Structure Size Enhanced Histogram
A Transfer Function for 3D Volume Visualization

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Abstract. Direct volume visualization requires the definition of transfer functions (TFs) for the assignment of opacity and color. Multi-dimensional TFs are based on at least two image properties, and are specified by means of 2D histograms. In this work we propose a new type of a 2D histogram which combines gray value with information about the size of the structures. This structure size enhanced (SSE) histogram is an intuitive approach for representing anatomical features. Clinicians – the users we are focusing on – are much more familiar with selecting features by their size than by their gradient magnitude value. As a proof of concept, we employ the SSE histogram for the definition of two-dimensional TFs for the visualization of 3D MRI and CT image data.

1 Introduction

Transfer functions (TFs) are tools for assigning optical properties to scalar volume data sets [1]. For direct volume rendering of such data, e.g. opacity can be set depending on the gray value at a given voxel position. Since the location of boundaries is of high interest, early work focused on the extraction of isocontours [2] and on finding optimal threshold values that correspond to intensity transitions [3]. A better distinction between different structures can be achieved when additional parameters like gradient magnitude are used for generating multi-dimensional TFs [4]. However, the definition of those TFs is a difficult task, and several techniques for helping the user have been proposed [5, 6, 7].

Based on two image properties, a 2D histogram can be created and used for the TF generation [4, 1]. One fundamental problem with all histograms is the fact that any spatial information is lost. One possible solution for that problem is the classification of the 2D histogram entries by their mean spatial position, i.e. replacing the frequency value at each 2D bin with a class label [8, 9]. For special applications, it is also useful to use distance information as second input for the 2D histogram instead of gradient magnitude [10, 11].

In this work we present a novel type of 2D histogram that combines gray value with information about the size of structures in the image data. For computing this structure size enhanced (SSE) histogram, we estimate the size of the structures by employing a multi-scale approach. Opacity assignment is based on the location of each bin in the SSE histogram. Spatial information is added by employing a distance map for a coarse classification of the 2D bins, or as an alternative by utilizing the approach of Roettger et al. [9].

2 Materials and methods

The main reason for the usage of 2D histograms for TF generation is the fact that different tissue types often share more or less the same gray value range in the image data – e.g. soft tissue in CT images. Thus, in a 1D histogram these structures are represented within a small range around one single bin. A special benefit of 2D histograms based on gray value and gradient magnitude is the distinction between the structures' boundaries and their inner region. A rendering that emphasizes these boundaries reveals much of the interesting information contained in the image data.

Considering how humans perceive different structures in image data, it can be noticed that one differentiates between different locations and also between different sizes of anatomical structures. Consequently, it is reasonable to incorporate spatial as well as structure size information into the 2D TF generation. For this purpose, we have developed the SSE histogram – a 2D histogram that uses structure size information in addition to the gray value. Furthermore, spatial information is added for classifying the 2D bins.

2.1 Structure size estimation

Each voxel in a 3D image data set (except those at the boundaries of the data) has 26 direct neighbors. The difference vector between the reference voxel's position P_{ref} and the positions P_n of each of its neighbors defines 26 direction vectors. Starting from P_{ref}, for each direction the number of steps that can be done satisfying a threshold condition is counted. A step is possible if the gray value I_{curr} at the new position falls within the range $[I_{\mathrm{ref}} - \tau \cdot I_{\max}, I_{\mathrm{ref}} + \tau \cdot I_{\max}]$, where I_{ref} is the gray value at P_{ref}, $I_{\max}$ is the gray value maximum in the data set, and $\tau \in (0, 0.5)$ is a tolerance value.

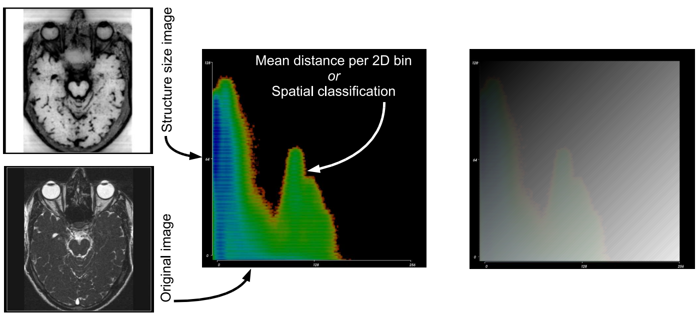


Fig. 1. The SSE histogram uses gray value information and the output of the structure size estimator as input (*left*). A non-classified SSE histogram is shown with color coding according to the bin population: *red* = low to *blue* = high. Distance map information can be used for a coarse classification, or spatial information à la Roettger [9] for an alternative classification approach (*center*). The opacity distribution that is used for an automatic TF initialization (white = 100% opaque, black = 0% opaque (*right*)).

Instead of defining the structure size as the sum of all counted voxels for all directions, we use a multi-scale approach that provides a more homogeneous *structure size image* with less artifacts compared to the simple voxel counting. For that, the algorithm checks for each of the 26 directions whether a certain number of steps $S_n, n = 1 \dots N$ could be done. S_n we call the *scale* at which the structure size is examined. The largest scale S_N corresponds to half of the data set (the minimum size for (x, y, z)), and each subsequent scale is defined as $S_{n-1} = S_n/2$. In this work, we use $N = 8$ different scales. Consequently, for a data set of size $512 \times 512 \times 512$ isotropic voxels S_N equals to 256 voxels and S_1 to 1 voxel. For all 26 directions, we determine the largest value n such that we can do at least S_N steps, and the accumulation of all n gives the value for the structure size. Further improvement is achieved by taking into account only the largest value n for two opposite directions.

An interesting property of this structure size estimation is that very small values are assigned to boundaries, whereas large homogeneous regions receive a much higher value. If we associate high opacity with small structure size values and low opacity with large structure size values, we can achieve visualization effects similar to approaches based on gradient magnitude computation.

2.2 SSE histogram

The image generated by the structure size estimator serves as second input for our SSE histogram. In this 2D representation small structures are located in the bottom area whereas larger ones in the top region. Thus, interesting structures can be selected directly by means of manipulation widgets [4]. We implemented closed splines with an adjustable number of spline points for selecting regions of interest in the SSE histogram.

Furthermore, it is possible to specify a TF for opacity simply based on the 2D bin location in an automatic manner. In medical images, large regions with

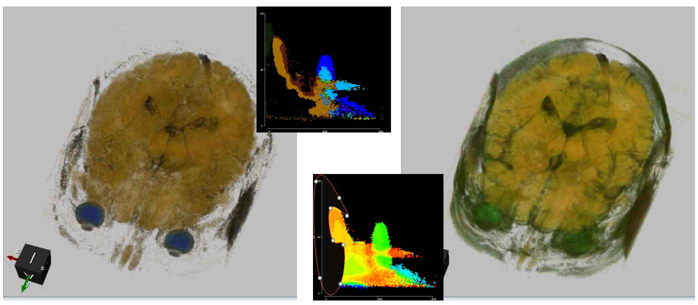
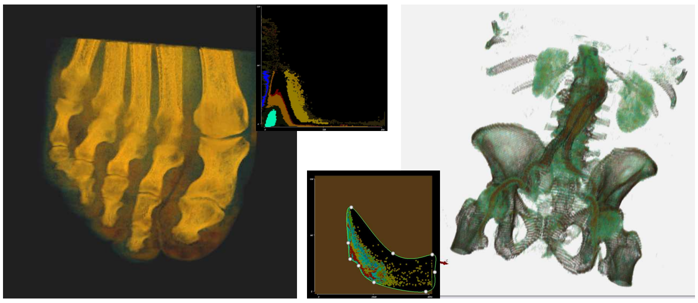


Fig. 2. Visualization of an MRI head data set employing a distance map for the SSE histogram classification. Only some (highlighted) classes have been picked(*left*). Color coding based on the mean distance for each 2D bin from a user given reference position – the center of the brain. The part belonging to low gray value values (red curve) has been masked out (*right*).

Fig. 3. CT data set of a foot. The classification method introduced by Roettger [9] has been used for creating 21 clusters, each labeled by a different color. Only some of the clusters are selected (highlighted structures), and the resulting 3D volume rendering is shown (*left*). CT data set showing an aortic stent in the abdominal region. The spline widet has been used to select the bins to be included in the 3D visualization (*right*).



a low gray value (e.g. air) are mostly of low interest, and dark regions are often set to full transparency. We achieve a similar behavior by defining an opacity TF that increases with gray value and decreases with structure size (fig. 1).

2.3 Histogram classification

In many applications one is interested in a special structure and its surroundings. For the purpose of a coarse classification of the 2D bins, we use a distance map that contains information about the Euclidean distance from the reference position that has to be provided by the user. For each 2D bin we can compute the mean distance and display it using a color look-up table. This enables the user to select a region in the SSE histogram with a close spatial relationship (fig. 2).

As an alternative, we have also implemented the spatial classification introduced by Roettger et al. [9] with a random assignment of colors to the classes in the SSE histogram (fig. 3). In contrast to their implementation, here the selection of a 2D bin only affects 2D bins of the same class if they are connected to the one selected in the SSE histogram. This avoids selection/deselection of regions that have a spatial relationship but are very different in gray value and/or structure size. In any case, we use the colors that are shown in the SSE histogram also for the definition of a color TF for the subsequent volume visualization.

3 Results

We used the SSE histogram for an automatic TF specification for visualizing MRI and CT data sets (figs. 2 and 3). A simple point-and-click selection of regions in the SSE histogram was possible in cases where there was a large cluster of 2D bins with the same classification label. If there were too much small class regions, we preferred the closed 2D spline for selecting the regions.

4 Discussion

In this work we have presented a new type of 2D histogram and shown its application to TF specification. Instead of using gradient magnitude as second input, we employ an image that represents the estimated size of all structures in the data set. The main advantage of our approach is its intuitiveness. In contrast to computer scientists, clinicians are often not familiar with the concept of gradient magnitude. Selecting *a large region with medium gray value*, which is provided by the SSE histogram, is much easier to grasp by non-experts in the field of image processing.

The quality and significance of the SSE histogram depends on the correctness of the structure size estimation. Our current approach is a trade-off between exactness and computing time. Future work will focus on faster algorithms for a more correct structure size estimation. A possible extension of our technique is the usage of distance maps with multiple reference points [10].

The specification of TFs based on the SSE histogram is highly automated and leads to visualization results that are comparable to those of existing approaches. We see the main advantage of our work in its high degree of comprehensibility, especially for non-experts in medical image processing.

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