Computers in Biology and Medicine 68 (2016) 109–120

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Visualization of boundaries in CT volumetric data sets using dynamic $M-|\nabla f|$ histogram

Lu Li [a], Hu Peng [b,*], Xun Chen [b], Juan Cheng [b], Dayong Gao [c]

[a] Electronic Science and Technology, University of Science and Technology of China, Anhui, China
[b] School of Medical Engineering, Hefei University of Technology, Anhui, China
[c] Department of Mechanical Engineering and Department of Bioengineering University of Washington, Seattle, WA 98195, USA

ARTICLE INFO

Article history:
Received 27 August 2015
Accepted 28 October 2015

Keywords:
Direct volume rendering
Multi-dimensional transfer function
Volume visualization
3-D CT volume
Boundary extraction

ABSTRACT

Direct volume rendering is widely used for three-dimensional medical data visualization such as computed tomography and magnetic resonance imaging. Distinct visualization of boundaries is able to provide valuable and insightful information in many medical applications. However, it is conventionally challenging to detect boundaries reliably due to limitations of the transfer function design. Meanwhile, the interactive strategy is complicated for new users or even experts. In this paper, we build a generalized boundary model contaminated by noise and prove boundary middle value (M) has a good statistical property. Based on the model we propose a user-friendly strategy for the boundary extraction and transfer function design, using M, boundary height (Δh), and gradient magnitude ($|\nabla f|$). In fact, it is a dynamic iterative process. First, potential boundaries are sorted orderly from high to low according to the value of their height. Then, users iteratively extract the boundary with the highest value of Δh in a newly defined domain, where different boundaries are transformed to disjoint vertical bars using $M-|\nabla f|$ histogram. In this case, the chance of misclassification among different boundaries decreases.

1. Introduction

Direct volume rendering is a widely used visualization technique to demonstrate the internal structures of volume data sets. To generate a meaningful visualization, transfer functions (TFs) should be designed to map data properties (e.g. scalar value, gradient) to optical properties (e.g. color, opacity). Color is used to generate a visual distinction between different data properties. Opacity determines the visual degree for each voxel of the volume data.

Since data properties may be changing with different applications, designing an ad hoc TF is quite necessary to make the structures of interest visible and distinguishable. The most commonly used 1-dimensional (1-D) transfer function maps scalar value to color and opacity based on the histogram of scalar value occurrences. Users need to select the materials of interest and set color and opacity by trial-and-error method.

The visualization of boundaries of 3-dimensional (3-D) computed tomography (CT) data has a wide range of applications and great significance for disease diagnosis and screening [1–3]. In order to highlight boundaries, gradient magnitude ($|\nabla f|$) has been adopted as a data property [4,5]. Adding $|\nabla f|$ as an independent dimension to the 1-D TF of scalar value, the 2-dimensional (2-D) $f-|\nabla f|$ histogram [6] has been proposed to facilitate boundary extractions. Boundaries in $f-|\nabla f|$ histogram are represented as arches, enabling users to extract different boundaries and design TFs for individual boundaries. Nevertheless, it is difficult to extract arches, especially considering the overlapping among arches. Low/high (LH) histogram [7], therefore, has been introduced to overcome the drawback by using the low and high intensities of materials around the boundary as two key data properties. In LH histogram, boundaries are expressed as points (without noise), lines and regions (with noise and bias), making the implementation of boundary extractions much easier.

As is known to all, boundaries represented in 2-D histograms are often extracted interactively, while the strategies are too complicated for new users or even experts to follow. For instance, in $f-|\nabla f|$ histogram users have to precisely pick out each arch by widgets. In LH histogram, users have to pick out each targeted region manually. Under the situation that the noise and overlapping is large, arches with smaller size are apt to be hidden by larger ones in $f-|\nabla f|$ histogram and different targeted regions tend to merge in LH histogram. Thus, it is a tedious or even impossible task for users via trial-and-error process.

* Corresponding author.
E-mail addresses: lilu630@mail.ustc.edu.cn (L. Li), hpeng@ustc.edu.cn (H. Peng), xun.chen@hfut.edu.cn (X. Chen), chengjuan@hfut.edu.cn (J. Cheng), dayong@u.washington.edu (D. Gao).

http://dx.doi.org/10.1016/j.compbiomed.2015.10.018
0010-4825/

Misclassification among different boundaries, to some extent, can be avoided by carefully choosing arches and regions in $f-|\nabla f|$ and LH histograms respectively. However, as the number of boundaries increases, the effect of misclassification will accumulate gradually. This will likely have a negative impact on the subsequent arches/regions selection. When the effect reaches a certain level, it is impossible for users to pick out the remaining boundaries with high quality. They have to extract boundaries using the original histogram from the very beginning.

In this paper, on one hand, we build a generalized boundary model contaminated by noise. On the other hand, based on the model we propose a novel multidimensional TF design method using boundary middle value (M), boundary height (Δh) and gradient magnitude ($|\nabla f|$) as data properties. Unlike traditional histograms presenting all boundary information once, the proposed method employs dynamic $M-|\nabla f|$ histogram and presents only one or a few boundaries at each step. A simple and iterative strategy of boundary extraction is also developed. We first sort different boundaries according to the values of their heights (Δh) from high to low. Users control the Δh value until a vertical bar occurs in $M-|\nabla f|$ histogram, then pick out the boundary represented by the bar in $M-|\nabla f|$ histogram. Boundaries are extracted one by one until the Δh value reaches 0. The misclassification among different boundaries can be reduced with the help of boundary ordering and the one-by-one extraction strategy. Besides, region elimination and region growing are further adopted to enhance the quality of rendering.

There are two main contributions. First, we establish a two-material boundary model contaminated by noise and prove that M has a good statistical property in this model. Second, we propose a novel 3-D TF in a newly defined domain, using boundary middle value (M), boundary height (Δh) and gradient magnitude ($|\nabla f|$). Based on the dynamic $M-|\nabla f|$ histogram, we propose an iterative boundary extraction method.

In the following section, we describe a variety of related methods. In Section 3, we build a generalized boundary model contaminated by noise. Based on the model we describe the construction and properties of the dynamic $M-|\nabla f|$ histogram, as well as refining techniques. In Section 4, we show several examples using our method and the traditional $f-|\nabla f|$ and LH histograms, and make a comparison. In Section 5, we present the conclusion and future work.

2. Background

In this section, we present a more detailed description of some important work on the design of transfer functions. As the aim of this paper is to visualize boundaries, we give a special attention to the relevant methods in literature. Transfer function, which maps data properties to optical properties, is of crucial importance to volume visualizations. According to the type of the extracted data properties, designs of TFs can be roughly divided into two categories, data-driven and graph-driven.

2.1. Data-driven TFs based on boundaries

Data-driven methods mainly focus on statistical features by means of histograms. The most widely used 1-D TF aims to map scalar value to opacity properties. However, it is inappropriate to employ the 1-D TF for the boundary visualization because the scalar values of the boundary vary greatly. In order to highlight boundaries, gradient magnitude ($|\nabla f|$) is added as a data property. Levoy [4] and Drebin et al. [5] put forward a 1-D TF to display different boundaries using gradient features. Later, Kindlmann and Durkin [6] proposed a 2-D $f-|\nabla f|$ histogram to enhance boundaries with the horizontal axis representing scalar values and the vertical axis representing gradient magnitude. The arches in the histogram represent boundaries among different materials. Although $f-|\nabla f|$ histogram improves the selection of the boundaries, there still exists a drawback. The overlapping regions caused by the intersections of the arches lead to ambiguities in the classification of boundaries. Kniss [8,9] added second derivative into $f-|\nabla f|$ histogram to select only the peaks of the arches to obtain much better rendering results.

Unlike the aforementioned histograms using statistical features directly, LH histogram is based on the concept of the boundary model proposed by Nickoloff and Riley [10] and treats boundaries as the transition of two idealized homogeneous regions. Lum and Ma [11] proposed the early concept of LH. LH means the high intensity and low intensity of the homogeneous regions. Arches in $f-|\nabla f|$ histogram are transferred to straight lines in a 1-D histogram with the x-axis representing L and H for an easily recognition. Sereda et al. [7] compacted the arches to points and regions using LH histogram for a more convenient extraction of boundaries. Compared with the $f-|\nabla f|$ histogram, LH histogram represents boundaries more compactly. Serlie et al. [12] derived the relationship between $f-|\nabla f|$ and LH histogram in a strict mathematic form based on the boundary model. One drawback of LH histogram is the time to establish the histogram. Praßni et al. [13] proposed a new way to efficiently construct LH histogram. Region selecting is a key issue to achieve automatic extraction of boundaries using LH histogram. Sereda et al. [14] used hierarchical clustering to automatically classify LH histogram to regions. Nguyen et al. [15] applied mean shift clustering to LH histogram and then used hierarchical clustering to group similar voxels.

2.2. Data-driven TFs for other features

Apart from visualizing boundaries using gradient information, curvature information [16,17] was also used to distinguish objects based on their shapes. Other statistical data properties such as mean value [18] and texture [19,20], were used in the designs of TFs to highlight the structures of interest. These local statistical properties may produce excellent results in specific applications.

2.3. Graph-driven TFs

Graph-driven methods mainly aim to visualize the local structures, which depend on topological analysis, such as skeletonization, region growing and level-set.

As a key concept for graph-driven methods, connectivity is the foundation of the skeletonization and region growing. Takahashi et al. [21] extracted topological structures of volume data sets, leading to a graph called a volume skeleton tree consisting of volumetric critical points and their connectivity. Ji et al. [22] segmented the 3-D teeth in cone beam computed tomography data by level-set. Volume data segmentation proposed by Gooya et al. [23] is based on manifold distance metrics with the features of scalar value, gradient and probabilistic measures.

Our proposed method mainly employs the gradient-based features and boundary model. Compared with the construction of LH histogram and $f-|\nabla f|$ histogram, the key improvement is that we build a generalized boundary model contaminated by noise and prove M has a good statistical property. Graph-driven method is employed to optimize the rendering result using region growing and region elimination based on local connectivity to reduce the misclassification, while LH histogram only uses region growing to fulfill the extracted boundaries without considering the misclassification between different boundaries.