its applications," in Visualization and Image Processing of Tensor Fields. Springer-Verlag, pp. 121–153. 2005.

[9] D. Akers, "CINCH: a cooperatively designed marking interface for 3 d pathway selection," in Proceedings of the 19th annual ACM symposium on User interface software and technology, vol. 15, no. 18, 2006, pp. 33–42. Doi>10.1145/1166253.1166260.

[10] R. Jianu, C. Demiralp, and D. H. Laidlaw, "Exploring brain connectivity with two-dimensional neural maps," IEEE Transactions on Visualization and Computer Graphics, vol. 18, no. 6, pp. 978-987, 2012. Doi>10.1109/TVCG.2011.82.

[11] W. Chen, Z. Ding, S. Zhang, A. M. Brandt, S. S. Correia, H. Qu, J.A. Crow, D.F. Tate, Z. Yan, and Q. Peng, "A Novel Interface for Interactive Exploration of DTI Fibers," IEEE Transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1449-1456, 2009. Doi>10.1109/TVCG.2009.112.

[12] H. Cai, J. Chen, A. P. Auchus, S. Correia, and D. H. Laidlaw, "InShape: In-situ shape-based interactive multiple-view exploration of diffusion MRI visualizations," in Advances in Visual Computing. Springer, pp. 706–715, 2012.

[13] S. Eichelbaum, M. Hlawitschka, and G. Scheuermann, "LineAO–improved three-dimensional line rendering," IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 3, pp. 63–70, 2013. Doi>10.1109/TVCG.2012.142.

[14] M. Zockler, D. Stalling, and H.-C. Hege, "Interactive visualization of 3d-vector fields using illuminated stream lines," in Proceedings of Visualization , 1996, pp. 107–113. Doi>10.1109/VISUAL.1996.567777.

[15] E. Praun, H. Hoppe, M. Webb, and A. Finkelstein, "Real-time hatching," in Proceedings of the 28th annual conference on computer graphics and interactive techniques (ACM SIGGRAPH), pp. 581-586, 2001. Doi>10.1145/383259.383328.

[16] B. Gooch, E. Reinhard, and A. Gooch, "Human facial illustrations: Creation and psychophysical evaluation," ACM Transactions on Graphics (TOG), vol. 23, no. 1, pp. 27–44, 2004. Doi>10.1145/966131.966133.

[17] D. H. Laidlaw, E. T. Ahrens, D. Kremers, M. J. Avalos, R. E. Jacobs, and C. Readhead, "Visualizing diffusion tensor images of the mouse spinal cord," in Proceedings of Visualization. pp. 127–134. 1998. Doi>10.1109/VISUAL.1998.745294

[18] A. Forsberg, J. Chen, and D. Laidlaw, "Comparing 3D vector field visualization methods: A user study," IEEE Transactions on Visualization and Computer Graphics, vol. 15, no. 6, pp. 1219–1226, 2009. Doi>10.1109/TVCG.2009.126.

[19] V. Interrante and C. Grosch, "Strategies for effectively visualizing 3D flow with volume LIC," in IEEE Visualization, 1997, pp. 421–424.

[20] M. S. Langer and H. H. Bülthoff, "Depth discrimination from shading under diffuse lighting," Perception, vol. 29, no. 6, pp. 649– 660, 2000.

[21] J. Chen, H. Cai, A. P. Auchus, and D. H. Laidlaw, "Effects of stereo and screen size on the legibility of three-dimensional streamtube visualization," IEEE Transactions on Visualization and Computer Graphics, vol. 18, no. 12, pp. 2130–2139, 2012. Doi>10.1109/TVCG.2012.216.

[22] A. Girshick, V. Interrante, S. Haker, and T. Lemoine, "Line direction matters: an argument for the use of principal directions in 3D line drawings," in Proceedings of the 1st international symposium on Non-photorealistic animation and rendering. ACM, 2000, pp. 43–52. Doi> 10.1145/340916.340922.

[23] R. McDonnell, M. Breidt, and H. H. Bülthoff, "Render me real?: investigating the effect of render style on the perception of animated virtual humans," ACM Transactions on Graphics (TOG), vol. 31, no. 4, p. 91, 2012. Doi>10.1145/2185520.2185587.

[24] D. Perani, F. Fazio, N. A. Borghese, M. Tettamanti, S. Ferrari, J. Decety, and M. C. Gilardi, "Different brain correlates for watching real and virtual hand actions," NeuroImage, vol. 14, no. 3, pp. 749–758, 2001.

[25] S. Han, Y. Jiang, G. W. Humphreys, T. Zhou, and P. Cai, "Distinct neural substrates for the perception of real and virtual visual worlds," NeuroImage, vol. 24, no. 3, pp. 928–935, 2005.

[26] S. Fan, T.-T. Ng, J. S. Herberg, B. L. Koenig, and S. Xin, "Real or fake?: human judgments about photographs and computer-generated images of faces," in ACM SIGGRAPH Asia 2012 Technical Briefs. p. 17. Doi> 10.1145/2407746.2407763.

[27] T. Isenberg. Evaluating and validating non-photorealistic and illustrative rendering. In Rosin, P. and Collomosse, J. (*eds.*), Image and Video based Artistic Stylisation (Computational Imaging and Vision), pp. 311–331. Springer, London, Heidelberg, 2013. Doi>10.1007/978-1-4471-4519-6_15.

[28] A. Bousseau, J.P. O'shea, F. Durand, R. Ramamoorthi, and M. Agrawala, "Gloss perception in painterly and cartoon rendering," ACM Transactions on Graphics (TOG), vol. 32, no. 2, 2013. Doi> 10.1145/2451236.2451244.

[29] C. Weigle and D. C. Banks. A comparison of the perceptual benefits of linear perspective and physically-based illumination for display of dense 3D streamtubes. IEEE Transaction on Visualization and Computer Graphics, vol. 14, no. 6, pp. 1723–1730, 2008.

[30] W. B. Thompson, P. Shirley, B. Smits, D. J. Kersten, and C. Madison. Visual glue. University of Utah, Technical Report UUCS-98-007, 1998.

[31] G. S. Hubona, P. N. Wheeler, G. W. Shirah, and M. Brandt, "The relative contributions of stereo, lighting, and background scenes in promoting 3d depth visualization," ACM Transactions on Human-Computer Interaction, vol. 6, no. 3, pp. 214–242, 1999. Doi>10.1145/329693.329695.

[32] C. Ware, Information visualization: perception for design (3rd ed.), Morgan Kaufmann, 2012.

[33] P. Rheingans and D. Ebert, "Volume illustration: Nonphotorealistic rendering of volume models," IEEE Transactions on Visualization and Computer Graphics, vol. 7, no. 3, pp. 253–264, 2001. Doi> 10.1109/2945.942693.

[34] A. Wenger, D. F. Keefe, S. Zhang, and D. H. Laidlaw, "Interactive volume rendering of thin thread structures within multivalued scientific datasets," IEEE Transactions on Visualization and Computer Graphics, vol. 10, 2004. Doi>10.1109/TVCG.2004.46.

[35] R.W. Fleming, A. Torralba, and E.H. Adelson, "Specular reflections and the perception of shape," Journal of Vision, vol. 4, no. 9, 2004.

[36] Y. Lee, L. Markosian, S. Lee, and J. F. Hughes, "Line drawings via ab-

stracted shading," ACM Transactions on Graphics, vol. 26, no. 3, p. 18, 2007. Doi>10.1145/1276377.1276400.

[37] H. Cai, J. Chen, A. P. Auchus, J. Huang, and D. H. Laidlaw, IEEE Visualization (poster), 2011.

[38] R. A. Rensink and P. Cavanagh, "Influence of cast shadows on visual search," Perception, vol. 33, pp. 1339-1358, 2004.

[39] D. Knill, P. Mamassian, and D. Kersten, "Geometry of Shadows," Journal of the optical society of America, vol. 14, no. 12, 1997.

[40] E. Tuftes, The visual display of quantitative information (2nd ed.), 2001.

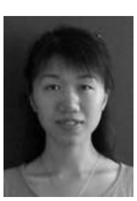
[41] J. Bertin, Semiology of graphics: diagrams, networks, maps, 1977 (French edition).

Jian Chen received the PhD degree in Computer Science from Virginia Polytechnic Institute and State University (Virginia Tech). She did her post-doctoral work in Computer Science and BioMed at Brown University. She is an Assistant Professor in Computer Science and Electrical Engineering at University of Maryland, Baltimore County, where she directs the Data Visualization, Computing, and Interaction lab (DaVinCI). Her research interests include design and evaluation of visualization techniques, 3D interface, and visual analytics. She is a member of the IEEE and the IEEE Computer Society.

Liming Xu received his B.S. degree in Computer Science at Mianyang Normal University in 2010. He is a Master's candidate in Computer Science at Zhejiang University and a visiting research assistant in the Computer Science and Electrical Engineering at University of Maryland, Baltimore County. His research interests include scientific visualization and visual perception.

Alexander P. Auchus holds degrees from Johns Hopkins University and from Washington University in St. Louis. He is an elected fellow of the American Neurological Association, the American Academy of Neurology, and the American Geriatrics Society. He has served on the faculty of Emory University, Case Western Reserve University and University of Tennessee. His present position is Professor and McCarty Chair of Neurology at the University of Mississippi Medical Center. His research interests are in neuroimaging biomarkers for Alzheimer's disease and other dementias.

Guohao Zhang received his B.S. degree in Engineering Physics at Tsinghua University in 2012. He is a PhD student in Computer Science at University of Maryland, Baltimore County. His research interests include data visualization and visual perception.



Keqin Wu received the B.S. and M.E. degrees in computer engineering from the Ocean University of China in 2001 and 2004, and the Ph.D. degree in computer engineering from Mississippi State University in 2012. She is a post-doctoral associate in the DaVINCI lab, Computer Science and Electrical Engineering at University of Maryland, Baltimore County. Her research interests include scientific visualization, medical imaging, and user interface design. She is a member of IEEE.

Zhigeng Pan received the PhD degree in Computer Science from Zhejiang University, China. He is the director of the Digital Media and Human-Computer Interaction Research Center, Hangzhou Normal University. His research interests include virtual reality, computer graphics, and human-computer interaction. He is a member of IEEE and ACM SIGGRAPH.

Mingmin Zhang received her Bachelor's degree from the Computer Science Department, Nanjing University, and her Master's and PhD degree from Computer Science and Engineering Department, Zhejiang University. She is an associate professor of Computer and Engineering Department, Zhejiang University. Her research interests include virtual reality, multi-resolution modeling, real-time rendering, visualization, and multimedia and Image processing.

James C. Lynch received the Ph.D. degree from Stanford University and did postdoctoral study at the Johns Hopkins School of Medicine. He has served on the faculty of the Johns Hopkins School of Medicine and the Mayo Clinic and Foundation. He is currently Professor and Vice Chair of the Department of Neurobiology and Anatomical Sciences at the University of Mississippi Medical Center.

David H. Laidlaw received the PhD degree in computer science from the California Institute of Technology, where he also did post-doctoral work in the Division of Biology. He is a professor in the Computer Science Department at Brown University. His research centers on applications of visualization, modeling, computer graphics, and computer science to other scientific disciplines. He is a senior member of the IEEE and the IEEE Computer Society.