Boundary emphasis transfer function generation based on HSL color space

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Abstract—Direct volume rendering has been received much attention since it need not to extract geometric primitives for visualization and its performance is generally better than surface rendering. Transfer functions, which are used for mapping scalar field to optical properties, are of vital importance in obtaining a sensible rendering result from volume data. Though traditional color transfer functions are in RGB color space, HSL color space that conveys semantic meanings is more intuitive and user-friendly. In this paper, we present a novel approach aims to emphasize and distinguish strong boundaries between different materials. We achieve it by using data value, gradient magnitude and dimension of the volumetric data to set opacity. Then, through a linear map from data value, gradient magnitude and second derivative to hue, saturation and lightness respectively, a color transfer function is obtained in HSL color space. Experimental tests on real-world datasets indicate that our method could achieve desirable rendering results with revealing important boundaries between different structures and indicating data value’s distribution in the volume by using different colors.

Keywords: Volume rendering, transfer functions, boundary emphasis, HSL space

I. INTRODUCTION

In direct volume rendering, a transfer function is used to map scalar field’s data properties (intensity, gradient magnitude, second derivative, etc) to optical parameters (opacity, colors, etc). The major role of transfer function is to reveal inner structures of different materials in the volume data, and helps user gain a deep insight into the data. Therefore, transfer function setting is a crucial step in the pipeline of volume rendering. However, in practice it is not easy to design a good transfer function suitable for all datasets. Major factors having a great influence on transfer function setting are: partial volume effect, non-uniform distribution of materials, and noise [1]. To solve these problems, several methods are proposed. They are proved to be effective to some kinds of datasets, but not very useful for others. To make transfer functions more effective, user interaction is sometimes necessary and specific knowledge of the data may also be helpful for users to adjust parameters of transfer functions. Another problem is that visual parameters increase substantially as the transfer function’s dimension expands. It is a difficult and time-consuming task for users, especially non-expert users, to tune different parameters properly to achieve desirable rendering results. Additionally, there is not a direct connection between visual parameters’ changes and the effect on the rendering image.

Consequently, how to devise an appropriate transfer function remains a cumbersome task and is still far from been solved.

There are two steps in transfer function setting. Firstly, opacity is obtained by calculating data’s gradient magnitude, second derivative, or curvature. This process could either be done in pre-classification stage or post-classification stage. Secondly, colors are assigned to different materials based on opacity settings. The roles of these two steps are different. Opacity is used to reveal inner structures in the data, while colors are to enhance visual effect.

This paper is organized as follows: In Section 2, we briefly review some related works. Details of our method are described in Section 3. Experimental results and discussion are given in Section 4. Finally, conclusion remarks are presented in Section 5.

II. RELATED WORK

Transfer function setting is considered to be one of the top 10 problems in volume visualization [2]. Early approaches are trial-and-error methods to design a transfer function. These methods are unintuitive and time-consuming; most importantly, a pleasing result is not always guaranteed. To alleviate these problems, some software tools are developed. For example, VolVis is a volume visualization tool that helps user adjust transfer function setting interactively [3].

There are some automatic approaches proposed to make transfer function setting effective. These approaches can be roughly classified into two categories: data-centric and image-centric approach. The former approach is based on evaluation of the volume data, while the latter approach is on evaluation of the rendered image.

A. Data-centric approach

Data-centric approaches are widely used and have proved to be powerful. Bajaj et al. [4] introduced contour spectrum to determine voxels corresponding to important iso-surfaces of the volume. Levoy proposed to use gradient magnitude to emphasize strong boundaries between different materials [5]. Kindlmann and Durkin extended Levoy’s work by introducing a higher dimensional transfer function domain based on gradient magnitude and second derivative [6]. To emphasize different structures, Kniss et al. introduced a 2D histogram of gradient magnitude and data values. In the histogram, boundaries appear as arcs and users could select them easily [7]. They also designed a set of widgets to ease the setup of transfer functions by data probing in the volume [7]. Gradient magnitude is not the only way to extract strong
boundaries. Kindlmann et al. used curvature to distinguish different materials according to shapes [8]. Shape information has also been used to derive a shape descriptor (longitudinal, surface-like, blooby) to distinguish different features on the foundation of material’s 3D shape [9]. However, due to partial volume effect, it is difficult for these methods to separate boundaries in which intensity overlaps. To overcome this problem, LH (low and high intensities within a boundary) histogram is proposed to classify each voxel to either in an organ or between different boundaries with low / high intensity across a boundary [10]. Aiming to capture global structures in volume, Takahashi et al. introduced a topology-based approach called volume skelentonization tree to yield critical points and connectivity of these points in the volume [11]. Although the approaches mentioned above are effective from a point of technical view, managing the complexity of visual parameters remains a challenge for non-expert users. Salama et al. [12] introduced an additionally semantic level and designed some high level parameters easy for users to understand. This approach significantly decreases the number of visual parameters to be adjusted. Besides semantic parameters, several new approaches such as distance have been presented [13]. Correa and Ma introduced a size-based method to distinguish features with similar or identical intensities according to feature’s relative size [14]. Visibility-based approach progressively probes the transfer function space towards the goal of maximizing visibility of significant structures users are interested in [15].

B. Image-centric approach

Image-centric approaches are based on evaluation of the rendered image and user interaction. He et al. extended evolutionary algorithm to volume visualization, in which the starting population of transfer functions is set as a global optimization problem and used particle swarm optimizer to obtain the optimal solution [7]. The Design Gallery generates a large collection of renderings for user to pick up a preferable one to guide transfer function design [18]. Tzeng et al. designed a novel interface using artificial neural network to train a high-dimensional transfer function [19]. Fang et al. presented an image-based transfer function that integrates 3D image processing tools to facilitate transfer function searching process [20]. Huang and Ma extended region growing approach to help users spot and define features of interest in the volume faster and more accurately [21]. Algorithms frequently used in pattern recognition are also applicable to transfer function design, such as k-means [22]. Sereda et al. developed a framework that facilitates the semi-automatic design of transfer functions by generating clusters in the transfer function domain [23].

Most of works listed above are focused on opacity transfer functions. Besides, color transfer functions form a crucial part in visual aesthetics. Color harmony has been proposed as a concept previous in art. Computer scientists designed some color wheels that serve as templates to represent harmonic color combinations. Wang et al. used the concept to develop an interface to help users choose harmonic colors and could also convert non-harmonic colormaps to harmonic ones while keeping original contrast relationship [24].

III. OUR WORK

Our transfer function design can be split into two steps. First, we assign opacity to each voxel in the volume based on gradient magnitude and second derivative. Second, using data properties obtained in calculating phase, colors are assigned to each voxel. In the following section, we describe these two steps in details.

A. Opacity transfer function

Our aim is to design an opacity transfer function which can emphasize strong boundaries of physically different structures or materials, since boundaries are crucial for users to gain a deep insight into the dataset. To achieve this, we use the gradient magnitude to derive opacity of each voxel in the volume. For those voxels of high gradient magnitude, it is very possible that they indicate a boundary between different materials; hence they should be assigned to high opacity to emphasize those boundaries users are interested in. To accomplish this, we define original opacity, denoted as $\alpha$:

$$\alpha = e^{-\frac{\beta}{\alpha}}$$  

Equation (1) has the following properties:

$$\lim_{\alpha \to 0} \lim_{\beta \to +\infty} \alpha = 1$$

We apply central difference to approximate gradient magnitude in our work by taking only 6 neighboring voxels into account because it is faster to calculate and effective compared with taking all 26 adjacent voxels into account. After obtaining original opacity of each voxel according to (1), we use the following some what modified formula to correct the original opacity [25]:

$$\alpha = \frac{e^{\beta (1-a)} - e^{-\beta}}{1 - e^{-\beta}}$$

where $\beta$ is a constant, $\beta = \ln d$, $d$ is the average dimension of volume dataset.

B. Color transfer function

Our color transfer function setting is inspired by previous work in [24]. The aim is to design a color transfer function which conveys semantic meaning to users. Consequently, contrary to many previous works, our color transfer function is set in HSL color space. Then the HSL triple is converted to RGB color space for traditional ray-casting algorithm. The reasons for setting color in HSL space but not in RGB space are: 1) HSL is more intuitive and offers more clues; therefore, one can guess at colors what he wants; 2) It is also easier to create sets of matching colors by keeping the hue the same and varying the lightness /darkness, and saturation; 3) The conversion from HSL color space to RGB color space is a trivial task.

In HSL color space, HSL stands for hue, saturation, and lightness respectively. The relation of HSL triple could be
represented in a cylinder, in which the angle around the central vertical axis corresponds to hue, the distance from the axis corresponds to saturation, and the distance along the axis corresponds to lightness or brightness.

Change of HSL triple has a direct effect on colors obtained. Compared with saturation and lightness, hue is vital in conveying color information of different materials. Therefore, we map data values to H (hue). The aim is to reveal intensity of each voxel in the volume according to voxel’s color in the rendering. For example, large intensities correspond to large angels in the HSL cylinder with a specific color in the diagram, while small ones represent small angels in the cylinder with other colors. The result is: given saturation and lightness of each voxel, in the final rendering result, the color of voxels indicates whether voxels’ data values to be large or small. This is a useful tool for users to distinguish different organs in medical datasets, for data value range of skin, bone and lung are previously known from CT scans. According to the rules mentioned above, we define H by using a linear map function from data values to angles in HSL cylinder, as follows:

\[
H = \begin{cases} 
30 & f(x, y, z) < \frac{z}{6} \\
90 & \frac{z}{6} \leq f(x, y, z) < \frac{z}{2} \\
150 & \frac{z}{2} \leq f(x, y, z) < \frac{z}{3} \\
210 & \frac{z}{3} \leq f(x, y, z) < \frac{2z}{3} \\
270 & \frac{2z}{3} \leq f(x, y, z) < \frac{2z}{5} \\
330 & \frac{2z}{5} \leq f(x, y, z) < r 
\end{cases}
\] (4)

where \(f(x, y, z)\) denotes data value of voxel at location \((x, y, z)\) in the volume and \(r\) refers to data range.

In HSL color space, S represents saturation and gradient magnitude indicates strong boundaries in the volume. High saturation of a voxel shows that it is on a boundary between two different materials. Hence, a linear map from gradient magnitude to S is defined as follows:

\[
S = \frac{f'(x, y, z) - f'_\text{min}}{f'_\text{max} - f'_\text{min}}
\] (5)

where \(f'_\text{max}\), \(f'_\text{min}\) and \(f'(x, y, z)\) represent max and min gradient magnitude, gradient magnitude at location \((x, y, z)\) in the volume, respectively.

We map second derivative to L (lightness) by applying the formula (6):

\[
L = \frac{f''(x, y, z) - f''_\text{min}}{f''_\text{max} - f''_\text{min}}
\] (6)

where \(f''_\text{max}\), \(f''_\text{min}\) and \(f''(x, y, z)\) denote maximum and minimum second derivative, second derivative of voxel at location \((x, y, z)\) within the data, respectively. High lightness in the rendering means large second derivatives.

Then H, S, L triple is converted to R, G, B color space according to a standard algorithm.

IV. RESULTS AND DISCUSSION

The presented method has been implemented using OpenGL and GLSL (OpenGL Shading Language). We tested its performance on a personal computer equipped with AMD Athlon(tm) 7750 Dual-Core Processor, 4G memory and NVIDIA GeForce GT 240 graphics card. To achieve a better interactive frame rate, data properties such as gradient magnitude are pre-computed. We validated our method on a variety of datasets that are commonly used in previous publications. Most datasets could be downloaded from [26]. We also compared our method with the method in [27], the method in [10], and the VolVis [3].

Fig.1 shows the volume rendering of Bonsai data, a CT scan with contrast dye. It is demonstrated that outer layer and inner layer of the base are visually distinguished. Contours of the plant’s branches and leaves are enhanced. In the rendering, green and magenta are used to indicate leaves and soil, respectively.

Fig.2 Volume rendering of Vismale data
Fig. 3. Volume rendering of Foot data using the method in [27] (left) and our method (right).

Fig. 4. Volume rendering of Lobster data using the VolVis [3] (left) and our method (right).

Fig. 5. Volume visualization of Sheep data using the method in [10] (left) and our method (right).

Fig. 2 shows the Vismale volume data. In Fig. 2 (left), green color corresponds to skin, while purple one represents bones. According to their relative position in the HSL cylinder and color map function, users could easily find their data value range within the volume. In the image, contours of skins and bones are emphasized, which can give user a better understanding of the dataset. In Fig. 2 (right), we use a threshold method to achieve a peeling effect in which skins are peeled off to highlight bone structures.

Fig. 3 shows the comparison of our method with the method in [27] on Foot volume data. It can be seen clearly from Fig. 3 that our method could reveal more detailed inner structures in the bone with emphasizing boundaries between different bones, while the method in [27] could only extract iso-surfaces with resulting in a loss of fine structures such as small toe.

We also compared our method with the VolVis [3]. With our approach, lobster’s feet and body are visually clearer and contours are more appealing to users. The rendering result using VolVis is of low quality; for example, the two antennas and the tail are blurring.

Finally, we compared our method with the method in [10] on Sheep data, a MRI scan of a sheep heart. This data is rather noisy and the regions of different structures overlap too much. In [10], it used LH histogram aiming to partition boundaries within the volume. Unfortunately, it only reveals surfaces within the sheep heart, but boundaries are invisible. On the contrast, our method can identify boundaries of the sheep heart, and the volume’s inner structures can also be observed.

V. CONCLUSIONS

In this paper we have presented a novel opacity transfer function based on gradient magnitude and a color transfer function in HSL color space. Experimental results demonstrate that our method can achieve pleasing results with emphasizing boundaries between different materials, when compared to other approaches such as LH histogram and volume skelentonization tree. The results also indicate that our method is suitable for visualizing medical dataset. By using our method, users can avoid the time-consuming and trial-and-error transfer function setting process. Moreover, our color scheme helps users gain an insight into data value’s distribution of boundaries between different organs. However, for data with large noise, the results with our method are undesirable, as the boundaries become too blurred to identify. In future, we will develop some user-interaction tools to improve the performance of our method on noisy datasets and experiment color transfer functions in other color space (CMYK, CIELIB, etc) to obtain a better color scheme.

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