Orientation Visualizing Transfer Function for Volume Rendering

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Abstract—Volume rendering has become an important technique for visualizing and exploring features in 3D scalar fields. However, it is difficult to visualize important structures and boundaries in volume datasets since different types of tissues are represented in overlap ranges of scalar values. In this paper, we propose a novel orientation visualizing transfer function to reveal inner structures and orientations of materials. In our approach, gradients are projected from 3D space onto RGB color space. Since both the directions and magnitudes of gradients are exploited, structures of similar scalar values and gradient magnitudes can still be distinguished by their orientations. Experiment results show our approach provides clear perspectives of the structures and unique features in visualizing orientation related details.

Keywords—orientation visualizing; transfer function; volume rendering; gradient

I. INTRODUCTION

Volume rendering has become an important technique for various visualization applications such as medical imaging and scientific visualization. In volume rendering, the scalar field is interpreted as a participating medium which emits and absorbs lights at the same time. The optical properties such as color and opacity are obtained from the underlying scalar field by a user-specified transfer function. In order to gain desired results, the specification of optical properties should be able to highlight tissues or features that are of interests. Transfer function specification is not a trivial task and it is an unintuitive task for average users to specify a transfer function that works properly, which is usually a monotonous process of trial and error.

Transfer function approaches widely used are mostly based on scalar values. Unfortunately, different tissue types are usually represented in similar or even overlapping ranges of scalar values in CT and MRI datasets [1]. Therefore, traditional transfer function approaches, which assign optical properties only based on scalar values, are inadequate to extract structures of interest from volume datasets.

The work presented in this paper focuses on visualizing boundaries and orientations of heterogeneous material, while traditional transfer function approaches pay more attention to relatively homogeneous material. We endeavor to visualize the gradients of scalar fields which imply the orientations of materials. The direction of gradients is also referred as the orientation of materials in the rest of this paper.

The presented approach requires a minimum of user interaction so that users are released from the monotonous work of transfer function specification by iterative trial and error in our system.

In the following section, we describe related works for this paper. Then in Section 3, we outline important aspects of the orientation visualizing transfer function. Experiment results of our approach to several datasets which are commonly used in previous publications and discussion are presented in Section 4. Conclusions and comments on future work are included in Section 5.

II. RELATED WORKS

Transfer function specification plays a crucial role in volume rendering, and there has been a great amount of research devoted to transfer function generation for volume rendering [2]. Early trail-and-error approaches which need expert intervention in generating the final image are unintuitive and time-consuming. Current approaches for transfer function specification can be divided into two groups: data centric and image centric. While the image-centric approaches are based on measuring the rendered image quality, the data-centric approaches are based on measuring properties in the dataset.

An approach of semi-automatic generation of transfer functions using the first and second derivatives for visualizing boundaries between materials was presented by Kindlmann and Durkin [3]. Then Kniss et al. [4] proposed a multi-dimensional transfer function which demonstrates superior capabilities in classifying boundaries and materials. In their solution, interaction widgets were introduced to manipulate a 2D histogram of the scalar values and the gradient magnitudes for transfer function specification. Sereda et al. introduced LH Histograms [5] and its extension, mirrored LH Histograms [6], to identify the materials that form the boundaries. Pra{\v{s}n}i{\v{n}} et al. [7] proposed a transfer function with boundary detection based on their improved LH technique. Correa and Ma [8] described a sized-based approach to distinguish features with similar or identical intensities by the relative sizes of the features. Later they suggested the occlusion spectrum method to classify structures by the ambient occlusion of voxels [9]. Curvatures have been used to distinguish different structures according to their shapes [10] [11]. Pra{\v{s}n}i{\v{n}} et al. [12] used a technique to distinguish features in the volume data based on the structure shapes such as shapes of longitudinal, surface-like, and blobby shapes can be distinguished.

Designing transfer functions with machine learning techniques is a promising research direction [13]. Transfer function specification can be regarded as a parameter optimization problem where stochastic search techniques can be utilized. He et al. [14] showed a genetic algorithms approach that starts by an initial population of randomly
generated or user-predefined transfer functions and then evolves by either user selection of intermediate images or predefined objective functions. In order to obtain high-quality visualizations, House et al. [15] utilized a genetic algorithm to guide the human-in-the-loop search through visualization parameter space and generate large databases of rated visualization solutions. Artificial neural networks and support vector machines are also used in transfer function specification. Tzeng et al. [16] employed neural networks in transfer function specification, then they extended the work and employed support vector machines as well [17]. They introduced an interface for high-dimensional transfer generation based on samples that the user has drawn onto slices of the volume. In a clustering approach by Tzeng et al. [18], an intuitive user interface was introduced to select different object classes in the cluster layer and operate directly on the classification and visualization results. Sereda et al. [19] introduced a hierarchical clustering of the fuzzy class to generate transfer function automatically. A fuzzy classification based system by Kniss et al. [20] allows users interactively explore the quantitative information computed during fuzzy segmentation.

Color selection and harmonics are also studied in volume visualization. Wu et al. [21] proposed a palette-style interface for intuitive volume exploration with Photoshop-style image editing operations. Wang et al. [22] described an interactive system with the use of color design principles to help users choose harmonic colors and convert non-harmonic color-maps into harmonic ones while keeping original contrast. Zhou and Takatsuka [23] proposed an automatic transfer function generation approach which use topological attributes to control color selection in a perceptual color space and create harmonic color transfer function.

In previous transfer function design approaches, gradients are used in ways such as gradient magnitude [24] and calculating the second derivative along the gradient direction [25], which the gradient directions of materials are not visualized. The gradient directions, which provide important clues for disambiguating boundaries between different structures, can be utilized more effectively. A noticeable fact in the boundary model by Kindlmann and Durkin [3] is the first derivative reaches its maximum at the middle of the boundary. Based on the significant relation between gradients and boundaries, we propose a novel transfer function approach to visualize orientations of materials by fully exploiting the use of both gradient directions and gradient magnitudes.

III. OUR APPROACH
A. Mapping 3D Space onto RGB Color Space

In our approach, we try to reveal the orientations of materials by mapping the gradients from 3D space onto RGB color space, as shown in Figure 1. The three coordinate components, x, y, and z correspond to the red, green, and blue channels in RGB color space. These three components blend together naturally and produce numerous colors. Figure 2 shows a 2D illustration of how 3D vectors are mapped onto various colors in RGB color space.

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**Figure 1.** Mapping 3D space onto RGB color space

**Figure 2.** How directions are mapped onto colors

B. Gradient Approximation

The Sobel operator, which is a discrete differentiation operator, is widely used in image processing, particularly within edge detection algorithms.

\[
G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \times A, \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \times A
\]

The gradient magnitude is given by:

\[
g = \sqrt{G_x^2 + G_y^2}
\]

The Sobel operator performs two separable operations, which are smoothing in a direction perpendicular to the derivative direction and central difference in the derivative direction [26].

In our approach, we use a way that is similar to Sobel operator in 3D scalar field to get an approximation of the gradients. The 3×3×3 kernels for 3D Sobel operator we used are shown in Table I. The gradients that 3D Sobel operator provides are not the most approximated gradients, but the filtering properties of the kernel are very effective in reducing noise and aliasing artefacts.

**TABLE I.** 3D SOBEL KERNELS FOR X, Y, AND Z DIRECTIONS RESPECTIVELY
\[ x^{-1} \quad x \quad x^{+1} \]

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C. Orientation Visualizing Transfer Function

With the trick of mapping 3D space onto RGB color space, a transfer function for orientation visualizing can be generated automatically. The \( r \), \( g \), and \( b \) components of the color are specified as linear mappings of the gradients \( G_x \), \( G_y \), and \( G_z \) obtained by the 3D Sobel operator, as follow:

\[
\begin{align*}
    r &= \frac{G_x - G_{x\min}}{G_{x\max} - G_{x\min}} \\
    g &= \frac{G_y - G_{y\min}}{G_{y\max} - G_{y\min}} \\
    b &= \frac{G_z - G_{z\min}}{G_{z\max} - G_{z\min}}
\end{align*}
\]

where \( G_z \) is the gradient obtained by the 3D Sobel operator in \( x \)-coordinate direction. \( G_{x\min} \) and \( G_{x\max} \) are the minimum and the maximum of \( G_z \) in the scalar field respectively. \( G_y \), \( G_{y\min} \), \( G_{y\max} \), \( G_z \), \( G_{z\min} \), and \( G_{z\max} \) are defined in the same way.

Instead of the computational expensive Euclidean distance which requires square root operations, the sum of absolute values of \( G_x \), \( G_y \), and \( G_z \) is used to estimate the gradient magnitudes \( G \):

\[
G = |G_x| + |G_y| + |G_z|
\]

\( F \) is a linear mapping of the original scalar value.

\[
F = \begin{cases} 
0, & f(x,y,z) < f_{\text{min}} \\
\frac{f(x,y,z) - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}}, & f_{\text{min}} \leq f(x,y,z) \leq f_{\text{max}} \\
1, & f(x,y,z) > f_{\text{max}}
\end{cases}
\]

The alpha value \( \alpha \) is specified as a linear interpolation of \( G \) and \( F \). The alpha blending factor \( \alpha \) is set to balance between a clear perspective on the interior and a sense of material thickness of the volume.

\[
A = (1 - \alpha)G + \alpha F
\]

In equation (5), \( f(x,y,z) \) represents the scalar value at location \((x,y,z)\) in the scalar field. However, \( f_{\text{min}} \) and \( f_{\text{max}} \) are not the minimum and the maximum values in the scalar field. Since the minimum or maximum scalar values can be distant from the body of the histogram. The histogram in Figure 3 provides a good example of the issue. The body of the histogram gather in the left half in Figure 3, but the maximum scalar value locate at the rightmost end. In this case, it is not preferable to equalize the scalar values with the original maximum and minimum. Proper values for \( f_{\text{min}} \) and \( f_{\text{max}} \) depend on the distribution of the dataset. Thus interactive widgets (the green line and the red line in Figure 3) are provided to adjust \( f_{\text{min}} \) and \( f_{\text{max}} \) on the scalar histogram in our system.

IV. RESULTS AND DISCUSSION

We have implemented our approach with OpenGL and GLSL (OpenGL Shading Language). Various datasets commonly used in previous publications have been used to validate our approach. The datasets used in our experiment were downloaded from [27] and converted into RAW format with the PVM tools distributed with the V^3 (Versatile Volume Viewer) volume rendering package. The result images are rendered directly from the raw datasets without any pre-process or modification.

Figure 4 and Figure 5 are rendering results of a foot dataset. Figure 4 is rendered with a 1D transfer function based on scalar value, and Figure 5 is a result of the orientation visualizing transfer function. Compared to Figure 4, in which very few of the inner structures are visible, the skeleton of the foot in Figure 5 is clearer and sharper. Figure 6 and Figure 7 are rendering results of a sheep heart dataset. In Figure 6, which is rendered with the 1D transfer function based on scalar value, only an outer layer of the sheep heart is visible from outside. On the contrary, a distinct perspective of the sheep heart is presented in Figure 7, which is rendered with the orientation visualizing transfer function. Because our approach is based on gradients, it is sensitive on the change of scalar values, i.e. heterogeneous material, and it can provide clear perspectives of the interior of material.

In Figure 5, the articulations and the phalanges are rendered in high contrast colors indicating their different gradient directions. Thus these two structures can be distinguished easily. It is a unique feature of the orientation visualizing transfer function to distinguish tissues by their orientations. In rendering rectangular objects such as an engine block, the unique ability of the orientation visualizing transfer function in distinguishing structures by their orientations is more remarkable. As in Figure 8 and Figure 9, the engine block with a rectangular is rendered frame in
distinct colors (red, green, and blue) according to the orientation of material.

Figure 8 is a result of orientation visualizing transfer function with $\alpha = 0$, and Figure 9 is a result of the same transfer function but with $\alpha = 1$. The two results illustrate the effect of the blending factor $\alpha$. Both results show clear perspectives on the interior of the engine block. By increasing the blending factor $\alpha$, the sense of material thickness is better preserved in Figure 9 while Figure 8 only illustrates boundaries.

V. CONCLUSION

In this paper we have presented a novel transfer function approach to visualize orientations of materials in datasets. The orientation visualizing transfer function demonstrates
superior capabilities in providing clear perspectives of structures and unique features in visualizing orientation related details. With our approach, materials of similar scalar values and gradient magnitudes can still be distinguished by their orientations, which are denoted by different colors in our results.

The work in this paper exploits the use of both directions and magnitudes of gradients to improve the visibility of resulting images. Properties such as second derivatives and classification information can be taken into account to reveal more details and further the visibility of rendering results.

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