Information-Guided Transfer Function Refinement

Shengzhou Luo and John Dingliana

Trinity College Dublin, Ireland

Abstract

This paper examines the methods for exploring volume data by optimization of visualization parameters. The size and complexity of the parameter space controlling the rendering process makes it challenging to generate an informative rendering. In particular, the specification of the transfer function (which is a mapping from data values to visual properties) is frequently a time-consuming and unintuitive task. We propose an information theory based approach to optimize the transfer function based on the intensity distribution of the volume data set and the ability for users to specify priority areas of importance in the resulting image in a simple and intuitive way. This optimization approach reduces the occlusion in the resulting images, and thus improves the perception of structures.

Categories and Subject Descriptors (according to ACM CCS): I.6.9 [Simulation, Modeling, and Visualization]: Visualization—Volume visualization

1. Introduction

Transfer functions play an essential role in volume rendering. They assign visual properties, including colour and opacity, to the volume data being visualized. Hence transfer functions determine which structures will be visible and how they will be rendered. However, obtaining an effective transfer function is a non-trivial task, which involves a significant amount of tweaking of colour and opacity. In addition to the complex structures contained in volume data, users have differing goals or features of interest depending on their specific tasks. Therefore, it is almost impossible to generate a transfer function that would suit all kinds of visualization tasks. Also, different subsets of the data may occlude each other and thus result in ineffective visualization.

2. Related Work

Various strategies have been proposed to simplify transfer function specification [PLB*01]. Data-centric strategies examine the properties of volume data sets. Overlapping intensity intervals corresponding to different materials make boundary detection difficult. Classical approaches try to detect boundary information between tissues by introducing derived attributes such as first and second-order derivatives to isolate materials [KD98]. Another strategy is based on the selection of rendered images. This strategy lets the user select one or more favourite images to guide the further search

of transfer functions [WQ07]. More recent approaches introduced visibility and measures derived from information theory. Correa and Ma [CM11] optimize the transfer function by maximizing the visibility of important structures based on the visibility histogram, which represents the contribution of voxels to the resulting image. Ruiz et al. [RBB*11] optimize the transfer function by minimizing the informational divergence (Kullback-Leibler distance) between the visibility distribution captured from several viewpoints and a target distribution specified by the user.

In contrast, our approach optimizes the transfer function by minimizing the variance of control point weighting, which is generated from the intensity distribution of the data set and user-selected regions to specify priority areas of importance in the resulting image. In our approach, the user has more control of the optimization by setting up control points for the optimization. For example, the user can leave out less relevant data ranges by not covering the data ranges with control point groups.

3. Motivation

In the specification of a 1D (intensity-based) transfer function, the user would set up several control points on the interface. Each control point often corresponds to a certain kind of material or structure. It is common that users have prior knowledge about which intensity ranges are relevant
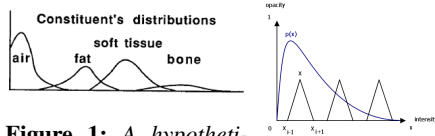
Figure 1: *A hypothetical constituent distribution of CT data [DCH88]*

Figure 2: *A transfer function*

or which regions should be emphasized in the data. This is especially the case in medical visualization. For instance, in computed tomography (CT) data the intensity ranges are determined by the Hounsfield scale [RBB*11]. The user may expect the constituent's intensities of CT data to be similar to Figure 1 and thus set up control points accordingly. However, small changes made to the opacity of control points may lead to dramatic changes in the rendered images. In many cases, minuscule modulation of opacity is required, but this kind of tiny adjustment of control points may be impossible to make by mouse interaction (due to limited accuracy of mouse movements).

Another consideration is that interior structures are likely to comprise far fewer voxels and are often occluded by the surrounding material. Consider the transfer function in Figure 2. The user finds three intensity intervals of interest and then sets up three sets of control points in order to visualize these intensity intervals. The opacity of the three peak control points are assigned equally as they are equally important. However, if the distribution of voxels follows $p(x)$ (the blue curve), the voxels of the leftmost intensity intervals may completely occlude voxels of the other two intensity intervals in the resulting image.

4. Method

In this section, we present an optimization approach for modulating the opacities associated with the control points in a transfer function. In order to help the user explore the features of interest within the data sets, we combine the automatic optimization process with intuitive user interaction to specify priority areas of importance in the resulting image.

4.1. Information Content of a Voxel

Information theory provides a theoretic framework to measure the information content (or uncertainty) of a random variable represented as a distribution [WS11]. Consider a discrete random variable X which has a set of possible values $\{a_0, a_1, ..., a_{n-1}\}$ with probabilities of occurrence $\{p_0, p_1, ..., p_{n-1}\}$, we can measure the uncertainty of the outcome with the entropy H(X), which is defined by $H(X) = -\sum_{x \in X} p(x) \log p(x)$, where the summation is over the corresponding alphabet and the convention $0 \log 0 = 0$ is taken. The term $-\log p(x)$ represents the information content associated with the result x. If the entire volume data set is

treated as a random variable, $I(a_x) = -\log p(x)$ represents the information content of a voxel a_x with intensity x, and the entropy gives us the average amount of information of a volume data. The probability p(x) is defined by $p(x) = \frac{n_x}{n}$, where n_x is the number of voxels with intensity x and n is the total number of voxels in the volume data.

4.2. Weighting of Transfer Function Components

The goal of our transfer function refinement approach is to balance the opacity settings so that voxels of more significance contribute more and voxels of less significance contribute less to the resulting images. Similar to the noteworthiness factor by Bordoloi and Shen [BS05], we also use opacity and probability (bin frequency) in our weighting. Given the intensity of the control points $v_1, v_2, ..., v_n$ of the transfer function t are $x_1, x_2, ..., x_n$ and the corresponding opacity are $\alpha(x_1), \alpha(x_2), ..., \alpha(x_n)$. The intensity range of the transfer function is normalized to $[0, 1]$. For the convenience of discussion, two control points v_0 and v_{n+1} are added to the lower bound and the upper bound respectively, and $x_0 = 0$, $\alpha(x_0) = \alpha(x_1)$, $x_{n+1} = 1$ and $\alpha(x_{n+1}) = \alpha(x_n)$.

We define the weight of the i-th edge (the segment between v_i and v_{i+1}) as

$$E(i) = -\int_{x \in [x_i, x_{i+1}]} \alpha(x) p(x) \log p(x) dx, i \in [0, n]$$

and define the significance factor of the i-th control point as the sum of the weights of its two adjacent edges

$$V(i) = E(i) + E(i-1), i \in [1, n]$$

Then the average significance factor of all the control points is

$$V_{mean} = \frac{\sum_{i=1}^{n} V(i)}{n}$$

Hence the energy function of the transfer function t can be defined as the variance of the significance factors of control points

$$F(t) = \sum_{i=1}^{n} (V(i) - V_{mean})^2$$

Consequently, minimizing the energy function is equivalent of flattening the curve of the significance factors of control points.

4.3. Optimization Algorithm

Constraints are introduced in the search of the parameter space. Control points would only be moved vertically in the transfer function space. In other words, only the opacity associated with control points would be changed. The intensity of control points remains the same. This constraint is based on our assumption that the intensity intervals associated with control points are the user's intensity intervals of interest.

The user has explored the volume data and set up the transfer function according to his/her needs. Our algorithm aims to help the user reduce occlusion while preserving the user's knowledge or judgements of the data set.

A greedy strategy is employed in our algorithm to minimize the energy function. In each iteration, there are two operations: reducing the opacity of the highest control point (with highest significance factor) and increasing the opacity of the lowest control point (with non-zero lowest significance factor). In our approach, the optimization ends when it reaches a user-specified iteration count. The two step sizes in reducing opacity and increasing opacity can both be user-specified, or the first one is user-specified and the second one is computed based on the first one and the ratio of the significance factors of the two chosen control points. The ratio of the two step sizes affects the overall opacity of the resulting image, for instance, the image becomes more opaque or translucent.

4.4. Region-Based Optimization

The optimization above described is an approach to balance the global opacity and thus reduce occlusions in the rendered images. Although global optimization can help deliver images with better overall visibility, small details may be under-enhanced in the global optimization and certain structures in the image may have to be further enhanced for specific purposes. A flexible method with user interactions is necessary to achieve various visualization goals.

We introduce difference factors to prioritize the user's region of interest. Assume each control point is assigned a unique colour, we can get the difference (or similarity) between a pixel of the region (which is selected in image space) and the colour of a control point (RGB colour space is used in our implementation).

Given the colour of the i-th control point is $c(i)$, the distance between a pixel r in the region R and the i-th control point is denoted by $d(r, c(i))$. In our approach, the sum of the squared distances D_s between each pixel in the region R and the i-th control point is used to measure the difference between the region and the control point.

$$D_s(R, i) = \sum_{r \in R} d(r, c(i))^2, i \in [1, n]$$

We define the difference factor between the region R and the i-th control point as

$$W(R, i) = \frac{D_s(R, i)}{\sum_{i=1}^{n} D_s(R, i)}, i \in [1, n]$$

Consequently, the modified significance factor (biased towards the region R) of the i-th control point is

$$V_R(i) = W(R, i)V(i), i \in [1, n]$$

To use the modified significance factor with the optimization algorithm described above, we simply need to replace $V(i)$

with $V_R(i)$ and compute the mean of significance factors accordingly in the energy function.

The difference factors measure the dissimilarity between a selected region and a control point. Therefore the difference factor would be small if the region has an overall colour similar to the colour of the control point. Since we are minimising the energy function, which is the variance of the significance factors, reducing the difference factor for a control point will result in its opacity value being increased. Optimized with the modified significance factors, the features (in this case, the intensity intervals) appear in the selected regions will be enhanced and other features will be de-emphasized in the rendered image.

The distances in $D_s(R, i)$ are squared, therefore, it results in a weighting which is more biased towards the selected region, compared to the weighting based on non-squared distances. Since the distance is measured in the colour space, the choice of colours for the control points affects the distance measured and thus affects the weighting function.

5. Results

In this section, we present some results to demonstrate the effectiveness of our approach on CT-knee ($379 \times 229 \times 305$) and VisMale head ($128 \times 256 \times 256$) datasets [Roe06]. Automatically generated transfer functions with evenly distributed control points (with opacity set to 0.5) are used as the input of the optimization. The colours of control point groups are evenly distributed in a spectrum (with hue from $0°$ to $360°$ in HSV colour space). In the optimization, the two step sizes for reducing opacity and increasing are both set to $1/255$. The results below are rendered with Voreen [MSRMH09] after transfer function optimization using our approach.

Figure 3 is a pair of knee joints rendered from the CT-Knee data set with the transfer function in Figure 5, which is a naive transfer function consisting of 6 control point groups of various colours with equal opacity. Figure 4 shows the resulting image rendered with the transfer function in Figure 7. We tested this specific example as joints are popular regions of interest in medical visualization and a number of researchers have extended volume rendering techniques to examine joints of human body [BCFT06]. The knee in particular is a commonly studied joint. In Figure 3, only parts of the skeleton are visible. The rest is occluded by the surrounding material (such as the skin and muscles). After optimization (Figure 4), the surrounding tissues become translucent, hence the skeleton is exposed and the knee joint is visible, while the overall context is preserved. Figure 6 shows how the energy function changes over the iterations of the solution. In practice we observed that the energy function usually converges at a small but non-zero value. In addition, as the number of control points increases, it takes more iterations for the optimization to achieve a stable state - a number of
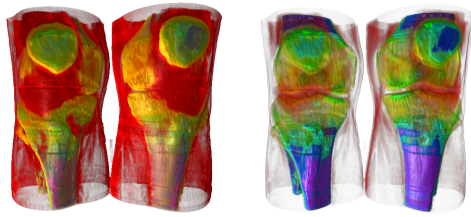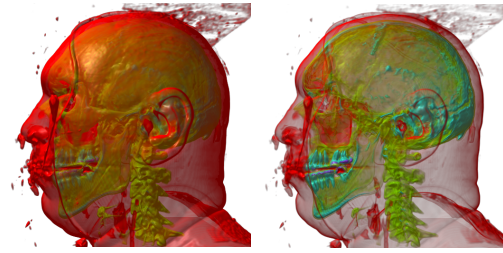
Figure 3: *Before optimization*

Figure 4: *After optimization*
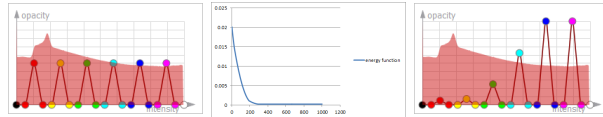

Figure 5: *A transfer function with 6 control point groups*

Figure 6: *Energy function converges at a small value*

Figure 7: *The transfer function after optimization*

Figure 8: *Before optimization*
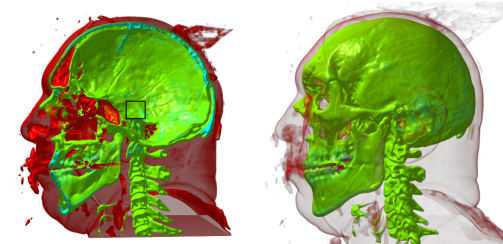
Figure 9: *After optimization.*

Figure 10: *The user selects a region on the skull under a clipping plane.*

Figure 11: *Result: skull is enhanced and the outer layer is de-emphasized.*

control point groups ranging from 4 to 16 was found too be the most effective.

The region-based weighting generation is also tested. Figure 8 shows the VisMale data set with a generated transfer function of 4 control point groups. After the optimization (Figure 9), the outside of the head is less opaque so the inner structures are revealed to the user. However, the intermediate material (i.e. the skull) also becomes less clear. If the goal is to make the skull more visible, the user could select a region consisting of parts of the skull (Figure 10) to generate a weighting and perform further optimization of the transfer function. In this step, a clipping plane is used in order to only select material of the skull without interference from the surrounding material. As shown in Figure 11, the skull becomes more clear after the region-based optimization.

6. Limitations and Future Work

Our approach requires to define intensity ranges (number of control points and region width) as an initial set-up for the transfer function. In addition, variations to the transfer function are limited to opacity values. Therefore prior knowledge of the data sets may be necessary in choosing optimal intensity ranges. In future work we plan to develop methods for identifying important features in the intensity ranges and refining the intensity ranges. In our implementation, RGB colour space is used in calculating the difference factors for region-based optimization. Other colour spaces especially perceptually uniform colour spaces such as CIE Lab will be investigated in future work.

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