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A Clustering Based Transfer Function for Volume Rendering Using Gray-Gradient Mode Histogram

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ABSTRACT Volume rendering is an emerging technique widely used in the medical field to visualize human organs using tomography image slices. In volume rendering, sliced medical images are transformed into attributes, such as color and opacity through transfer function. Thus, the design of the transfer function directly affects the result of medical images visualization. A well-designed transfer function can improve both the image quality and visualization speed. In one of our previous paper, we designed a multi-dimensional transfer function based on region growth to determine the transparency of a voxel, where both gray threshold and gray change threshold are used to calculate the transparency. In this paper, a new approach of the transfer function is proposed based on clustering analysis of gray-gradient mode histogram, where volume data is represented in a two-dimensional histogram. Clustering analysis is carried out based on the spatial information of volume data in the histogram, and the transfer function is automatically generated by means of clustering analysis of the spatial information. The dataset of human thoracic is used in our experiment to evaluate the performance of volume rendering using the proposed transfer function. By comparing with the original transfer function implemented in two popularly used volume rendering systems, visualization toolkit (VTK) and RadiAnt DICOM Viewer, the effectiveness and performance of the proposed transfer function are demonstrated in terms of the rendering efficiency and image quality, where more accurate and clearer features are presented rather than a blur red area. Furthermore, the complex operations on the two-dimensional histogram are avoided in our proposed approach and more detailed information can be seen from our final visualized image.

INDEX TERMS Gray-gradient mode histogram, clustering analysis, transfer function, volume rendering.

I. INTRODUCTION

In recent years, a series of imaging techniques have been widely used in medical field, such as computer tomography (CT), single-photon emission computed tomography (SPECT), magnetic resonance Imaging (MRI), dynamic single-photon emission computed tomography (D-SPECT), intravascular ultrasound (IVUS), optical coherence tomography (OCT), etc [1]–[3]. In clinical diagnosis, visualization of medical images plays an important role in detecting internal information and three-dimensional reconstruction [4]. Two main streams of visualization are surface rendering and volume rendering [5]. Surface rendering uses segmentation technology to extract surface information of an object [6]–[8]. And volume rendering transforms a three-dimensional data fields into a two-dimensional image, including the direct visualization of scanned volume data [9]–[11].

Due to the important role of transfer function on volume rendering, increasing number of research has been carried out on transfer function, both in gradient characteristics based

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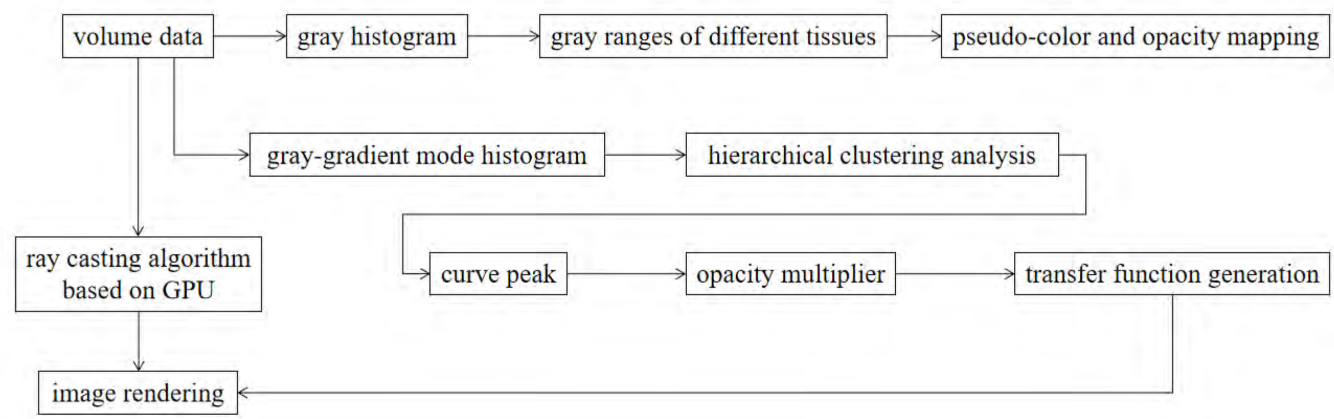

FIGURE 1. The flowchart of automatic transfer function design based on histogram clustering analysis.

methods and histogram based methods. Lifang *et al.* [12] proposed a transfer function using gradient characteristics of volume data, where a curve function was obtained through first directional derivative, second directional derivative and data value of volume data. M. Gargesha et al. used natural colors with opacity in volume rendering, and the value of opacity was calculated by color and gradient of volume data [13]. And a Gaussian transfer function based on boundary was introduced by Zhao *et al.* to increase the accuracy and efficiency of transfer function. In the proposed method, gradient magnitude threshold was considered to extract the boundary which is used in the design process of Gaussian transfer function [14]. Liu *et al.* introduced multiple segmentation results into volume rendering by mapping a series of materials to separate intervals. The transfer function was segmented based on different gray intervals of materials [15]. Moreover, Wang *et al.* introduced multi-feature fusion in transfer function to improve the quality of volume rendering, where an improved weighted k-means clustering was used [16] after feature extractions including curvature, gray and gradient magnitude.

In terms of histogram based volume rendering, Zhou *et al.* proposed a clustering method to classify volume data by using gradation-gradient color histogram, where identified information was transformed into the hue, saturation, and light (HSL) color space [17]. And a S-KA histogram based multi-dimensional transfer function was given by Chen *et al.* to classify internal voxels and find the class of boundary voxels [18]. Yang *et al.* used a multi-dimensional transfer function based on f-LH histogram to improve the accuracy of boundary visualization, where a modified Low and High (LH) histogram construction algorithm was presented [19]. Meanwhile, Xia *et al.* introduced a hybrid transfer function using both gradient histogram and size histogram to present spatial information, contributing to a better performance of images [20]. A transfer function based on two-dimensional histogram was introduced by Shen *et al.* to perform the tissue boundary via gradient magnitude and gray level, contributing to contain more detail information of volume data set [21]. Moreover, Sun *et al.* designed a two-dimensional histogram image segmentation based transfer function for volume rendering, where an algorithm of feature difference evaluation was introduced to improve the separation performance. And the efficiency of transfer function was increased via the two-dimensional histogram image segmentation [22].

However, how to improve the accuracy of volume data division by histogram is always a problem to be solved. In this paper, we propose a two-dimensional transfer function based on clustering analysis of gray-gradient mode histogram to divide volume data accurately. The attributes of volume data including gray and gradient are embedded into a two-dimensional histogram by analyzing the data in a data field. Moreover, the volume data is clustered according to the spatial information in the histogram, and then the transfer function is generated through the clustering results.

The remaining part of the paper is organized as follows. The proposed method is detailed in Section II. The experimental results are shown in Section III and Section IV concludes the paper with future work.

II. METHOD

In this paper, we aim to design a two-dimensional transfer function based on cluster analysis of gray-gradient mode histogram. The attributes of volume data including gray and gray gradient are embedded into a two-dimensional histogram by analyzing the data field. And the volume data is clustered according to the spatial information from the histogram, and then the transfer function is automatically generated through the clustering results. The flowchart of transfer function design based on histogram clustering analysis is shown in Fig. 1.

In Fig. 1, both gray histogram and gray-gradient mode histogram are obtained through original volume data. And different tissues can be distinguished according to different gray ranges, which is used in the pseudo-color and opacity mapping. Meanwhile, the hierarchical clustering analysis is processed based on the gray-gradient mode histogram, where the curve peaks are extracted. Moreover, the gradient mode is mapped to an opacity multiplier, which is multiplied by the opacity of all points in the volume element. In this way, the transfer function is finally generated and the image rendering can be achieved using ray casting algorithm based on GPU via generated transfer function.

A. THE MAPPING RELATIONSHIP IN THE TRANSFER FUNCTION

In our study, the transfer function is decomposed into three components, i.e. color transfer function, opacity transfer function and gradient transfer function. The three transfer functions are independent. When processing volume data, only the attributes of volume data, such as gray value, gradient modulus are considered rather than the raw volume data. Thus, the computational complexity of programs is greatly simplified, the operation efficiency is improved, and the design of transfer function is simplified. The transfer function is designed as a piecewise-linear scalar mapping relationship, where line segments can be inserted several times, contributing to an easier automatic design.

1) COLOR TRANSFER FUNCTION

The color transfer function maps the attribute of volume data to a color value (RGB). In volume rendering, the gray value of volume data is mapped to the pseudo-color value using the mapping relationship given as follows:

$$RGB = f_1(h) \tag{1}$$

where h represents the gray values, and RGB represents the pseudo-color. The f_1 is a mapping relationship where the sampling points satisfying gray values are uniformly assigned pseudo-color values. The following function can be obtained by transforming the above mapping relationship into functional relationship:

void AddSegment (double x1, double x2, double r, double g, double b);

where $x1$ and $x2$ are independent variables representing the given threshold of the gray values and ranging from -2048 to 2047, r, g, and b are mapping values representing RGB color values and ranging from 0 to 1. After the function runs, all points in volume data whose gray value h satisfies $x1 < h < x2$ can be assigned a uniform RGB color value. The function can be called multiple times and different color values are assigned to the sampling points of different gray values. Using the color transfer function above, the gray value of sampling points in ray casting can be mapped to pseudo-color values.

2) OPACITY TRANSFER FUNCTION

The opacity transfer function is a piecewise-linear scalar mapping function, which maps the attributes of volume data to the opacity. The mapping relationship of the function is expressed as follows:

$$A = f_2(h) \tag{2}$$

where h represents the gray values, and A represents the opacity. The f_2 is a mapping relationship which means that the sampling points satisfying gray values are uniformly assigned opacity values. The following function can be obtained by transforming the above mapping relationship into functional relationship:

void AddSegment (double x1, double x2, double A);

where $x1$ and $x2$ are independent variables representing gray values, A is a mapping value representing the opacity and ranging from 0 to 1. After the function runs, all points in volume data whose gray value h satisfies $x1 < h < x2$ can be assigned a uniform opacity. The function will be applied to assign different opacity to different volume data, thus mapping the gray value of sampling points to different opacity values.

3) GRADIENT TRANSFER FUNCTION

The gradient transfer function maps the gradient mode to an opacity multiplier, which enhances the display effect of a boundary region. The mapping relationship of the function can be given as follows:

$$n = f_3(g) \tag{3}$$

where g represents the gradient mode of a volume data, and n represents an opacity multiplier. The f_3 is a mapping relationship which means adding a multiplier to the opacity of sampling points satisfying the gradient modes. The following function can be obtained by transforming the above mapping relationship into functional relationship:

void AddPoint (double x, double n);

where x is an independent variable representing gradient modes, n is a mapping value representing the opacity multiplier. In the implementation process, a threshold is set and the opacity of the point whose distance between the gradient mode and x within the threshold will be multiplied by n. The gradient transfer function is designed according to the way of adding points, which means that the number of added points is equal to the number of boundaries appearing in the process of visualization.

B. GRAY HISTOGRAM

Gray histogram of images is the statistical characteristic of image gray values. As it is shown in Fig. 2, frequency distribution of volume data can be obtained by gray histogram and different tissues have different waves. Different peaks in a gray histogram represent different object regions, while valleys are transition points between two adjacent object regions. Threshold segmentation based on gray histogram is to segment the object region represented by peaks in the histogram. The valleys on the left and right sides of a peak correspond to the range of gray value of a tissue and the extraction of these valleys will contribute to the segmentation of image elements. We select the gray value corresponding to the valley as the segmentation threshold to segment images. And the gray value corresponding to a valley satisfies the

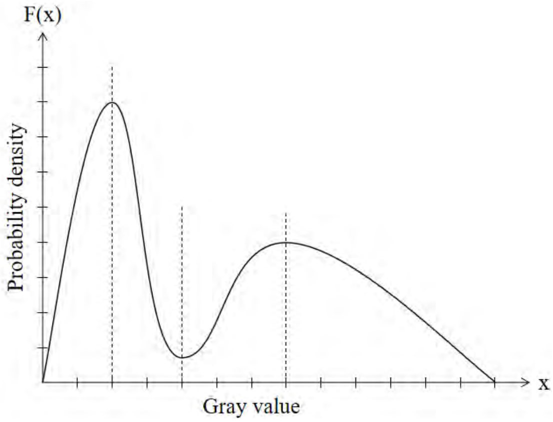

FIGURE 2. The principle of threshold segmentation based on gray histogram.

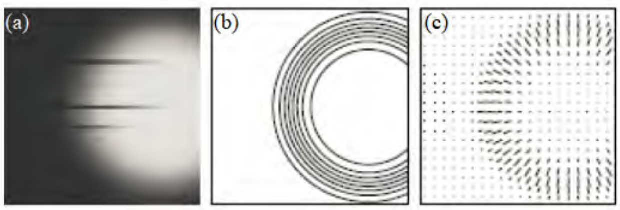

FIGURE 3. Relationship between the gradient and iso-surface of a boundary, where (a) represents data value, (b) represents the iso-surface and (c) represents the gradient.

following formulas:

$$\frac{\partial F(x)}{\partial x} = 0 \tag{4}$$

$$\frac{\partial^2 F(x)}{\partial x^2} = 0 \tag{5}$$

In our experiment, in order to prevent the false valley caused by noises, we first smoothed the image using median filtering method, and then carried out the threshold segmentation based on gray histogram [23].

C. GRAY-GRADIENT MODE HISTOGRAM

The gradient is a vector, and the gradient mode is the change rate in the direction of maximum gradient change. In a two-dimensional image, the gradient mode at the boundary is larger or tends to maximize, while the gradient mode in the interior is smaller or approaches to zero. The relationship between the gradient and iso-surface is shown in Fig. 3.

Fig. 4 is a histogram corresponding to the gradient modes of a boundary, where f represents the volume data value, f' represents the gradient mode, F_0 to F_3 respectively represents the gray values of four different substances and the arc represents the adjacent relationship between different substances. The highest point in an arc has the largest gradient mode and is used to represent the boundary between different substances, while the end of an arc has the lowest gradient mode and is used to represent the interior of different substances adjacent to the boundary [24]. However, in practical application, each arc is not so obvious, accompanied by many

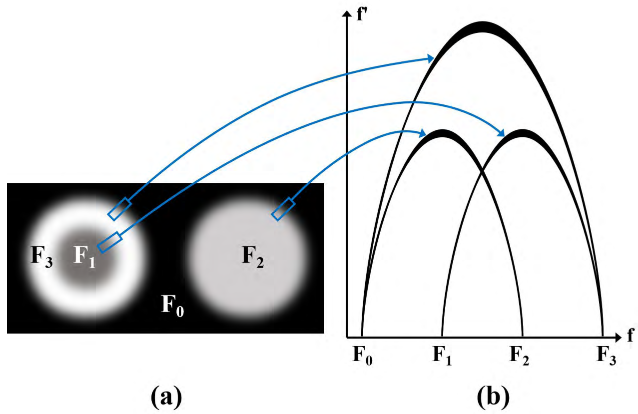

FIGURE 4. The gray-gradient mode histogram corresponding to a gray image, where (a) is a gray image and (b) is a gray-gradient mode histogram.

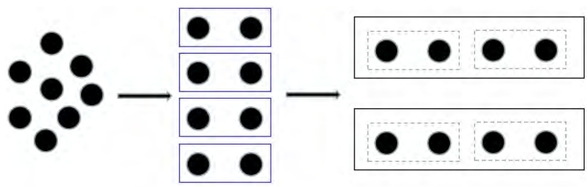

FIGURE 5. The schematic diagram of merging algorithm of hierarchical clustering.

scattered points, and these arcs cannot be distinguished by computers, so it is necessary to classify these points into different categories that is, different arcs through clustering.

D. THE PROPOSED AUTOMATIC TRANSFER FUNCTION

In this paper, we use the merging algorithm of hierarchical clustering to classify data which is shown in Fig. 5. In this algorithm, the similarity of any two data is calculated, and the two data with the highest similarity are combined and replaced by the average of the two data. The process is iterated until the termination condition of clustering is satisfied.

We use Euclidean distance to calculate the similarity of data points, and the closer the distance between two data points, the higher the similarity between them. And the Euclidean distance can be mathematically calculated as,

$$Dist = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{6}$$

where $Dist$ is the Euclidean distance, (x_1, y_1) and (x_2, y_2) are coordinates of two data in the gray histogram image. The advantage of hierarchical clustering is that the number of categories do not need to be determined initially, which can be truncated according to the threshold we set, that is, when the distance is greater than the threshold, the clustering process stops [25].

The frequency distribution of volume data can be obtained by gray histogram. Different tissues will have different waves. In the gray-gradient mode histogram, the boundary between different tissues is represented by a different arc, the highest point of each arc corresponds to the boundary

TABLE 1. Gray ranges of human tissues.

Tissue	Air	Pulmonary organ	Muscle and fat	Internal organ	Enhanced vessel	Skeleton
CT value	-1100~-900	-900~-250	-200~100	100~200	200~400	400~1000

between two different substances, and the end point of the arc corresponds to the interior of the two substances, so the boundary acquisition of different volume elements is represented by the vertex acquisition in the histogram.

Different tissues of human body have different ranges of CT values, and the CT range table of human tissues can be obtained because CT value is defined as the corresponding value of attenuation coefficient of X-ray and tissue in CT images. According to this table, RGB color values are set, where the color values are defined according to the observation requirements. Table 1 is the gray range of each tissue in the experimental data set.

For the color transfer function and opacity transfer function, the independent variables of transfer functions and the corresponding attributes of data can be coded into a look-up table. The look-up table is used as a mapping of a gray range, where different gray ranges in Table 1 are mapped to different colors. In the volume rendering, when the position of a sampling point is defined, the value of independent variables of the point can be obtained through the sampling point, and then the value of color and opacity of the sampling point can be set via the look-up table. For the gradient transfer function, the independent variable corresponds to the highest point of different curves in the gray-gradient mode histogram. After clustering analysis, the highest point of each curve can be extracted, and the gradient modes can be mapped to an opacity multiplier, which is multiplied by the opacity of all points in the volume element whose gradient modes satisfies the condition. Finally, the complete transfer function (TF) can be obtained in equation (7), where h and g are the gray value and gradient mode of a volume data respectively. The complete transfer function we designed contain three transfer functions: the color transfer function (f_1) used to set color, the opacity transfer function (f_2) used to set opacity, and the gradient transfer function (f_3) to set opacity multiplier. And $f_3(g)$ is set as 1.0 at the non-edge.

$$TF = f_1(h) + f_2(h) f_3(g) \tag{7}$$

In this paper, the piecewise-linear scalar function simplifies the automatic design. The piecewise-linear scalar function above includes the color, opacity and gradient transfer functions, and three transfer functions are independent. The complete transfer function is composed of three different transfer functions. According to the calculated eigenvalues, a number of line segments or points are added to set different optical attributes for different data. Through the above design, the transfer function can be adjusted according to the current data set. According to different data sets, the attributes calculated by transfer function are different. Using color transfer function, opacity transfer function and gradient transfer function according to the attributes including gray value and gradient mode can achieve the goal of automation and high compatibility. Because the transfer function design process only considers the data attributes, avoids the coordinate problem of the volume element points, greatly improves the efficiency of the transfer function, makes the volume visualized image achieve real-time moving effect, and the quality of the rendered image is also high.

FIGURE 6. A CT image of human thoracic.

III. RESULT

Our experiments are implemented on Windows 10 operating system, using VTK 7.1.0 and Visual Studio 2017. The data set selected in our experiment is the sequence of human thoracic CT images with coronary artery disease (CAD). The CT images contain basic human internal organs and M-type stents mounted on the aorta. The format of images we used is medical DICOM files. The size of each image is 255*255 pixel, and the CT value ranges from - 2048 to 2047. The image sequences contain 210 DICOM files in total and the slices are arranged in order from top to bottom. Our experiment focuses on the three-dimensional reconstruction of human heart and aorta, so the transparency of human skin, muscle tissue and lung is set to 0 in order to better observe the aorta and the stent on the aorta. Fig. 6 is a sample of the sequence of CT images:

In Fig. 6, different tissues is shown as different gray values, and the gray value of a certain tissue is within a certain range. Thus the tissues of different part of human body can be clustered by inspecting the gray values. When the data set is loaded, the number of points contained in each gray value will be counted. The data are represented in a bar chart, and the gray-histogram obtained is shown in Fig. 7.

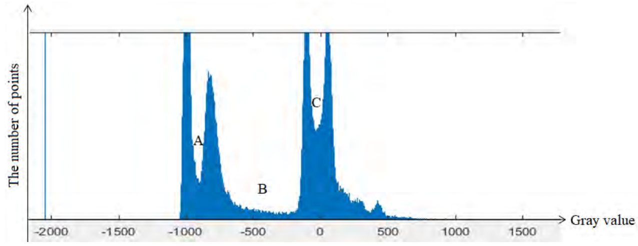

FIGURE 7. The gray-histogram obtained from CT images.

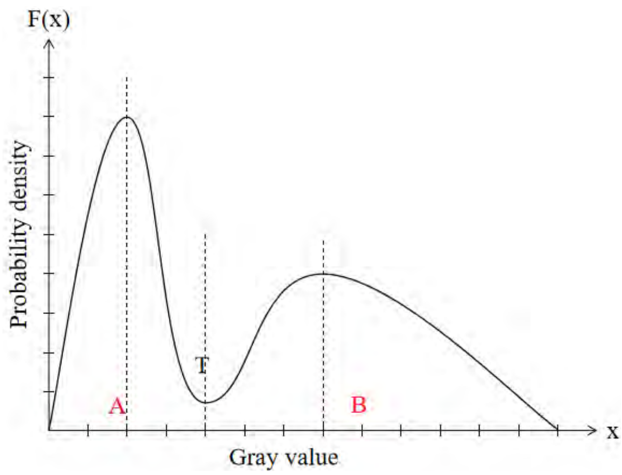

FIGURE 8. The schematic diagram of inserting line segments.

The parameters in color transfer function and opacity transfer function are gray values of volume data, so the number of points at each gray value is not considered in the transfer function. Thus, in Fig. 7, we only consider the number of peaks and the abscissa corresponding to the valleys. After smoothing the gray histogram with median filtering method, the gray values A, B and C corresponding to the valleys on both sides of two successive peaks are taken, and Table 1 shows that the peaks belong to a tissue range of human body. Thus, the pseudo-color values are obtained, and the color transfer function is designed as follows:

colorTransferFunction -> AddSegment (A, B, r_1, g_1, b_1);
colorTransferFunction -> AddSegment (B, C, r_2, g_2, b_2);

In VTK, the prototype color transfer function is defined as:

$f_1(A, r_1, g_1, b_1)$;
$f_1(B, r_2, g_2, b_2)$;

By using the two functions above, the color values of points with gray values between A and B are mapped linearly from r_1, g_1, b_1 to r_2, g_2, b_2. However, in our proposed method, the color values of points with gray value ranging from A to B should be the same, thus we defined the colorTransferFucntion $g(A, B, r_1, g_1, b_1)$ as an encapsulation of two functions:

$$
\begin{aligned}
&F_1(A, B, r_1, g_1, b_1)\{\\
&\qquad f_1(A, r_1, g_1, b_1);\\
&\qquad f_1(B, r_1, g_1, b_1);\\
&\}
\end{aligned}
$$

Moreover, in order to prevent the linear color mapping between the intervals of multiple gray-scale regions when

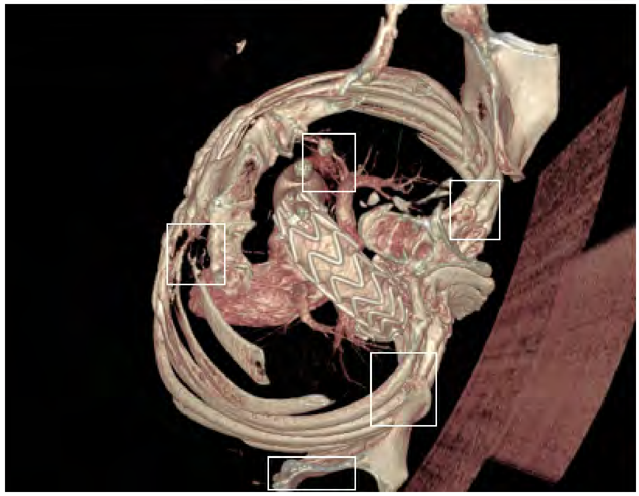

FIGURE 9. The volume rendering result based on both color transfer function and opacity transfer function.

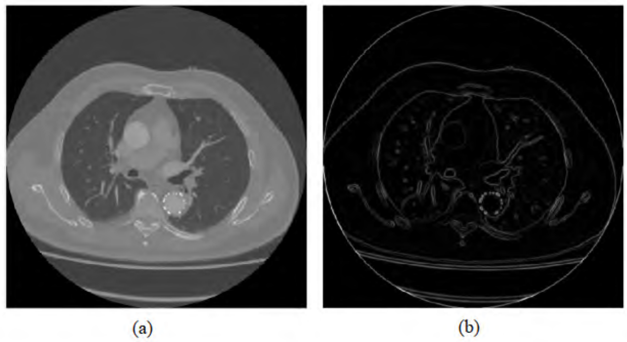

FIGURE 10. The gradient image of CT images, where (a) is an original CT image, and (b) is a corresponding gradient image.

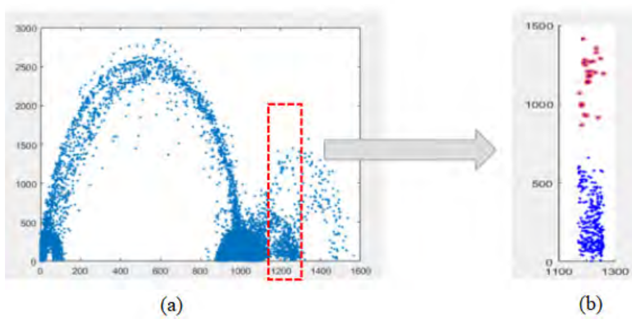

FIGURE 11. A local clustering graph of histogram, where (a) and (b) represent the gray-gradient mode histogram and local clustering graph respectively.

F_1 is used continuously, the edge values of each gray-scale region need to be processed.

$$
\begin{aligned}
&F_1(A, B, r_0, g_0, b_0)\{\\
&\qquad f_1(A-1,\ r_0, g_0, b_0);\\
&\qquad f_1(A, r_1, g_1, b_1);\\
&\qquad f_1(B, r_1, g_1, b_1);\\
&\qquad f_1(B+1, r_0, g_0, b_0);\\
&\}
\end{aligned}
$$

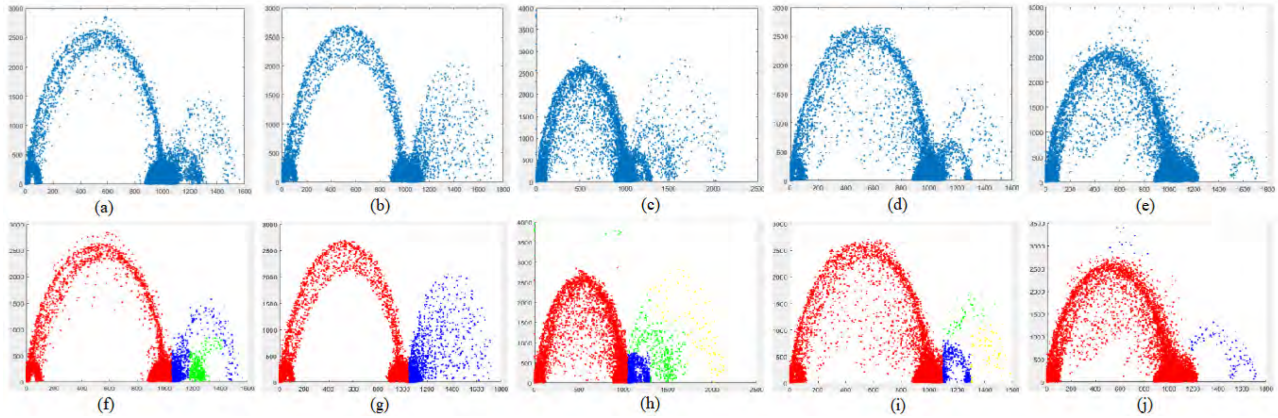

FIGURE 12. The result of clustering analysis based on gray-gradient mode histogram, where (a), (b), (c), (d), (e) are gray-gradient mode histogram, and (f), (g), (h), (i), (j) are corresponding results of clustering analysis.

By setting the color of edges in a gray-scale region as r_0, g_0, b_0, we can solve the impact of continuous use of F_1 on image quality.

Because of the different observation objects, the opacity of the area to be observed is set to a non-zero value, and the opacity of the area not needed, such as external air, skin and muscle tissue is set to 0. The final opacity transfer function is designed as:

opacityTransferFunction -> AddSegment (A,B,a_1);
opacityTransferFunction -> AddSegment (A,B,a_2);

The prototype opacity transfer function in VTK is expressed as:

$f_2(A, a_1)$;
$f_2(B, a_2)$;

And after using the two functions above, the opacity values of points with gray values between A and B are mapped linearly from a_1 to a_2. We use the same method as the color transfer function to set the same opacity for the points with gray values ranging from A and B.

Corresponding to all the waves in the gray histogram, a series of gray values are obtained by extracting the valley, and then the complete color transfer function and opacity transfer function are obtained by inserting line segments. And the process of inserting line segments is presented in Fig. 8. The whole gray value is divided into two segments A and B by the valley point T. And in the process of inserting line segments, the two segments A and B are set to different color and opacity. The volume rendering effect without adding gradient transfer function is shown in Fig. 9.

It can be seen in Fig. 9 that the resulted volume rendering without gradient transfer function have blurred edge features which are marked in white squares hence it is impossible to distinguish bone from medulla clearly. After introducing the gradient transfer function, the voxel opacity at the edge increases to highlight the edge features. As it is shown in Fig. 10 (b), the gradient reflects the edge features of the image well.

Fig. 11 is a local clustering graph of histogram. It can be seen that points are distributed in an arc in (a). We use a clustering method to intercept a section of abscissa and cluster the points in the coordinate range. Meanwhile, the result of clustering analysis is shown in Fig. 12.

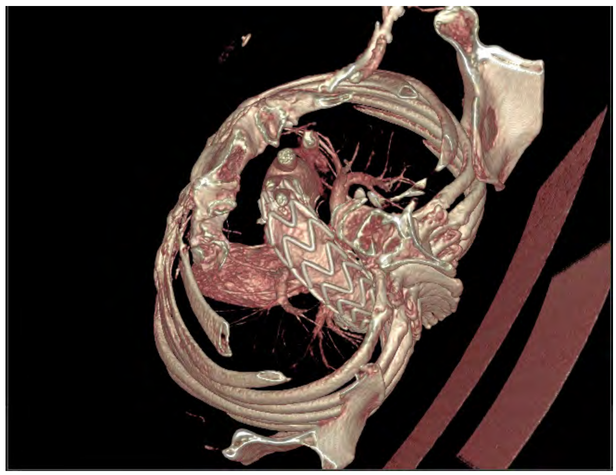

FIGURE 13. The result of volume rendering based on two-dimensional transfer function.

After clustering all segments, N arcs are obtained, which are N groups of data. The average G_n of all points in the abscissa at the maximum gradient modes is mapped to the opacity multiplier n. And the following gradient transfer functions are obtained:

gradientTransferFunction-> AddPoint(G_1, n_1);
gradientTransferFunction-> AddPoint(G_2, n_2);

The prototype gradient transfer function can be defined as

$f_3(G_1, n_1)$;
$f_3(G_2, n_2)$;

When the gradient is between G_1 and G_2, the opacity multiplier is mapped linearly to n_1 and n_2. To solve this problem, in our gradientTransferFunction, the opacity multiplier is set as n_1 when the gradient interval is (G_1-g, G_1+g).

A complete two-dimensional transfer function is obtained by adding N points and combining the color transfer function and opacity transfer function above. Compared with one-dimensional transfer function, two-dimensional transfer

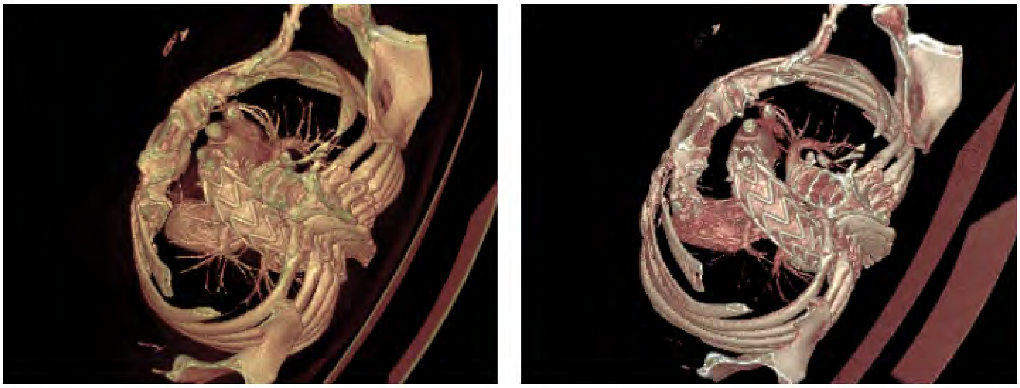

FIGURE 14. The contrast result of volume rendering, where (a) based on the original transfer function in VTK, and (b) based on our proposed transfer function.

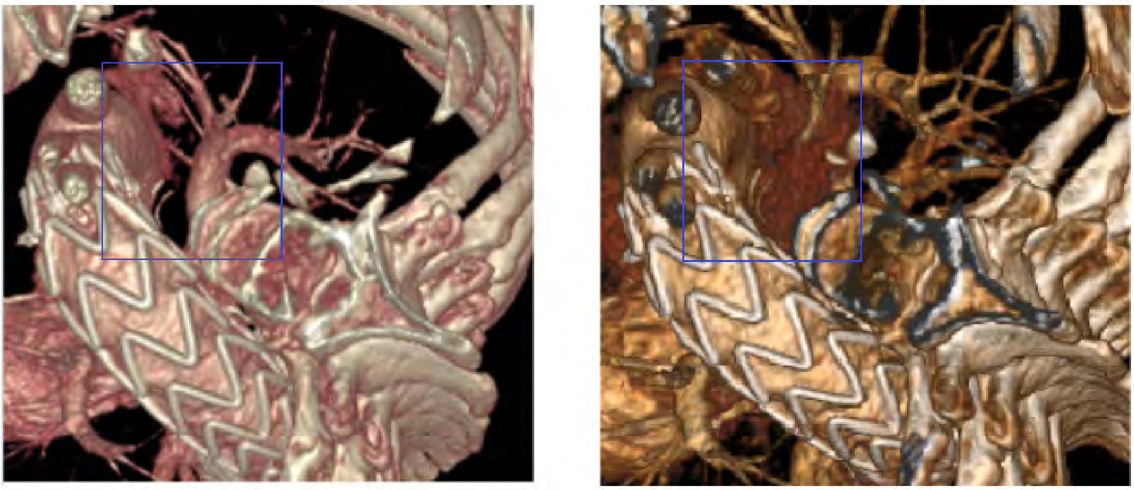

FIGURE 15. The comparison result of volume rendering, where (a) based on our proposed transfer function, and (b) based on RadiAnt DICOM Viewer.

function has better performance in three-dimensional reconstruction and more prominent edge information. The result of volume rendering based on two-dimensional transfer function is shown in Fig. 13.

Moreover, in our experiment, we compare the rendering result with the original transfer function in Visualization Toolkit (VTK), as well as RadiAnt DICOM Viewer, a commercial DICOM viewing software. The transfer function implemented in VTK needs manual adjustment, i.e. trial-and-error method, to achieve better visualization result by constantly changing parameters. In VTK, it requires observers to have a detailed understanding of the data set, and two-dimensional transfer function adjustment parameters will bring great trouble to observers. Manual adjustment method consumes a lot of time, and some detail information are lost in the rendering results. The contrast result of volume rendering is shown in Fig. 14.

In RadiAnt DICOM Viewer, the function of volume rendering is provided. The volume rendering transfer in the software consumes a certain time to optimize, and the image will gradually become clear. However when the viewer changes the perspective, the image will become blurred again, leading to a bad experience of human-computer interaction. Figure 15 compares the results of volume rendering obtained by our proposed method and the RadiAnt DICOM Viewer. It can be seen from the figures that details are shown clearly in the blue square without a blurred area.

IV. CONCLUSION

In this paper, we use ray casting algorithm to realize volume rendering. On the basis of two-dimensional transfer function, we designed and implemented an intuitive and effective automatic transfer function based on clustering analysis of gray-gradient mode histogram. The contributions of our paper can be summarized as the following points: 1) Compared with traditional transfer function, the proposed transfer function based on clustering analysis of gray-gradient mode histogram automatically identify the zones of human tissues. By applying the transfer functions, the volume rendering is achieved in an intuitive and effective way without tedious operations of operators by exploring the data manually. 2) Our approach only need to use the attributes of volume data, such as gray value and gradient modes, this strategy has avoided the coordinate problem of sampling points. It means that the gray value of each pixel in a CT image are extracted to form a new image. Through the operation of the new image, the points with same gray value are set to the same color, without considering the coordinate position of these points in the original CT image. In this way, mapping method from data attributes to optical attributes via transfer functions are simplified, hence the operation efficiency is improved, and the experience of human-computer interaction becomes more friendly. 3) Functional classification and piecewise design make the transfer function universal and adaptable to different data sets, where different issues can be distinguished. Our proposed transfer function is not specific to a specific data set, and different transfer functions are inserted in segments through a clustering method to construct a complete transfer function, contributing to a better effect.

In future, in order to optimize the clustering accuracy and rendering speed of gray-gradient mode histogram, we will consider to introduce artificial intelligence method to classify volume data to improve the classification accuracy and reliability. Meanwhile, a clustering based multi-dimensional transfer function can be taken into account to achieve better rendering effect. And more interactive tools and methods will be used to improve our interface and provide timely feedback to users.

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