Gradient vector and local distribution based volume visualization

Xiao Li, Shengzhou Luo, Jianhuang Wu, Xin Ma

Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences
The Chinese University of Hong Kong
xin.ma@siat.ac.cn

Abstract - Transfer function design is a crucial step in direct volume rendering process. In real world datasets, different tissues may share overlap ranges of scalar values which makes distinguishing them a difficult task. In this paper, we present a novel transfer function setting in statistical space to emphasize strong boundaries in the volume data and explore local neighborhood's intensity distribution of all the voxels. By combing the information got, an opacity transfer function is obtained. Moreover, gradient vector is another important data metric to differentiate various structures yet not been paid much attention. A color scheme is designed in RGB color space to map gradient vector to r, g, b component to not only visualize different materials but also reveal scalar value's variation in the volume. We test our method on several volumetric data and experiment shows that mean-deviation scatter plot in statistical space could reveal distribution patterns of each voxel in the volume clearer and more compact compared with intensity-space could reveal distribution patterns of each voxel in the volume. We test our method on several volumetric data and experiment shows that mean-deviation scatter plot in statistical space could reveal distribution patterns of each voxel in the volume clearer and more compact compared with intensity-space could reveal distribution patterns of each voxel in the volume. Moreover, our method could effectively visualize strong boundaries and the proposed color scheme could reveal scalar value’s variations in different directions thus provide users with more deep insight into the data.

Index Terms - transfer function; local distribution; boundary emphasis; gradient vector.

I. INTRODUCTION

Direct Volume Rendering (DVR) is a powerful technique to visualize inner structures in volume datasets thus gives user a deep insight into the data. It has broad application areas, especially useful in diagnostics for physicians in medicine. However, several aspects have limited its deployment in reality. Among these aspects, the Transfer Function (TF) design is a crucial yet challenging task in DVR to obtain a desirable rendering result. TF is used to map scalar field’s data properties (intensity, gradient magnitude, second derivative, etc) to optical parameters (opacity, colors, etc). In practice, major factors that have a great influence on TF setting are: partial volume effect, non-uniform distribution of materials, and noise [1]. To overcome these difficulties, various approaches have been presented. However, they are proved to be effective in some aspects. TF setting could be interpreted as a segmentation problem. Handicap is that in volumetric data, due to partial volume effect, different materials share an overlap intensities range which makes classification between them become a grand challenge. Early one-dimensional TFs, which map intensity to opacity, nevertheless, could not solve the intensity overlap problem effectively. Hence, many data-centric approaches merged and one-dimensional TF is extended to multi-dimensional TF. Of them, gradient magnitude is perhaps one of the most commonly applied data metric. Its aim is to approximate gradient magnitude at each sample point in the volume because data’s exact distribution is unknown due to information lost in discrete sampling process.

There are several ways to calculate gradient magnitude and central difference is used most frequently. It is easy and fast to implement, but its drawbacks are obvious. First of all, very few neighboring voxels are taken into account hence significant information (data value’s distribution and variance) of neighboring voxels is lost. Second, a linear function to approximate data value’s distribution is not accurate. These encourage us to analyze data value’s distribution and statistical properties of neighboring voxels to obtain more information of each voxel. Based on the information got, opacity of each voxel is calculated according to our method. Moreover, gradient vector is considered to be an important yet been ignored data measurement that is able to assist distinguish distinct features. Based on the consideration, a color scheme that map gradient vector to RGB color space is presented. We will discuss all the details in the following sections.

The overall organization is as follows: In section 2, we briefly review some related works that make the foundation of our research. Details of our method are presented in section 3. In section 4, we test our method by applying some real-world datasets that are commonly used, especially in medicine. Some discussions are also given. Finally, conclusion is made in section 5.

II. RELATED WORK

TF setting could roughly be divided into two categories: data-centric and image-centric. Data-centric approaches are based on evaluation of the volume data, while image-centric approaches are on the basis of evaluation of the rendered image. Our method is primarily data-centric approach.

In DVR, users are most interested in boundary because it could reveal important information in the volume data. Bajaj et al. [2] introduced contour spectrum to determine voxels that are corresponding to important iso-surfaces of the volume. To overcome the difficulty of one-dimensional TF’s inadequacy to extract interior structures of interest from volume data, Levoy proposed to use gradient magnitude to emphasize strong boundaries between different materials [3]. Kindlmann and Durkin extended Levoy’s work by introducing a higher dimensional transfer function domain based on gradient magnitude and second derivative [4]. To emphasize different
structures, Kniss et al. [5] presented a 2D histogram of gradient magnitude and data values. In the histogram, boundaries appear as arcs and users could select them easily. They also designed a set of widgets to ease the setup of TF by data probing in the volume. Gradient magnitude is not the only way to extract strong boundaries. Kindlmann et al. [6] used curvature to distinguish different materials according to shapes. 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 [7]. 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 [8]. Aiming to capture global structures in volume, Takahashi et al. [9] introduced a topology-based approach called volume skelentonization tree to yield critical points and connectivity of these points in the volume. 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. [10] 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 [11]. Correa and Ma introduced a size-based method to distinguish features with similar or identical intensities according to feature’s relative size [12]. Visibility-based approach progressively probes the transfer function space towards the goal of maximizing visibility of significant structures users are interested in [13].

The above approaches have a great disadvantage that they don’t consider data value’s distribution of the neighboring voxels. Traditional histograms and scatter plots (scalar value and gradient magnitude that most commonly used) entirely lose spatial information. However, analyzing data value’s distribution and statistical properties of neighboring voxels is of great significance since “a feature by definition is a spatially connected region in the volume domain with a unique position and certain statistical properties” [14]. To tackle the problem, several methods have devoted to neighborhood-based visualization. Roettger et al. [14] suggested an automatic TF by adding spatial information to the histogram of a volume and each feature at the corresponding class can be selected interactively by pointing and clicking in the TF space hence facilitate the TF adjustment process. Besides spatial information, statistical property is another important data metric. Histogram that is most commonly utilized in previous research could not reveal local properties of a given voxel or region. Therefore, Lundstrom et al. [15] proposed Partial Range Histograms (PRH) to detect tissue automatically and used histograms of local neighborhoods to capture tissue characteristics to facilitate the classification process. In distribution based volume visualization, distribution is utilized to explicitly probe local frequency distribution of data values in neighborhoods that centers around each voxel and users are allowed to input predicate-based hypotheses about patterns in local distributions such that rendering images show how neighboring voxels match the hypotheses [16]. Laidlaw et al. [17] determined the mixtures of materials within a single voxel by sampling the voxel several times to obtain a histogram of the results, and probabilistically choosing which materials best comprise the distribution. Aiming at solving the partial volume effect, its effectiveness is dependent on which materials are contained in the volume. Image processing algorithms such as sharpen, filter and edge detection that rely on neighborhood have been extended and integrated with convolution operators to volume rendering by Fang et al. [18].

III. OUR WORK

To analyze data value’s distribution of a given voxel, we define the neighborhood as voxels that lie within the given Euclidean distance from the central voxel. Several types of neighborhoods exist, as illustrated in Fig. 1. We call them cross, block and sphere neighborhood, a little bit similar with concept proposed in [15]. Fig. 1 shows voxel’s distribution of each neighborhood type. Cross neighborhood is the simplest type, as central difference used it to approximate gradient magnitude. Sphere neighborhood has a good property that it is isotropic. However, statistical properties calculated utilizing this type of neighborhood is time-consuming. The performance of block neighborhood is between them, which means that it could capture enough local data properties while doesn’t require too much time-consuming calculations to obtain these properties. Mean value and deviation are two important data metrics that could describe data value’s distribution of each voxel. Mean value of neighborhoods voxel is computed as

$$M(v) = \frac{1}{|N(v)|} \sum_{v \in N(v)} I(v)$$

(1)

where $N(v)$ is the set of neighboring voxels of $v$ with neighborhood type cross, block or sphere, $v$ is all elements of set $N(v)$ and $I(v)$ is data value. Deviation is another metric which describes deviation of all neighboring voxels, as

$$D(v) = \frac{1}{|N(v)|} \sum_{v \in N(v)} (I(v) - M(v))^2$$

(2)

![Fig.1. Three types of neighborhoods (left to right: cross, block and sphere).](image-url)
Fig. 2. Three types of scatter plot of TeddyBear dataset (Top left: Histogram, Top right: intensity-gradient magnitude, Bottom: mean-deviation).

Fig. 3. Color map from x, y, z space to r, g, b color space.

The larger \( D(v) \) is, the bigger possibility that voxel lies on a boundary between different materials in the volume. So contrary to traditional scalar value and gradient magnitude plot graph, we could plot statistical properties of each voxel on a graph with mean value as the horizontal axis and deviation the vertical axis, as illustrated in Fig. 2. Compared with intensity-gradient scatter plot and histogram, the picture shows the advantages of mean-deviation scatter plot are: (1) it reveals more information about how statistical properties of each voxel distribute in the volume; (2) distribution patterns are not only clearer but also more compact.

We define the original opacity by applying the formula as

\[
\alpha = \exp\left(-\frac{M(v)}{D(v)}\right) \tag{3}
\]

where \( M(v) \) is mean value obtained from (1) and \( D(v) \) is deviation computed in (2), respectively.

After obtaining original opacity of each voxel according to (3), we use the following some what modified formula to correct the original opacity [19]:

\[
\alpha' = \frac{e^{\beta(\alpha - 1)} - e^{-\beta}}{1-e^{-\beta}} \tag{4}
\]

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

In much previous work, various colors are commonly used to distinguish different materials in the volume and the same color represents the same structure. Actually, colors could reveal much more details in the datasets except to differentiate materials. In our work, we aim to show changes of gradient direction of each voxel in the volume. In our approach, gradient vector of x, y and z direction are mapped directly to r, g and b component in the RGB color space. Given a voxel at location \((x, y, z)\), we have

\[
|G_x| = |f(x+1,y,z)-f(x-1,y,z)| \tag{5}
\]

\[
|G_y| = |f(x,y+1,z)-f(x,y-1,z)| \tag{6}
\]

\[
|G_z| = |f(x,y,z+1)-f(x,y,z-1)| \tag{7}
\]

\[
G_x = \sqrt{G_x^2 + G_y^2 + G_z^2} \tag{8}
\]

So we map to \( r, g, b \) as \( r = G_x/G, g = G_y/G \) and \( b = G_z/G \). It is very obvious that \( r^2+g^2+b^2=1 \) as illustrated in Fig. 3. Some \( r, g, b \) triples such as \((1, 1, 1)\) could not be obtained. However, it has little influence on the rendered image.

Besides, as different materials share the same data value range in the datasets, gradient magnitude could be applied to differentiate these materials. But for distinct materials that of the same intensity and same gradient magnitude, gradient direction could still be used to distinguish these structures. So gradient vectors could reveal more clues in the dataset compared with intensity-gradient magnitude scatter-plot that is commonly used as the TF domain. In our method, gradient vectors, gradient magnitude and intensity are mapped in 3-D space. We use a standard vector to represent the gradient vector and its direction and length correspond to gradient vector’s direction and magnitude, respectively. In order to show intensity of the given voxel, we use different colors to render various gradient vectors. Therefore, compared with traditional intensity-gradient magnitude scatter-plot diagram, our presented diagram reveals more clues about intensity’s changes in the volume of each voxel. Users could identify their interested area in the picture by drawing some shear frustums, each denoted by four parameters \( v, \theta, r_1, r_2 \), in which \( v \) represents the gradient direction, \( \theta \) is the bounding angle around \( v \), \( r_1 \) and \( r_2 \) are ranges of the gradient magnitude as illustrated in Fig. 4.

To measure the difference between two voxels in user interested area, we apply the following formula

\[
D = w_1 E_x + w_2 E_x + w_3 E_y + w_4 E_z \tag{9}
\]
where $w_p, w_r, w_s, w_l$ are weights of the measures. $E_p$ measures the Euclidian distance between two voxels in the volume. $E_r$ is to evaluate directional deviation of two gradient vectors and $E_s = \arccos \left( \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\| \mathbf{v}_1 \| \| \mathbf{v}_2 \|} \right)$. Difference of gradient magnitude is measured by $E_l$. $E_l$ represents difference of two data values. In the measurement, $E_p, E_r, E_s, E_l$ are normalized to $[0, 1]$. This measure could be applied in a region growing visualization case.

IV. Results and Discussions

We conduct experiments on several datasets to demonstrate the effectiveness of our presented method. We implement it using OpenGL and GLSL (OpenGL Shading Language). Statistical properties are pre-computed because they are constants during the rendering process and a higher frame rate could be achieved. Our program is run on a personal computer (AMD Athlon 7750 Dual-Core Processor, 4G memory) equipped with NVIDIA GeForce GT 240 graphics card. Experiments are conducted on several common datasets that are publicly available on the Volume Library. The original datasets in pvm format are converted into raw format with the PVM tools distributed with the V^3 (Versatile Volume Viewer) volume rendering package. The result images are rendered from the raw datasets.

First of all, we evaluate the Engine dataset. In Fig. 5, it is shown that: 1. A clear perspective is obtained about the interior of the engine block and strong boundaries between different materials are clear, such as piston in the middle in red; 2. Different colors that represent gradient directions show how intensity in the volume changes within x, y and z directions. For example, the red part in the center (piston) indicates intensity changes a lot in the x direction while stays constant in the y and z direction. Moreover, the blue and green parts indicate that intensity varies a lot in the y and z direction, respectively.

The sheep heart dataset is another volumetric data that is usually tested in volume rendering. One of the difficulties is that because it is a MRI dataset, there are so much noise that strong boundaries become too blurred to indentify. In Fig. 6, our method could still capture some boundaries in the volume, although not very clear. Besides, intensity changes in the volume space remains very clear. In the rendering image, the green and red part corresponds to data value’s changes in the y and x direction, respectively. In the rendering image, red shows the muscle tissue, while green indicates fat tissue and boundaries between fat and muscle.

By applying the foot data, the method in this paper is compared with our previous work. In the rendering images Fig. 7(a) and Fig. 7(b), it can be seen clearly that both of them reveal detailed interior structures of the bone with emphasizing boundaries between different bone structures such as small toe and tubes in the bone are clear and distinguishable. However, in Fig. 7(a), intensity changes could not be seen since they are the same material and share almost the same color. While in Fig. 7(b), data value’s change along the gradient direction could see vividly. For example, in the bottom of the picture, green indicates intensity varies a lot in the y direction and changes little in other two directions and in the middle part the red color shows large intensity variation in the x direction, which means although they are all bones, the material quality are different. Moreover, of the joints that connect two bones, intensity alters much both in x and z directions. In contrast, in Fig. 7(a), these details are not visible. Hence, our method provides users with more deep insight into the data.

Fig. 8 illustrates rendering image of a head with aneurysm. Perspective of different tissues is vivid and blood vessels are denoted by yellow and the round part in the middle of the picture indicates the existence of aneurysm. Our experiment shows that TF in mean-deviation statistical space could also reveal important boundaries in the data.
We also evaluate the tooth dataset and a rendering image is shown in Fig. 9. TF based on statistical mean-deviation space is generated automatically without user interaction or selection of interested area. Some voxels that are of small deviation is filtered according to a threshold rule before visualization. From the left picture, the pulp-dentine is clearly seen in the middle part in purple, and the enamel around the pulp-dentine is visible and in white color. While on the right side, after a filter based on deviation, layer of enamel is peeled off and pulp-dentine is emphasised.

Finally, the rendering image of vismale data is revealed in Fig.10. From the picture, bones and skins could be seen vividly and their outlines are clear. In the rendering image, skin is denoted by purple; while tooth, crania and some parts of the bones are indicated by green, which means their distinct material quality compared with other bone structure such as cranium.

V. CONCLUSIONS

In this paper, we define the concept of neighborhoods and explore local statistical properties of each voxel in the volume. Three types of neighborhoods (cross, block and sphere) are introduced. We also compare standard intensity-gradient magnitude scatter-plot with the scatter-plot based on novel
normalized gradient vectors along the x, y and z direction are clues about intensity’s changes in the volume. In our method, normalized gradient vectors along the x, y and z direction are mapped directly to r, g and b component in RGB color space. As a result, an automatic TF is got which facilitate users to avoid time-consuming parameter adjusting. Experiments show that our method could both effectively emphasize strong boundaries within the volume and the color scheme gives user more deep insight into the data about intensity variations in volume space and material quality of different structures. Besides, contrary to traditional scalar value-gradient magnitude scatter plot, we propose a new user interaction widget, in which users could select interested areas by gradient vectors and gradient magnitude as well as scalar value. Finally, we show that TF base on statistical space (mean-deviation scatter plot) could also capture strong boundaries in the volumetric data.

However, for MRI datasets, which are typically of large noise, rendering result is not satisfactory. Besides, user’s domain knowledge in the data may be very useful and should be incorporated into the TF design process. Finally, our color scheme is on the basis of RGB color space, while HSL color space is closer to human perception of colors. CMYK and CIELIB are color space that are commonly used but don’t receive much attention in DVR. An exploration of these problems may be very helpful to achieve a better image quality.

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REFERENCES


