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V. Ostromoukov and M. Zwicker
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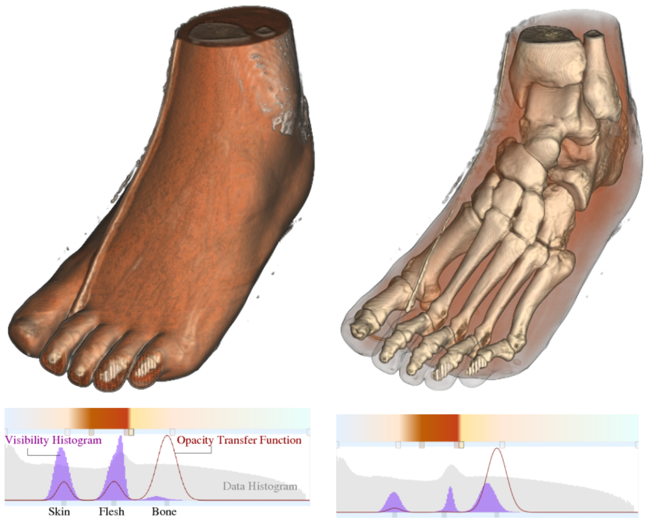
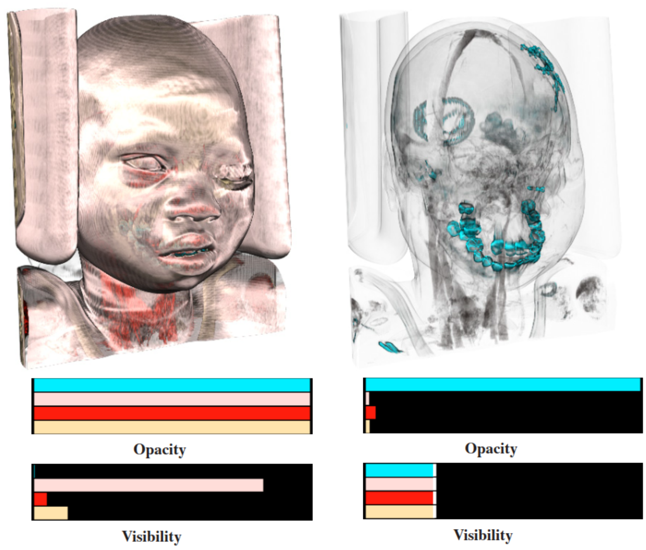
# Literature Review




(a) A user-defined opacity transfer function and the initial visibility histogram

(b) Here the visibility histogram has been modified to match the user-defined opacity transfer function.

Figure 1: Visibility histograms [CM09]




(a) Feature opacities are equal

(b) Feature visibilities are equal

Figure 2: Opacities and feature visibilities of 4 features highlighted in different colors [WZC*11]

## 1. Introduction

## 2. Visibility Histograms and Visibility-Driven Transfer Functions

Visibility has been studied in measuring viewpoint quality [BS05] and enhancing ghost and cutaway views [VKG04] in volume visualization.

In traditional transfer function design, the visibility of structures revealed in volume rendering is a consequence of adjusting transfer function parameters, rather than a design parameter [PB13]. Correa and Ma [CM09] introduced visibility histograms to guide transfer function design for both manual and automatic adjustment. Visibility histograms (Figure 1), which summarize the distribution of visibility of voxels from a given viewpoint, are powerful feedback mechanisms of volume visualization [Ems08]. Visibility histograms encode the information required to measure the efficacy of transfer functions and are advantageous in guiding and automating the manipulation of transfer functions.

Wang et al. [WZC*11] extended the previous work on visibility histograms and proposed a feature visibility metric, in order to measure the influence of each feature to the volume rendered image. As shown in Figure 2, their approach allows the user to directly specify the desired visibility for the features of interest, and subsequently the opacity transfer function is optimized using an active set algorithm [Pol69].

Ruiz et al. [RBB*11] proposed an information-theoretic framework which obtains opacity transfer functions by minimizing the Kullback-Leibler divergence between the observed visibility distribution and a target distribution provided by the user. Later, Bramon et al. [BRB*13b] extended this approach to visualize multimodal volume data.

Cai et al. [CTN*13] described a method to derive opacity transfer functions by minimizing the Jensen-Shannon divergence between the observed visibility distribution and a user-defined target distribution. The target distribution can be defined using Gaussian function weighting.

In addition, various methods were proposed regarding the use of visibility for enhancing different aspects of volume visualization. Marchesin et al. [MDM10] introduced a volume rendering technique that manipulates the voxel opacity values in a view-dependent way, in order to enhance visibility of internal structures in the volume data set. Bronstad et al. [BATK12] described local opacity transfer functions with feature detection along the ray profile implemented on the GPU. In their approach, visibility histograms are employed to access the performance of the feature detection algorithm.

Jung et al. [JKF12] presented a dual-modal visualization method, which uses visibility metrics to provide visual feedback regarding the occlusion caused by the volume data in one modal on the other modal. Jung et al. [JKE*13] extended visibility histograms to multimodal volume visualization. They demonstrated the use of visibility histograms together with region of interest segmentation was effective in visualizing PET-CT volume data sets.

Instead of computing the visibility of all voxels, Zheng et al. [ZCM13] employed local visibility histograms to ensure both the features of interest and contextual information are visible in multimodal volume visualization. Schlegel and Pajarola [SP13] proposed a visibility-difference entropy metric. They presented an automated approach using this metric for generating a set of transfer function candidates with high ratings and are strongly distinct in what they reveal.

Qin et al. [QYH15] presented the voxel visibility model as a quality metric for transfer function design. The voxel visibility model is a mapping function from data attributes of voxels to their visibility attributes. Instead of specifying transfer functions, this approach allows users to directly adjust the visibility of each voxel, and then the corresponding opacity transfer functions can be obtained by minimizing the distance between the desired voxel visibility distriubtion and the actual voxel visibility distribution.

### 2.1. Visibility-Based Sketching and Picking

The visibility of a sample refers to the alpha contribution of a sample to the final image, taking into account also the degree to which it is occluded by other samples in the view.

Guo et al. [GMY11] proposed a sketch-based manipulation technique for volume visualization based on clustering of depth, visibility, alpha and intensity. Subsequently, they described another sketch-based technique to specify local transfer functions for topology regions using contour trees [GY13].

Wiebel et al. [WVFH12] found that the user usually perceives features at a screen position with the highest visibility along the ray and they exploited this information in their volume picking technique. Based on the WYSIWYP technique, Stoppel et al. [SHW14] presented an algorithm called surfseek for selecting surfaces on the most visible features in direct volume rendering. The algorithm detects feature boundary points using WYSIWYP and then constructs a weighted graph and computes its minimal cut, from which it reconstructs the desired surface.

## 3. Related Work

A number of approaches have been proposed to automate the design of transfer functions, and these are discussed in detail in Section **??**. Here, we briefly discuss the most closely related previous works to the contribution of this chapter.

Maciejewski et al. [MWCE09] described a method to structure attribute space in order to guide users to regions of interest within the transfer function histogram. Chan et al. [CWM*09] developed a system to optimize transparency automatically in volume rendering based on Metelli's episcotister model to improve the perceptual quality of transparent structures. Correa and Ma [CM09] proposed the visibility histogram to guide the transfer function design. In a later work [CM11], they generalized the visibility histogram and proposed a semi-automatic method for generating transfer functions 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] also used visibility as a main parameter for the transfer function specification. Their method obtains the opacity transfer function by minimizing the informational divergence between the visibility distribution captured by a set of viewpoints and a target distribution defined by the user. Later, Bramon et al. [BRB*13b] extended this approach to deal with multimodal information.

| air | fat | soft tissue | bone (cancellous/dense) |
|---|---|---|---|
| -1000 | -100 to -50 | +100 to +300 | +700 to +3000 |

Table 1: Hounsfield units of some typical substances [Fee09]

## 4. Background

### 4.1. Transfer Function Specification

In the specification of a 1D (intensity-based) transfer function, the user essentially assigns a color and/or opacity to a certain point in the histogram of scalar values in the data set. In practice, the user would be presented with an interface that allows them to set up several control points which corresponds to a certain kind of material or structure. The user then defines a mapping from each control point to some visual property (e.g. color) resulting in voxels of the corresponding intensity to be rendered in that color. Figure 3 displays four typical shapes used in transfer function design. If a volume data set contains complex structures, tent-like shapes are desirable in revealing isosurfaces of structures and seeing through inner structures. Otherwise, the ramp shape and other shapes can also reveal structures effectively.

In order to design transfer functions effectively, it is commonly required that users have prior knowledge about which intensity ranges are relevant 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 (Table 1). The user may expect the constituent's intensity of CT data to follow the Hounsfield scale and thus set up control points accordingly.

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 4. 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

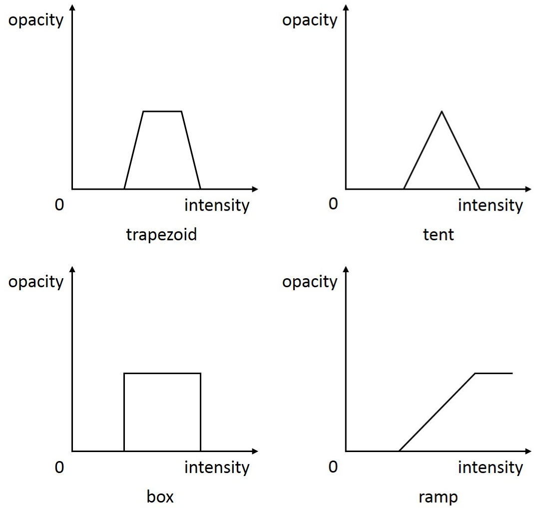



Figure 3: Typical transfer function shapes [KG00]

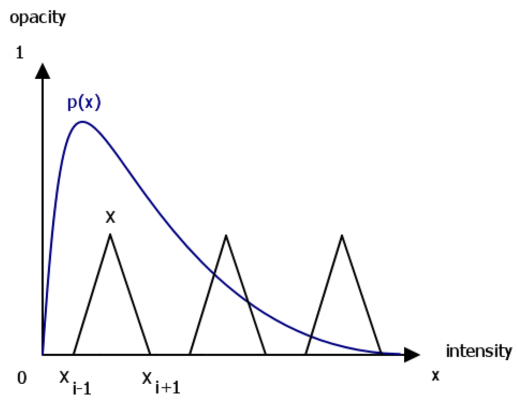



Figure 4: A transfer function with tent-like shapes

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.

### 4.2. Entropy of Volume Data

In computer graphics, information-theoretic measures, such as entropy and mutual information, have been applied to solve multiple problems in areas such as view selection [BS05] [BRB*13a], flow visualization [XLS10], multi-modal visualization [HBKG08] [BRB*13b] and transfer function design [BM10] [IVJ12]. 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.

Bordoloi and Shen [BS05] described a noteworthiness factor to denote the significance of the voxel to the visualization. The noteworthiness should be high for the voxels which are desired to be seen, and vice versa. The noteworthiness of voxel $j$ is defined as $W_j = \alpha_j I_j = -\alpha_j log f_j$ , where $\alpha_j$ is the opacity of voxel $j$ looked up from the transfer function, $I_j$ is the information carried by voxel $j$, which can be derived from the frequency of its histogram bin $f_j$. -log $f_j$ represents the amount of information associated with voxel $j$.

## 5. Related Work

Several computational models of visual saliency for modeling human attention have been developed. Itti et al. [IKN98] developed a computational model of visual attention based on the center-surround operators in an image. This center-surround mechanism has the intuitive appeal of being able to identify regions that are different from their surrounding context. Based on the perceptual principles, Chen et al. [CWM*09] introduced several image quality measures to enhance the perceived quality of semitransparent features. Jänicke and Chen [JC10] described a quality metric for analyzing the saliency of visualization images and demonstrated its usefulness with examples from information visualization, volume visualization and flow visualization.

Lee et al. [LVJ05] proposed saliency for meshes based on a multi-scale center-surround mechanism that operates on local curvature. Kim and Varshney [KV06] presented the use of a center-surround operator using the Laplacian of Gaussian-weighted averages of appearance attributes to enhance selected regions of a volume and validated their work using an eye-tracking user study. Shen et al. [SWL15] extended this technique to spatiotemporal volume saliency to detect both spatial and temporal changes.

Visibility measures the impact of individual voxels on the image generated by a volumetric object and visibility distribution can be utilized as a measure on the quality of transfer functions as users explore the transfer function space. Visibility has been studied to measure the quality of a given viewpoint [BS05] [VKG04] and to enhance the rendering process with cutaway views. Correa and Ma [CM11] introduced visibility histogram, which describes the accumulated visibility of each intensity value in the transfer function.

Ruiz et al. [RBB*11] proposed an automatic method to generate a transfer function by minimizing the Kullback-Leibler divergence between the observed visibility distribution and a target distribution provided by the user. Wang et al. [WZC*11] extended the idea of the visibility histogram to feature visibility and introduced an interaction scheme where the opacity of each feature was generated automatically based on user-defined visibility values. Visibility distribution is also used in automating color mapping [CTN*13] and 2D transfer functions [QYH15].

## 6. Related Work

Transfer function specification is a non-trivial and unintuitive task in volume visualization. Compared to typical transfer function approaches, which are often subjective, it is desirable to have objective feedback regarding the clarity of features in volume visualization.

Correa and Ma [CM09] introduced visibility histograms to guide transfer function design for both manual and automatic adjustment. Visibility histograms (Figure 1), which summarize the distribution of visibility of voxels from a given viewpoint, are a powerful feedback mechanism for volume visualization [Ems08]. Wang et al. [WZC*11] extended visibility histograms to feature visibility histograms, in order to measures the influence of each feature to the resulting images. They described a scheme that allows users to specify a desired visibility for features of interest and subsequently the opacity transfer function is optimized using an active set algorithm [Pol69].

Researchers have developed a variety of parallel strategies to accelerate sequential optimization algorithms [Spe12]. Phua et al. [PFZ98] proposed a parallel extension to quasi-Newton methods [Yan01]. Their approach generates several search directions at each iteration and then applies different line search and scaling strategies in parallel along each search direction. Peachey et al. [PAL09] presented another approach to parallelize the quasi-Newton methods. In their applications, the objective function evaluation typically requires minutes or hours of processing time. Therefore, they introduced an approach that evaluates the objective function in parallel over a cluster of computers and continues to the next iteration before all evaluations finish in order to accelerate convergence.

## 7. Related Work

The visualization of time-varying data is an important and active topic in the visualization community. Transfer function specification for static volume data has been widely studied over the years [PLB*01]. However, much less work has been done for transfer function design of time-varying data.

Jankun-Kelly and Ma first studied transfer function specification for time-varying data [JKM01]. Kniss and Hansen applied the techniques from multidimensional transfer function based volume rendering to the visualization of multivariate data from weather simulations [KHGR02]. Akiba et al. [AMCH07] described three approaches for the data-fusion problem in multivariate data visualization. One approach, which is to use one variable for each color channel in RGB space, is popular because of its simplicity but is limiting due to the difficulty for viewers to interpret the resulting color. The second approach, is to use one of the values based on some criterion e.g. [HE98] use alternating sampling for rendering two volumes and this has been shown to work well for medical imaging but not for fluid flow visualization. The third approach is to compute a weighted sum of all the values. This approach is more flexible however this may not be guaranteed to lead to an effective visualization as blending different colors might lead to ambiguous mixing of different hues.

### 7.1. Conclusions

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