Available online www.jocpr.com

Journal of Chemical and Pharmaceutical Research, 2014, 6(7):2008-2014

Research Article

ISSN : 0975-7384
CODEN(USA) : JCPRC5

The design of medical image transfer function using multi-feature fusion and improved *k*-means clustering

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ABSTRACT

The high quality rendering of important information in volume data is the key to medical visualization. For the purpose to improve unsatisfactory rendering result of the single high-dimensional feature transfer function, a method for transfer function design using multi-feature fusion is proposed. Firstly, the weighed multi-scale morphological opening-closing filter is utilized to remove the noises and small details, and then the features of 3-D volume data such as gray value, gradient amplitude and curvature are extracted. Finally, the improved weighted k-means clustering is applied to construct the transfer function. Since the classification of volume data integrates into multiple features, it reveals more internal structure relations. Medical visualization experiments show that this method increases the contrast of different tissues and obtains better volume rendering quality and efficiency.

Keywords: volume rendering, transfer function, multi-feature fusion, *k*-means, visualization

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INTRODUCTION

Medical image visualization is a process that reconstructs the medical image information and displays them in three-dimensional (3D) visualization. As an effective tool of interpreting the internal structure of objects, volume rendering is widely applied in 3D medical image visualization. Transfer function [1-5] transforms the data values of 3D data field into optical parameters; the performance of transfer function directly determines the quality of visualization. Typical transfer function separates the different objects or structures in the data field. By classifying the data and mapping the volume data to optical quantities such as color and opacity.

Many efforts have made to find an appropriate transfer function in medical visualization. Levoy [1] presented the one-dimensional (1D) transfer function of straight volume rendering, which directly maps the scalars in the volume data to color and opacity, realizing a mapping from the data values to optical features. However, the classification of 1D transfer function in visualization applications is very limited. Multi-variable volume data is introduced to improve the classification of transfer function. Kindlmann [2] employed the first and second-order gradient in designing the transfer function. Second-order gradient calculation model yields better rendering effects in the complex data filed. Kniss [3] et al. proposed a design of the two-dimensional (2D) transfer function based on the gray-gradient histogram, in which users can add geometry controls such as color and opacity, by adjusting and installing these controls to generate the 2D transfer function. Carlos[4,5] et al. presented a scale-based transfer function design by analyzing texture features in various scales and is merited with the ability of highlighting the tissues of interest. Whitaker[6] employed curvature to design multi-dimensional transfer function, this provided a good solution to surface smoothing and non-photorealistic rendering [7]; Peng [8] adopted shape features to design transfer function, by analyzing the various shape features of volume data, followed by highlighting the interesting structures with the same shape. From the existing transfer function design, it can be observed that high dimensional transfer function lacks interactive capability, while the interactive transfer function design lack automatic design and data analysis, and its also difficult to separate the interesting region effectively.

Analysis of the above methods points to the fact that much more features are not included, therefore highlighting of the tissue structure of medical volume data may fail. This paper proposed a multi-feature fusion method to design transfer function, in which curvature is utilized sufficiently to describe the bending and structure of different tissue details, and render them separately.

2. Image pre-processing

There are various noises jamming in the medical images. Morphological opening (closing) can eliminate the maximum (minimum) regions less than the structuring elements while preserving the objects. Therefore, multi-scale morphological opening-closing and weighted stacking are adopted to remove the noise, that is

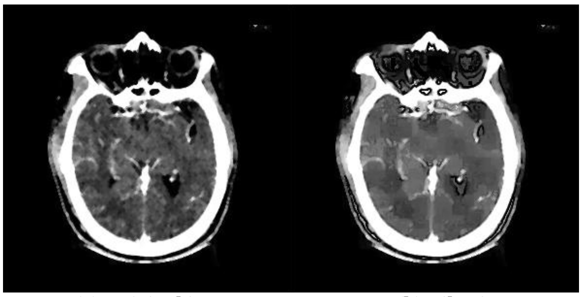
$$f_l = \frac{1}{\sum_{i=1}^{n} a_i} \sum_{i=1}^{n} a_i [(f \circ b_i) \bullet b_i] \tag{1}$$

where f is the original image, f_l denotes the filtered image; a_i denotes the weighting coefficient, b_i is a round structuring element whose radius is i, n is the radius of the maximum structuring element, " $\circ$ " and " $\bullet$ " respectively represent the morphological opening and closing operations.

The bigger structuring element may cause contour bias, therefore, we adopt weighted filter to remove the noise. The relationship between weighted value and the scale of structuring element is inversely proportional. It means that when the scale of structure element is larger, the corresponding weighted value is smaller. This can alleviate the contour bias to some degree. The weighted value a_i defines as following:

$$a_i = 5 / i \tag{2}$$

Figure .1 illustrates the filtering result



(a) Original image **(b) Filtering**

Figure 1.Multi-scales filtering

3. The design of transfer function

A. The definition of transfer function

In the direct volume rendering, transfer function [9] establishes the mapping relation between 3D field data and optical features; it is the Cartesian product from a scalar set D to the optical characteristic set Q [10].

$$\tau : D_1 \times D_2 \times \cdots \times D_M \to Q_1 \times Q_2 \times \cdots \times Q_N \tag{3}$$

Where D is the definition domain of transfer function, indicating the value property of 3D data field, and Q is the range, indicating the visual optical properties, τ represents the mapping rule from data property to the optical property. Considering the requirement of visualization, choosing the appropriate data and optical qualities is paramount to the design of the transfer function. Gray value, gradient amplitude and curvature feature are choosen to classify the volume data, regarding color values and opacity as optical properties.

B. Feature extraction

The most simple and conventional transfer function is 1D transfer function and it only uses sampling point or one of the multiple sampling point scalar values, which can classify different objects for simple application. Different tissues mostly have different CT values, and show different gray values in medical CT images. The gray values are often directly used to design the transfer function. However, for the complex 3D data field, different substances may have the same scalar values, in this case, 1D transfer function cannot solve the problems, and more features are required to implement the classification.

1) Gradient amplitude
In the volume rendering, the same substances typically have similar scale quantities. Thus, exquisite changes occur at the border among different objects, and this can correspondingly be characterized by gradient amplitude [10, 11] changing.

Suppose $f(x,y,z)$ presents the 3D data field, Then, in 3D domain, gradient is as follows:

$$\nabla f = (\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}) \tag{4}$$

The gradient amplitude operation is:

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2 + \left(\frac{\partial f}{\partial z}\right)^2} \tag{5}$$

Where $\|\nabla f\|$ demonstrates the magnitude of gradient. The 3D data field consists of discrete sampling points, so the gradient amplitude is obtained by computing the local and neighboring sampling points. The central difference method was adopted to compute the gradient, with the boundary gradient possessing local maximum and the object gradient inside it approaching zero, thus the transfer function based on gradient values is constructed. The gradient formula by central difference describes as follows:

$$\begin{cases} \frac{\partial f}{\partial x} = \frac{1}{2}[f(x+1,y,z) - f(x-1,y,z)] \\ \frac{\partial f}{\partial y} = \frac{1}{2}[f(x,y+1,z) - f(x,y-1,z)] \\ \frac{\partial f}{\partial z} = \frac{1}{2}[f(x,y,z+1) - f(x,y,z-1)] \end{cases} \tag{6}$$

2) Higher order derivatives
The high order derivatives extract features of data field more accurately. Ideally, when the gradient of border surface in data field reaches the maximum, the second-order derivative in the gradient direction is 0. Compared with gradient maximum in extracting border surface, using the second-order derivative minimum to extract the border surface and entity structure of the volume data, is more efficient and accurate. This paper utilizes the more accurate Hessian matrix to compute the second-order derivative of the gradient.

$$D^2_{\nabla f} f = \frac{1}{\|\nabla f\|^2} \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix} \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial xy} & \frac{\partial^2 f}{\partial xz} \\ \frac{\partial^2 f}{\partial xy} & \frac{\partial^2 f}{\partial y^2} & \frac{\partial^2 f}{\partial yz} \\ \frac{\partial^2 f}{\partial xz} & \frac{\partial^2 f}{\partial yz} & \frac{\partial^2 f}{\partial z^2} \end{bmatrix} \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} & \frac{\partial f}{\partial z} \end{bmatrix} \tag{7}$$

3) Curvature
As the significant feature of the curve, curvature [6] used to design transfer function to distinguish shape and render details of different objects. In 3D space, the curvature of an arbitrary point P is calculated by the curved surface formed by fitting neighboring points. Meanwhile, the same curve has different curvatures, such as the maximum positive curvature, the minimum negative curvature and the principal curvature.

When computing curvatures, in order to avoid bias between the principal direction of curves and the imputing data field axe, not directly calculating the curvature of every sampling point, but using neighbor sampling points to construct a surface is the way to go. According to the least square approximation principle, we can get N times curve surface fitting equation. When N=2, therefore the quadratic surface equation is

$$z(x,y) = Ax^2 + By^2 + Cxy + Dx + Ey + f \tag{8}$$

The coefficients in (8) can be expressed in first-order and second-order derivatives as follows.

$$\begin{cases} A = \frac{1}{2}\frac{d^2z}{dx^2}, \quad B = \frac{1}{2}\frac{d^2z}{dy^2}, \quad C = \frac{1}{2}\frac{d^2z}{dxdy} \\ D = \frac{dz}{dx}, \quad E = \frac{dz}{dy} \end{cases} \tag{9}$$

By the combination of coefficients in (9), we can obtain five curvature features, where the maximum positive curvature K_+ and minimum negative curvature K_- respectively define as following.

$$K_+ = (A+B) + \sqrt{(A-B)^2 + C^2} \tag{10}$$

$$K_- = (A+B) - \sqrt{(A-B)^2 + C^2} \tag{11}$$

The maximum positive curvature and minimum negative curvature can be severed as a feature for data classification. After forming the feature space by extracting multiple features, each voxel is classified by the improved weighted k-means (k-WMeans) algorithm, where each classification corresponds to a transfer function. By adjusting each transfer function and mixing the color and opacity, the final rendering result is achieved.

4. K-WMeans clustering

The k-Means is one of the classical clustering algorithms, but it is sensitive to noise and isolated data, and therefore influences the mean values. Sun [12] et. al. employed the k-WMeans algorithm to overcome the weakness of k-Means, and achieved better clustering results. k-WMeans procedure used to classify the feature space is described as following steps.

Step 1 Randomly select k objects as the initial cluster center.

Step 2 According to the weighted average value of objects in the cluster, each object is assigned to the lowest cluster dissimilarly;

Step 3 Update the weighted average values of cluster, i.e. compute the weighted average values of objects in each cluster;

Step 4 Stop until it results without change.

The k-WMeans clustering classify the vowels into k classes. During the course of classification, the effect of each data to recognition is different; consequently, the weight W_j is determined by different data.

$$W_j = \frac{W'_j}{\sum_{j=1}^{n} W'_j} \tag{12}$$

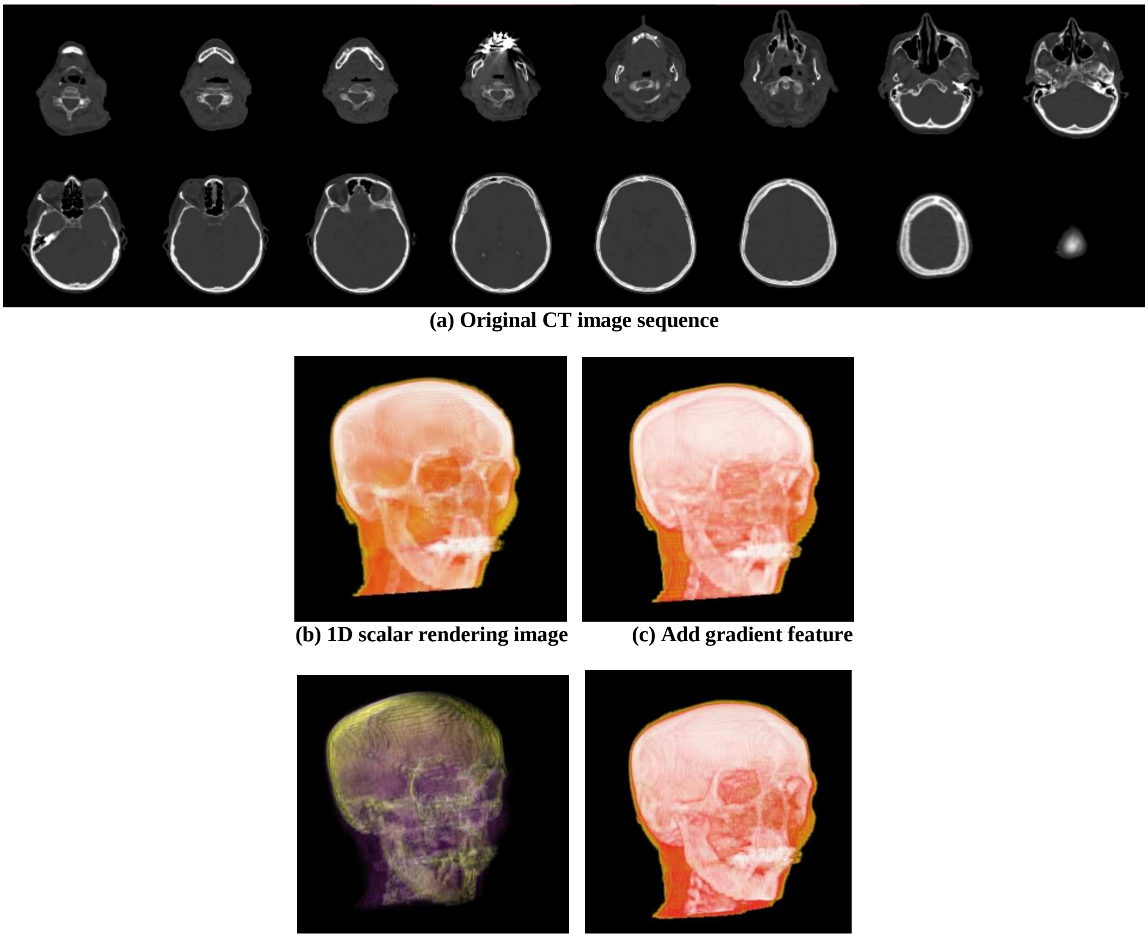
Where $W'_j = \frac{1}{n}\sum_{i=1}^{n} d(x_i, x_j)$, $d(x_i, x_j)$ is the dissimilarity degree between x_i and x_j. When x_i and x_j are similar or closer, the value of $d(x_i, x_j)$ is closer to 0, vice versa.

There are many methods [13] for calculating the dissimilarity degree. This paper employs conventional distance to measure dissimilarity degree. When the weight is smaller, the distance is more similar or closer, and vice versa.

With the k-WMeans clustering algorithm, a label matrix $L\{x, y, z\}$ within $[1, n]$ is produced, where n denotes the class number defined by user. For the aim of improving rendering results, the n transfer functions are firstly generated, and then mapped onto classification results $\{1, n\}$ and then to the corresponding transfer function $F\{1, n\}$. The final rendering result is obtained by mixing the color transfer function and opacity transfer function, and adjusting each transfer function with labels slightly. Since the classification employs the gray value, gradient amplitude and curvature as the features, the right classification is greatly improved.

5. Experiments and analysis

In order to validate the rendering performance, the multi-feature transfer function is designed and implemented on a Windows platform with C++ and VTK5.8.0. To substantiate the advantages of multi-feature transfer function, the experiments adopt a progressive principle.



(a) Original CT image sequence

(b) 1D scalar rendering image **(c) Add gradient feature**

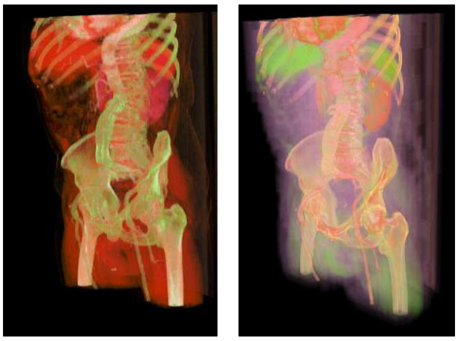
(d) Shape-based rendering image **(e) Proposed method**

Figure 2.Brain CT rendering (k=8)

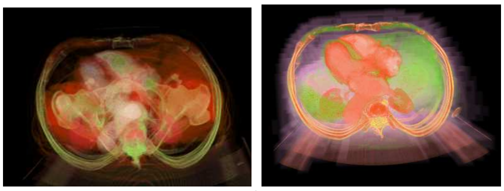
Figure.2 (a) is 128×128×53 brain CT image sequence, experiment images are selected with 3-4 intervals from the CT sequence. Figure.2 (b) shows the rendering result with 1D scalar transfer function, which only employs gray feature, and roughly distinguish the contour of different matters. Figure.2(c) is the rendering result after integrating gray and gradient features; it has stronger ability and show more details than Figure.2 (b), especially at the edges. Figure.2 (d) shows the rendering result of a single shape feature based transfer function design. Figure.2(d) is the proposed rendering image which fuses the gray, gradient and curve features, it can be seen that the multi-feature method can exhibit more details than the single feature based transfer function.

Figure.3 is 512×512×174, 48Mb CT data of lumbar, where the first column is the rendering of proposed method and the second column is the rendering results of adopting shape feature. Since multiple features have been considered, the proposed method can obviously distinguish the contour between different matters with better classification and rendering effects.

Elevation



Side Elevation



Planform

Figure 3.Comparison of lumbar imaging(k=8)

Table 1 compares the imaging time-costing between single feature and the proposed method, it can be seen that the shape-based rendering [8] is superior to the proposed method for small data, but for a large data, the advantages of the proposed method is obvious, and it is more propitious to rendering 3D medical image.

Table.1. Comparison of time costing of 3D visualization

Methods	Image number	Data size	Rendering average time（s）
Proposed	Image.2(e)	848 Kb	4.2
	Image.3 left column	40 Mb	25.4
Reference[8]	Image2(d)	848 Kb	3.8
	Image3 right column	40 Mb	32.1

CONCLUSION

The design of medical image transfer function using multi-feature fusion is proposed. Initial filtering of the original CT images are carried out by multi-scale morphological opening-closing operations, then the gray, gradient and curvatures are extracted to classify the volume data, and the improved weighted k-means clustering is employed to construct the transfer function. The medical image 3D visualization experiments show that with the increase in the number of features, the rendering effect is improved and the detail rendered is obvious. Compared with single feature and other similar methods, the transfer function design with multi-feature clustering proves to be more available for improving the 3D visualization effect.

Acknowledgment
This work is supported by the National Natural Science Foundation of China (No.61261029), Jinchuan Company Research Foundation (JCYY2013009), Gansu Province Science and Technology Support Program (1204GKCA051) and Gansu Province higher education fundamental Research funds (212090).

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