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Fast Volumetric Data Exploration with Importance-Based Accumulated Transparency Modulation

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Abstract

Direct volume rendering techniques have been successfully applied to visualizing volumetric datasets across many application domains. Due to the sensitivity of transfer functions and the complexity of fine-tuning transfer functions, direct volume rendering is still not widely used in practice. For fast volumetric data exploration, we propose Importance-Based Accumulated Transparency Modulation which does not rely on transfer function manipulation. This novel rendering algorithm is a generalization and extension of the Maximum Intensity Difference Accumulation technique. By only modifying the accumulated transparency, the resulted volume renderings are essentially high dynamic range. We show that by using several common importance measures, different features of the volumetric datasets can be highlighted. The results can be easily extended to a high-dimensional importance difference space, by mixing the results from an arbitrary number of importance measures with weighting factors, which all control the final output with a monotonic behavior. With Importance-Based Accumulated Transparency Modulation, the end-user can explore a wide variety of volumetric datasets quickly without the burden of manually setting and adjusting a transfer function.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation—Display algorithms

1. Introduction

By employing the physically based absorption-emission optical model, direct volume rendering techniques have been successfully applied to visualizing volumetric datasets across many application domains. Contemporary volume rendering techniques can generate very appealing visual results, and can achieve real-time interactive renderings on modern graphics hardware. However, to generate such compelling results usually requires an expert at transfer function editing to both setup an initial transfer function and manually adjust the transfer function to achieve the desired results. In general, the initial transfer function setup is a bottle neck for volume visualization since exploration of datasets depend on a transfer function that can extract the relevant features. To further complicate the volume rendering experience, the resulting image is very sensitive to transfer function adjustment; small changes can lead to large visual differences. Automatic transfer function design removes the difficulty from the end-user but automatic methods for generating initial transfer functions have not proved to be general across many different datasets.

To make direct volume rendering useful in practice, semi-automatic methods for generating an initial transfer function and transfer function editing have been an active area of research. Semi-automatic methods which provide the end-user with a simplified interface, perhaps incorporating domain knowledge, provide an easier method for transfer function design [KD98]. Some semi-automatic, or fully automatic, methods for initial transfer function generation can employ artificial intelligence algorithms, which rely on a large computational process and a populated knowledge base [TLM05]. Other methods, such as the Maximum Intensity Difference Accumulation (MIDA) [BG09], do not modify the transfer function but rather modify the rendering, thereby allowing fast inspection and exploration of volumetric datasets.

In this paper, we present Importance-Based Accumulated Transparency Modulation, which is a novel rendering algo-

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rithm generalized and extended from MIDA. After related work (Section 2), we introduce formulas of Importance-Based Accumulated Transparency Modulation (Section 3). We discuss common importance measures that can be applied (Section 4). We further discuss importance measures in multi-dimensional space (Section 5). Then we propose designing guidelines for fast volume exploration applications using our algorithms (Section 6). The results are presented and discussed in Section 7, and the paper is concluded in Section 8.

2. Related Work

Modern volume rendering techniques can be traced back to work done in the 1980s. Kajiya [KVH84] used ray tracing to render objects represented by densities within a volume grid, based on light scattering equations. Work of Drebin et al. [DCH88] and Levoy [Lev89] laid out the foundation for volume rendering, such as gradient-based shading and volume classification. Max [Max95] reviewed several different models for light interaction with volume densities, including absorbing, glowing, reflecting, and scattering.

Volume classification has also been an active area of research. Kindlmann et al. [KD98] proposed the histogram volume, which captures the relationship between volumetric quantities in a position independent, computationally efficient fashion. They presented semi-automatic methods of generating transfer functions for direct volume rendering. Kniss et al. [KKH02] presented multi-dimensional transfer functions for interactive volume rendering. Correa et al. [CM08, CM09] proposed visibility-driven and size-based transfer function designing techniques for volume exploration. Yet, transfer function design with multi-dimensional histograms still requires strong background knowledge about the data and is time consuming. Methods have been proposed to accelerate the transfer function design process. Rezk-Salama et al. [RSKK06] introduced an additional level of abstraction for parametric models of transfer functions, and they proposed using semantics models for transfer function design. Tzeng et al. [TLM05] proposed an approach to the volume classification problem that couples machine learning and a painting metaphor to allow more sophisticated classification in an intuitive manner. Kohlmann et al. [KBKG09] presented a method for the interactive identification of contextual interest points within volumetric data by picking on a direct volume rendering image. Wan et al. [WOCH09] presented an interactive visualization tool, which simplified 2D transfer function modification to several parameters that can be quickly adjusted. They applied the tool on confocal datasets in neurobiology research.

Depth complexity in volumetric datasets can lead to visual clutter. As de-cluttering is often one requirement for rendering volumetric datasets, many techniques have been proposed. Lorensen et al. [LC87] presented the marching cubes algorithm to extract iso-surfaces from volume datasets. Wallis et al. [WMLK89] proposed maximum activity projection that extracts "hot-spots" from the volume data, and the algorithm is later commonly referred as Maximum Intensity Projection (MIP). Malzbender [Mal93] presented a volume rendering technique using the Fourier Projection-Slice Theorem, and generated "X-ray-like" images. Levoy [Lev92] improved the algorithm by adding depth cueing and shading to the Fourier Volume Rendering. Weiskopf et al. [WEE03] proposed clipping methods that are capable of using complex geometries for volume clipping. Rezk-Salama et al. [RSK06] proposed opacity peeling technique that reveals structures in the volume dataset, which are difficult to visualize by transfer functions without explicit segmentation.

Viola et al. [VKG04, VKG05] presented importance-driven volume rendering. Features within the volumetric data are first classified according to object importance, and for each feature, various representations (levels of sparseness) from a dense to a sparse depiction are defined.

Bruckner et al. [BG09] introduced Maximum Intensity Difference Accumulation (MIDA), which combines the advantages of Direct Volume Rendering and Maximum Intensity Projection. MIDA was extended for rendering multi-channel data and applied to visualization in neurobiology research [BSG*09]. We based our work on the ideas introduced by MIDA, and we incorporated concepts from importance-driven volume rendering into a generalized formulation.

3. Importance-Based Accumulated Transparency Modulation

3.1. Maximum Intensity Difference Accumulation (MIDA)

Equation 1 is the standard front-to-back volume compositing equation:

$$\begin{aligned} c_{dst} &\leftarrow c_{dst} + (1-\alpha_{dst})\cdot c_{src} \\ \alpha_{dst} &\leftarrow \alpha_{dst} + (1-\alpha_{dst})\cdot \alpha_{src} \end{aligned} \tag{1}$$

MIDA modulates the accumulated color and transparency by inserting a modulation factor β into the volume compositing equation (Equation 2):

$$\begin{aligned} c_{dst} &\leftarrow \beta\cdot c_{dst} \\ \alpha_{dst} &\leftarrow \beta\cdot \alpha_{dst} \\ c_{dst} &\leftarrow c_{dst} + (1-\alpha_{dst})\cdot c_{src} \\ \alpha_{dst} &\leftarrow \alpha_{dst} + (1-\alpha_{dst})\cdot \alpha_{src} \end{aligned} \tag{2}$$

The modulation factor β is calculated by the difference of the current maximum scalar intensity (s_{acc}) and the incoming sample's scalar intensity (s_i) along a viewing ray, specifically by the following equation (Equation 3):

$$\beta = \begin{cases} 1-(s_i - s_{acc}) & \text{if } s_i > s_{acc} \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

Assuming the important features of the volumetric datasets are of high scalar values, MIDA changes the volume compositing behavior by decreasing the accumulated color and opacity when the incoming sample's scalar intensity is higher than any of those before it along the viewing ray, so that high scalar value features in the volumetric datasets won't be occluded as much as in a standard compositing. For practical use, important features may not be just those of high scalar values. Depending on the applications, important features can also be those of high gradient magnitude or of high depth value along the viewing ray. MIDA provides a method to control the volume compositing behavior, and it can be generalized to make it suitable for other features of different characteristics.

3.2. Generalized Formulation from MIDA

Equation 4 is our generalized formula:

$$
\begin{aligned}
&\alpha_{dst} \leftarrow \beta \cdot \alpha_{dst}\\
&c_{dst} \leftarrow c_{dst} + (1-\alpha_{dst}) \cdot c_{src}\\
&\alpha_{dst} \leftarrow \alpha_{dst} + (1-\alpha_{dst}) \cdot \alpha_{src}\\
&\textit{where}\\
&\beta = B(\Delta_{imp}(f_i, f_{acc})), \textit{such that } B \in (0,1]\\
&f_i = F(\textit{incoming sample})\\
&f_{acc} = F(\textit{accumulated samples})
\end{aligned}
\tag{4}
$$

We name equation 4 Importance-Based Accumulated Transparency Modulation, as it modulates the accumulated transparency α_{dst} with a factor β, which is calculated by the difference of importance between the incoming sample and accumulated result along a viewing ray. In equation 4, F is a measure of importance, which should be designed according to application requirements. f_i is the importance of the incoming sample for compositing, and f_{acc} is that of the same measure applied to accumulated result. Δ_{imp} is the function calculating the quantified difference between f_i and f_{acc}, and the difference is usually calculated by, but not restricted to, subtraction. B is an assembling function, which re-maps importance difference to the desired range of modulation factor β. In general, we want to decrease the value of β when incoming sample has a higher importance measure than that of the accumulated result, and keep β as one otherwise.

For MIDA, the measure of importance F is the maximum scalar intensity. MIDA is a special case of Equation 4 except that we don't change the accumulated color as MIDA does. Equation 4 only inserts the transparency modulation operation before the standard volume compositing equation. We treat transparency and color separately because they behave differently: color can accumulate to greater than one and the result can be tone-mapped to the normal display range, while transparency can never accumulate above one, which is full opacity. By extending the volume compositing to high dynamic range, features can be better highlighted. The discussion of sophisticated tone-mapping [DCWP02, YNCP06] is beyond the scope of this paper and we use the brightness/contrast and a gamma curve to adjust the high dynamic range result (see Figure 8).

In the next section, we look at some common measures we can use for importance-based accumulated transparency modulation.

4. Importance Measures for Accumulated Transparency Modulation

In Equation 4, we don't specify the formula how importance is measured or how importance difference is calculated, as they are application-dependent. But there are common importance measures that can apply to a wide variety of volumetric datasets, just like the maximum intensity measure given by MIDA.

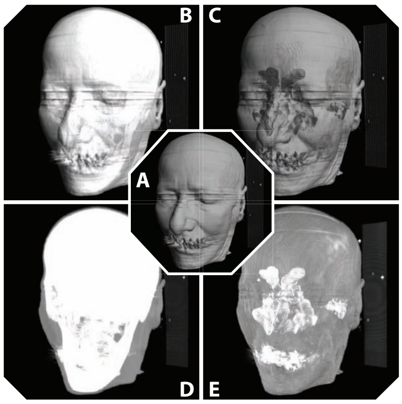

Figure 1: *The Cadaver Head dataset is rendered with different methods. A: Normal direct volume rendering; B: Accumulated transparency modulation with maximum intensity measure; C: Accumulated transparency modulation with maximum gradient magnitude measure; D: Maximum intensity projection; E: Maximum gradient magnitude projection. Features such as cavities inside of the skull, which used to be occluded by the skull if maximum intensity measure is used, are visualized by using the maximum gradient measure. The transfer functions used for all the results are the same, which is a simple linear ramp grayscale colormap combined with a linear opacity ramp.*

4.1. Gradient Magnitude Measures

One problem of the maximum intensity measure given by MIDA is that internal features of lower scalar intensity may be occluded by external structures (Figure 1B). A natural extension of the maximum intensity measure to deal with the problem is using gradient magnitude as the importance measure, as widely used in transfer functions [Lev89, KKH02, KD98].

By replacing the maximum intensity measure, we obtain the maximum gradient magnitude measure, which calculates the importance by maximum gradient magnitude. The equation to calculate β is:

$$\beta = B(\Delta_{imp}(grad_i, grad_{acc})) = \begin{cases} 1-(grad_i - grad_{acc}) & \text{if } grad_i > grad_{acc} \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

In Equation 5, $grad_i$ is the gradient magnitude of the incoming sample, and $grad_{acc}$ is the current maximum gradient magnitude along the viewing ray. When the incoming sample has a higher gradient magnitude than the accumulated maximum gradient magnitude, the accumulated transparency is increased, to reveal the features having more importance.

As seen from the result (Figure 1C), features of high gradient magnitude values can be enhanced. The result from calculating importance difference by Equation 5 combines characteristics from direct volume rendering and maximum gradient magnitude projection. Comparing maximum intensity projection with maximum gradient magnitude projection (Figure 1D, E), the latter can better reveal sharp features of the datasets.

If we calculate the importance difference by two adjacent samples, the accumulated maximum gradient magnitude $grad_{acc}$ becomes $grad_{i-1}$, and Equation 5 becomes:

$$\beta = B(\Delta_{imp}(grad_i, grad_{i-1})) = \begin{cases} 1-(grad_i - grad_{i-1}) & \text{if } grad_i > grad_{i-1} \\ 1 & \text{otherwise} \end{cases} \tag{6}$$

Equation 6 increases the accumulated transparency whenever an increase of gradient magnitude is detected along a viewing ray.

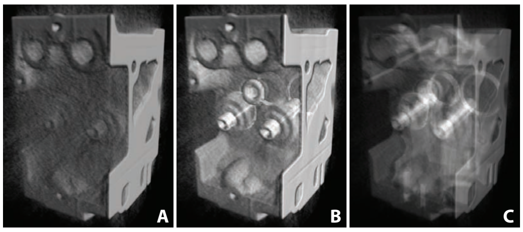

Figure 2: *The Engine Block dataset rendered with different methods. A: Direct volume rendering; B: Accumulated transparency modulation with maximum gradient magnitude measure; C: Accumulated transparency modulation with importance difference calculated by gradient magnitudes of adjacent samples.*

Figure 2 compares the difference of the results using the two gradient magnitude measures. The result of calculating the gradient magnitude difference of adjacent samples has a more transparent look, as more samples along the viewing ray contribute to the final result. The result also tends to have a wider dynamic range, if the dataset contains many non-transparent voxels. As stated in Section 3.2, we use brightness/contrast and gamma curve to tone-map the high dynamic range output to normal display range, which is sufficient and effective for fast data exploration.

4.2. Scalar Intensity Measures

Inspired by Equation 6, we can use the scalar intensity as the importance measure, but only consider the difference between two adjacent samples. The equation to calculate β becomes:

$$\beta = B(\Delta_{imp}(s_i, s_{i-1})) = \begin{cases} 1-(s_i - s_{i-1}) & \text{if } s_i > s_{i-1} \\ 1 & \text{otherwise} \end{cases} \tag{7}$$

In Equation 7, s_i is the scalar intensity of the incoming sample, and s_{i-1} is that of the previous sample along the viewing ray. With this scheme, the accumulated transparency is increased whenever there is an increase of scalar intensity along the viewing ray.

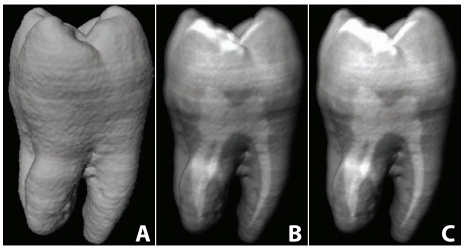

Figure 3: *The Tooth dataset rendered with different methods. A: Direct volume rendering; B: Accumulated transparency modulation with importance difference calculated by scalar intensity increase; C: Accumulated transparency modulation with importance difference calculated by scalar difference. By using scalar intensity measures, structures such as enamel and pulp of the tooth can be clearly seen, which are obscured if only maximum intensity or gradient measures are used.*

Figure 3B shows the result of the tooth dataset when Equation 7 is applied. To better see the boundaries between different structures with different scalar intensities, we can increase the accumulated transparency whenever a change of scalar intensity is detected. Then the equation to calculate β becomes Equation 8:

$$\beta = B(\Delta_{imp}(s_i, s_{i-1})) = 1 - |s_i - s_{i-1}| \tag{8}$$

Figure 3 compares the results of the tooth dataset when two scalar intensity measures are applied. We can see that the different features of the tooth are visualized very easily, which can't be clearly observed by using any of the previously proposed measures. The difference between using the two scalar intensity measures is rather subtle, with Figure 3C having a more transparent look.

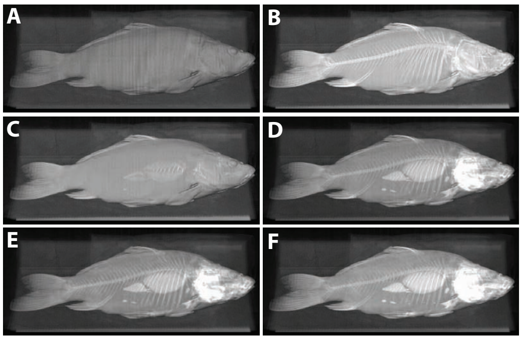

Figure 4: *The Carp dataset rendered with different methods. A: Direct volume rendering; B-F: Accumulated transparency modulation with importance measures: (B) Maximum intensity, (C) Maximum gradient magnitude, (D) Gradient magnitude increase, (E) Scalar intensity increase, (F) Scalar intensity difference. Internal organs as well as bones are better revealed in D, E, and F.*

Figure 4 compares the results of the carp dataset. We can see that maximum intensity measure is good at revealing bones, and maximum gradient magnitude measure subtly shows us some of the internal organs. The latter three measures have similar results, and all can visualize more internal features.

4.3. Depth Measure

Standard volume compositing with simple transfer function settings often results in quick accumulation of the voxel transparency, and deeper structures are often occluded by those before them. To compensate the transparency accumulation along the viewing direction, we can use depth values to calculate importance in accumulated transparency modulation. Depth measure assumes important features are always further down along the viewing ray, and the equation for calculating β is:

$$\begin{aligned}\beta &= B(\Delta_{imp}(d_i, d_{i-1})) \\ &= 1-(d_i - d_{i-1}) \\ &= 1-(Sample\ Step)\end{aligned} \tag{9}$$

In Equation 9, d_i and d_{i-1} are the depth values of the incoming sample and its previous sample along the viewing ray. With depth measure, accumulated transparency can never reach full opacity, as the sample step is always greater than zero. All samples along the viewing ray contribute to the final result, and the resulting image always has a transparent look. Figure 5 compares the results of direct volume rendering and that of accumulated transparency accumulation with depth measure. The occluding structures of the latter become transparent. It shows great advantage by allowing the high dynamic range color accumulation, as we can better keep local contrast from shading and detailed features, which will otherwise result in blurry images, if only the transparency in the transfer function is increased.

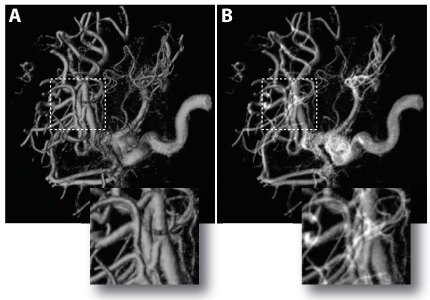

Figure 5: *The Aneurysm dataset rendered with A: Direct volume rendering; B: Accumulated transparency modulation with importance difference calculated from depth difference. The enlarged regions have many overlapped vessels. With the depth measure, the occluding vessels become transparent, revealing underlying vessels.*

Figure 6 shows the rendered result of the head of visible male dataset. We found that by using gradient magnitude thresholding and accumulated transparency modulation with depth measure together, boundaries of different features are clearly visible, yet adjusting the parameters only takes seconds.

Figure 6: *The head of Visible Male dataset rendered with accumulated transparency modulation. The importance difference is calculated by depth difference, and the gradient magnitude threshold is increased for de-cluttering.*

5. Importance Measures in Multi-Dimensional Importance Difference Space

Section 4 introduced several common importance measures that can be used in accumulated transparency modulation. We also see that different measures can reveal different features of the datasets. In addition to the common measures, we can design more rules to calculate the importance differences, based on the application requirements. Then we want to calculate the modulation factor β, out of a series of importance differences. In order to design applications that are easy to use, we need to determine parameters that influence the final visual output monotonically, and expose these parameters to the end-user as simple widgets such as sliders and numeric inputs.

Consider N importance difference rules $\{\Delta_{imp_i} | i = 1,..,N\}$, and the N importance differences calculated from the rules $\{\delta_{imp_i} | i = 1,..,N\}$. The N importance differences form the basis of the N-dimensional parameter space (importance difference space), from which we want to calculate β. In practice, the weighted average is the most straightforward and commonly used:

$$\begin{aligned}\beta &= B(\delta_{imp_1}, \delta_{imp_2}, .., \delta_{imp_N}) \\ &= 1 - Clamp(w_1 \cdot \delta_{imp_1} + w_2 \cdot \delta_{imp_2} + .. + w_N \cdot \delta_{imp_N}, 0, 1) \\ &= 1 - Clamp(\sum_{i=1}^{N} w_i \cdot \delta_{imp_i}, 0, 1)\end{aligned} \tag{10}$$

In Equation 10, $\{w_i | i = 1,..,N\}$ are the weights specifying the influence of each importance measure, and the final output is the blending of the individually applied measures. Since when importance differences are fixed, β is linear to each weight w_i, the final output, which is visually monotonic to the scaling of modulation factor β, is also monotonically influenced by each weighting factor of the importance measures. Thus, the weights are provided to the end-user for adjustment.

Figure 7 shows the results when two importance measures (maximum intensity and maximum gradient magnitude) are applied and weighted. The final rendering combines features from those when the two measures are applied separately, and is monotonically influenced by the weighting factors.

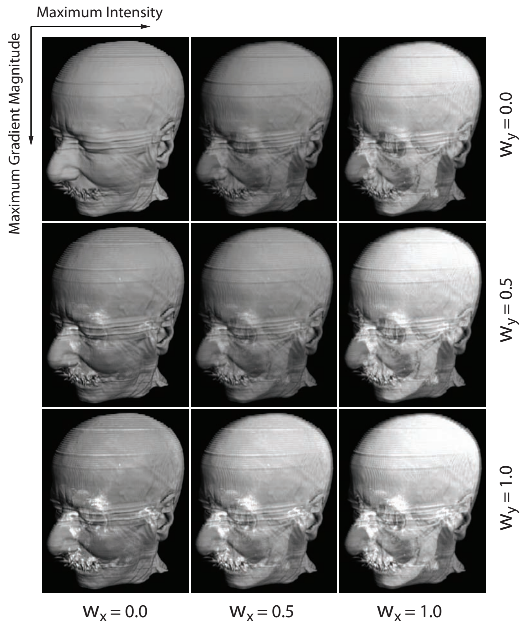

Figure 7: *The Cadaver Head dataset rendered with accumulated transparency modulation. Two importance measures are applied, and their effects are controlled by two weighting factors: w_x and w_y. The results show that when the two weights change, we can have features such as bones and cavities visualized at the same time, which used to be visualized by two different importance measures applied separately.*

6. Application Design for Fast Volumetric Data Exploration

We have introduced a simple formula for calculating modulation factor β (Equation 10), which is capable of combining features together from applying different importance measures. We also show that the weights in Equation 10 influence the visual output monotonically, so they are easy for end-user to adjust. In our experiments on different datasets, we also found that some simple forms of transfer function manipulation can be very helpful, such as scalar intensity and gradient magnitude thresholds. Although these parameters are applied to the transfer function, they can be controlled with sliders and are very useful when used jointly with importance measures of accumulated transparency modulation.

Based on our current and previous work, we propose the following guidelines for designing parameter setting widgets of fast volume exploration applications:

- **Settings are parameterized to values that each changes one dimensionally.** A good example is gradient magnitude thresholding. It comes essentially from 2D transfer function design, but we only expose one simple parameter to the end-user.
- **Settings take effect only on final rendering, without intermediate results.** Rather than switching back and forth between intermediate results such as a histogram and the final rendering, the user needs to focus on the final result for fast operations.
- **Parameters have monotonic and easily predictable behavior.** In practice, software with hundreds of parameters to control one output result can still be easy and efficient to use, thanks to the fact that each parameter contributes monotonically and has predictable influence on the result.

Though a full featured volume visualization application can have more complicated widgets designed for maximum output quality, if easy-to-use, efficiency, and effectiveness are the design goals for a volume exploration application, following these guidelines is sufficient. We developed a prototype application based on these guidelines, which is discussed in the next section.

7. Results and Discussion

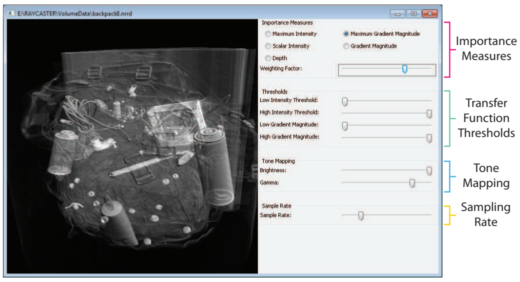

Figure 8: *The user interface of our prototype program.*

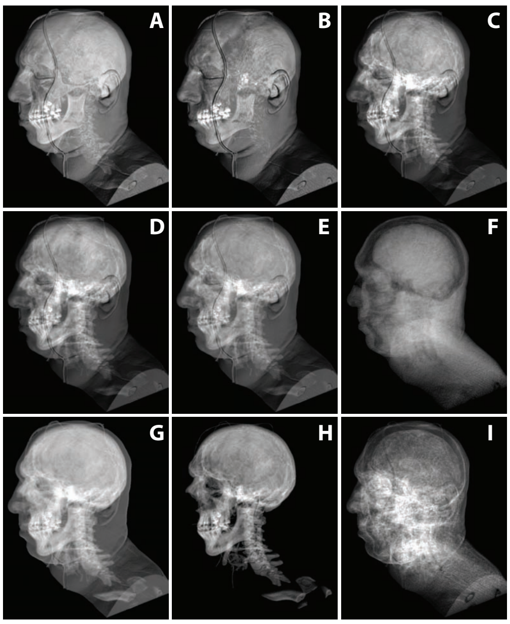

Figure 9: *The Visible Male dataset rendered with importance-based accumulated transparency modulation algorithm. A: Maximum intensity weight only; B: Maximum gradient magnitude weight only; C: Intensity increase weight only; D: Gradient magnitude difference weight only; E: Intensity difference weight only; F: Depth weight increased and high gradient magnitude threshold decreased to reveal the brain; G: Mixed weights; H: Mixed weight with low intensity threshold increased; I: Mixed weights with high intensity threshold decreased.*

Integrating importance-based accumulated transparency modulation algorithms into existing volume rendering applications is easy. We incorporated the proposed importance measures into a prototype application and tested it on a wide variety of datasets. The user interface of the application is shown in Figure 8, and the results from one of the datasets we tested are shown in Figures 9. However, all the figures of this paper are generated with this application. The initial transfer function for all of the figures is a simple linear ramp grayscale colormap combined with a linear opacity ramp.

Compared with transfer function design and editing in standard direct volume rendering, importance-based accumulated transparency modulation can visualize features more quickly, and the same importance measures and operations can be applied to a wide variety of datasets. We have shown certain importance measures derived from the local properties of the volume datasets, such as scalar value, gradient magnitude and depth, which are also widely used in transfer function design. To further extend the variety of importance measures and the usefulness of our method, global properties can also be considered. Unlike transfer function design and editing in standard direct volume rendering, which becomes difficult to manipulate when the dimension of parameter space exceeds three, importance-based accumulated transparency modulation can virtually incorporate arbitrary number of importance measures and yet still maintain ease of interaction. By setting the weights of importance measures as user-adjustable parameters, which all have monotonic influence on the final rendering, the user can learn this predictable behavior of the application quickly. For unfamiliar volume datasets that the user does not have much knowledge of, experimenting by trial-and-error may be the most proper, if not the only, method for initial exploration. Importance-based accumulated modulation provides the user such a platform — the user can highlight interesting structures by quickly changing the weights for importance measures, and obtain an overall idea about the content of the datasets. Even the least skilled user can get started quickly by randomly dragging the sliders for the weights. While in order to effectively use traditional multi-dimensional transfer functions relying on histogram volumes, the user needs to be capable of reading features from the histogram and have a good understanding of the histogram volume.

As accumulated transparency modulation changes the volume compositing behavior by only modifying the accumulated transparency, an initial transfer function is still required. For high-quality results with images rendered with specifically colored features, extensive transfer function editing is still required. Accumulated transparency modulation provides an easy method for exploration of the volume data quickly, thus it can serve as a guide for further transfer function manipulation, or can be used jointly with transfer function editing. Since accumulated transparency modulation is a view-dependent method, there is possibility that some importance measures lead to visual artifacts when the user is rotating the datasets, due to the abrupt change of the calculated importance from adjacent voxels. But in practice, the phenomenon is rarely observed, because features in the datasets usually span multiple voxels and project to multiple pixels of the final results, which make the visual artifacts rare except for highly noisy data.

8. Conclusion and Future Work

In this paper, we presented Importance-Based Accumulated Transparency Modulation, which is generalized from previous work on MIDA. We have shown that by using different importance measures and calculating the transparency modulation factor β, we can visualize different features from a volumetric dataset. Multiple measures can be also easily incorporated into a simple form, and the final rendering is monotonically controlled by the weights of the measures.

For future work, we would like to explore other importance measures, and how they can be applied to specific application areas. Combining Importance-Based Accumulated Transparency with transfer functions that have classified the data such that occluded relationships could be exposed would be an interesting application.

Acknowledgments

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