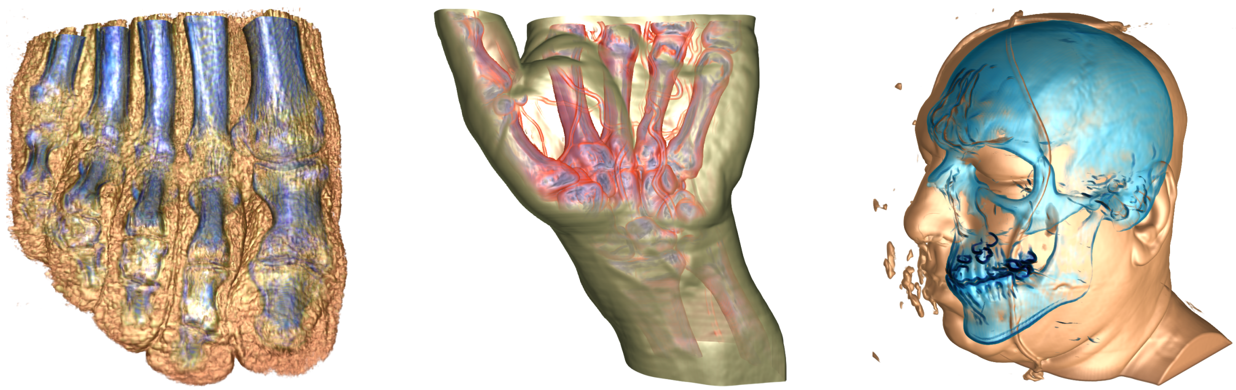
Importance-Aware Composition for Illustrative Volume Rendering

Francisco de Moura Pinto
Instituto de Informtica - UFRGS
fmpinto@inf.ufrgs.br

Carla M. D. S. Freitas
Instituto de Informtica - UFRGS
carla@inf.ufrgs.br



(a) Gradient highlight (b) Illumination-based importance (c) Combined importance measures

Figure 1. A few examples of illustrative effects achieved using the proposed composition method.

***Abstract*—Non-photorealistic volume rendering, often referred as volume illustration, augments typical visualization methods to selectively emphasize or de-emphasize structures within a volumetric dataset. Illustrative visualization techniques may affect not only the rendering style of specific portions of the dataset but also their visibility, ensuring that less important regions do not occlude more important ones. Cutaway views completely remove occluding, unimportant structures – possibly also removing valuable context information – while current solutions for smooth reduction of occlusion based on importance lack precise visibility control, simplicity and generality. We introduce a new *front-to-back* sample composition equation for direct volume rendering that directly takes into account a measure of sample importance. The proposed method allows smooth and precise importance-based visibility control in single-pass volume rendering, assuring visibility of important structures. We provide a mathematical justification of our composition equation and demonstrate its generality by presenting several illustrative effects, which were obtained by using our composition method and a set of importance measures calculated on the fly.**

***Keywords*-Direct volume rendering; importance; composition;**

I. Introduction

Direct visualization is a very useful method for understanding volumetric datasets. Most optical models employed in direct volume rendering (DVR) are physically based and consider the dataset as a 3D object made of a cloud-like material whose particles emit and absorb light. The particles have optical properties, such as color and opacity, whose values are determined by a transfer function (see [1] for an excellent survey on typical volume illumination models). However, physical realism may not be the best choice for clearly depicting the information within the dataset.

Illustrative (non-photorealistic) volume rendering exchanges realism for clarity, and basically consists in visually emphasizing interesting data features, often suppressing secondary structures by using simplified or sparse representations. It has become a very important research theme, and many illustration techniques have been adapted to volume visualization since the pioneer works by Rheingans and Ebert [2], and Treavett and Chen [3]. Silhouette enhancement, tone and cartoon shading, halos, depth cueing, line and point drawing are well-known illustration styles.

One of the main challenges in providing informative volume visualizations is visibility control. Making an interesting volume portion opaque, e. g. by adjusting the transfer function, may prevent other important features from being clearly perceived due to occlusion, while making it transparent enough to ensure visibility of all interesting structures may lead to a blurred rendering, which prevents shape perception. Some volume illustration techniques control visibility using view-dependent cuts, deformation or fading to expose interesting structures. Viola and Gröller [4] presented a deep discussion on such approaches.

To ensure visibility of important volume structures, Viola et al. [5] defined importance as visualization priority and proposed importance composition. Their method makes volume's portions more transparent only if they occlude more important structures. Importance composition requires two-pass rendering and depends on segmentation of the volume.

This paper proposes a modification of the discrete, front-to-back composition equation typically employed in DVR in order to directly take into account sample importance in a single-pass rendering. Our approach allows precise visibility control, ensuring visibility of most important volume features, and does not rely on segmented data. We also provide a mathematical justification of our composition equation, and suggest several ways of calculating importance measures for volume samples on the fly to achieve a set of view-dependent illustrative effects. The presented technique can be easily integrated into most existent volume visualizers.

Next section discusses related work. Our new importance-aware composition equation is described in detail in Section III. Section IV suggests several ways of assigning importance values to volume samples in order to achieve interesting illustrative effects. In Section V we discuss some important aspects of our proposal as well as implementation details. Finally, Section VI brings our conclusions and comments on future work.

II. Related work

Algorithms for direct volume rendering typically step along per-pixel-cast viewing rays collecting volume samples. A transfer function is applied to each sample to determine its color and opacity, which are combined – usually through the *over operator* – with the previously accumulated color and opacity to perform integration of color contribution. In DVR, the trade-off between global visibility and sharpness of structures is one of the main concerns in designing effective visualization tools. The most direct way of controlling these attributes is through adjustment of a transfer function (TF). Correa and Ma [6] introduced visibility-driven TF design, which modifies a opacity TF to make the visibility of volume materials roughly proportional to the respective, initially specified opacity. Transfer functions, however, have known limitations in separating volume materials [7] and their effect is typically global. Kraus [8] proposed integration in data space rather than in 3D object space. His method prevents large, quasi-homogeneous regions from becoming too opaque due to opacity accumulation.

Viola et al. [9], [5] presented the most comprehensive work on visibility control based on explicit importance (visualization priority) values. They proposed the use of cutaway views and several techniques for smooth visibility control in volume visualization. Cutaway views completely remove portions of less important structures. The drawback is the lack of contextual information in clipped regions. Alternatively, they also introduced importance composition, which uses the relative importance of objects intercepted by a viewing ray to control the fading or sparseness of less important objects, but this strategy does not provide precise visibility control because occlusion also depends on the size of occluding objects along viewing rays. Besides, as the main drawback of their work, importance composition relies on segmented data and does not allow single-pass rendering. Our approach takes into account importance in a single-pass rendering using a new composition equation, does not depend on segmented data and allows precise visibility control.

Opacity modulation is a common way of emphasizing or de-emphasizing specific volume structures. This strategy was already present in the work by Levoy that introduced DVR [10], and is commonly used to emphasize boundaries. Opacity modulation is often used for partially suppressing contextual information in focus-plus-context volume visualization. The ClearView technique by Krüger et al. [11] extracts contextual and focus layers from volume data and composes them after applying fading to unimportant regions. Bruckner et al. [12] used view- and illumination-dependent modulation of opacity to achieve context-preserving visualizations that suppress low detail areas.

While modulation of samples' opacity is a common strategy in DVR, the modulation of previously accumulated color and opacity during front-to-back ray integration, to the best of our knowledge, was unexplored until Rautek et al.'s work [13]. The reason may be the fact that modulating the accumulated color values severely compromises the physically-based emission-absorption illumination model [1] on which most DVR tools are based. However, illustrative volume rendering does not prioritize realism, and compelling visualizations can be produced by ignoring or changing aspects of realistic rendering models. Rautek et al. [13] developed a framework that allows the selection and quantification of several interaction-dependent illustrative effects through high-level human-readable rules. One of such effects – the flat rendering – is obtained through modulation of accumulated color and opacity. Bruckner and Gröller [14] considered modulation of accumulated color values in developing MIDA, a technique that mixes the advantages of typical DVR and maximum intensity projection (MIP). These authors, however, used simple strategies to control the modulation of the accumulated color and opacity. Our approach to importance-based visibility control strongly relies on this mainly unexplored degree of freedom and constitutes a sophisticated mechanism to control such modulation.

III. Importance-Aware Composition

Direct volume rendering is usually based on either the *back-to-front* or the *front-to-back* composition depending on the order in which volume samples are collected along the viewing rays. Front-to-back composition is the obvious choice in volume ray casting and is also frequently employed in slice-based volume rendering. Equation 1 represents the front-to-back composition. C_i and α_i are the previously accumulated color and opacity, respectively, C_{i+1} and α_{i+1}

are their updated values, and C_s and α_s are the color and opacity of the incoming volume sample, which are obtained from the transfer function. The initial values (C_0, α_0) are zero, and C_s is an associated (opacity-weighted) color.

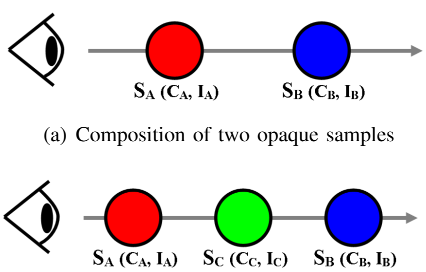
$$C_{i+1} = C_i + (1 - \alpha_i)C_s \tag{1a}$$

$$\alpha_{i+1} = \alpha_i(1 - \alpha_s) + \alpha_s \tag{1b}$$

Since importance is a measure of visualization priority, importance-aware DVR must ensure that less important volume regions do not occlude more important ones. Our goal is designing a front-to-back composition equation that controls samples' visibility based on importance. The next subsections describe and justify our composition method.

A. Visibility Control

In the following discussion visibility is a value in $[0, 1]$ that quantifies the amount of occlusion affecting a volume sample. It is one minus the accumulated opacity from all samples previously collected along the viewing ray in front-to-back composition. The color and opacity accumulated up to the i-th sample are respectively C_i and α_i (Equation 1). The visibility of the $i+1$-th sample is $1-\alpha_i$, the value that weights its color contribution in Equation 1a. Therefore, we can control the visibility of the next sample by modulating the accumulated opacity α_i. Any modulation of α_i applies also to C_i, since it is an opacity-weighted color. This modulation considers all previous samples as a single sample with color C_i and opacity α_i, i. e., the accumulated values.



(a) Composition of two opaque samples

(b) Composition of three opaque samples

Figure 2. Two simple composition scenarios.

We want to control the visibility of each incoming sample based on its importance and the accumulated importance from previous samples. We thus need a function $vis(I_s, I_i)$ of the sample importance I_s and the accumulated importance I_i that produces the minimum visibility required for the incoming sample. If the required visibility is not allowed by the accumulated opacity, we need to scale down the accumulated opacity and color (α_i and C_i) to ensure proper visibility of the incoming sample. However, for a meaningful importance-based composition of samples, no modulation of the accumulated values must be performed when the incoming sample is less important than the accumulated importance. The modulation is accomplished using the scale factor m, defined in Equation 2, which is applied to accumulated color and opacity at every sample composition step. The scale factor m_i (calculated after the i-th composition step) depends on the accumulated opacity (α_i), the sample importance (I_s) and the accumulated importance (I_i).

$$m_i = \begin{cases} 1 & \text{if } I_s <= I_i, \\ 1 & \text{if } 1 - \alpha_i >= vis(I_s, I_i), \\ \frac{1 - vis(I_s, I_i)}{\alpha_i} & \text{otherwise.} \end{cases} \tag{2}$$

Since m is a scale (modulation) factor, Equation 2 states that accumulated color and opacity are modified only when the incoming sample's importance is greater than the accumulated importance, and the visibility allowed by the accumulated opacity is less than the required visibility. Note that the modulation factor from the third case of Equation 2 scales down the accumulated opacity α_i ensuring the visibility required by the current sample. We use as visibility function the exponential curve defined by Equation 3.

$$vis(I_s, I_i) = 1 - \exp(I_i - I_s) \tag{3}$$

Our choice for an exponential function comes from the analysis of the composition of completely opaque samples. Figure 2 illustrates two simple cases where two and three opaque samples are combined along a viewing ray. One of the assumptions on which our proposal is based is that the importance accumulated during the composition of completely opaque samples must be the importance of the most important sample. By introducing the modulation factor m into the original front-to-back composition equation (Equation 1) and taking into account importance update we obtain an importance-aware composition equation (Equation 4) that is valid for opaque samples.

$$C_{i+1} = mC_i + (1 - m\alpha_i)C_s \tag{4a}$$

$$\alpha_{i+1} = m\alpha_i(1 - \alpha_s) + \alpha_s \tag{4b}$$

$$I_{i+1} = max(I_i, I_s) \tag{4c}$$

Accumulated opacity is always one for opaque samples, therefore Equation 4b can be neglected in the following discussion. Figure 2a illustrates the composition of two opaque samples, S_A and S_B, along a viewing ray, with colors C_A and C_B and importances I_A and I_B, respectively, being $I_B > I_A$. In this case, $C_1 = C_A$, $I_1 = I_A$, and the ray integration ends up with $C_2 = mC_A + (1 - m)C_B$ and $I_2 = I_B$. If we consider a third sample S_C between S_A and S_B, as shown in Figure 2b, with color C_C and importance I_C, being $I_A < I_C < I_B$, the ray integration steps are as described in Equation 5. In both cases the accumulated importance is the same (I_B), and thus the first sample (S_A) has the same importance relative to the accumulated one. Therefore, the color contribution of S_A must be the same in both cases. In the first case (two samples), C_A is modulated by m, and in the second case (three samples) C_A is modulated by $m_2 \times m_1$, therefore we need a visibility function $vis(I_s, I_i)$ such that $m = m_2 \times m_1$.

$$
\begin{aligned}
&C_1 = C_A; \quad I_1 = I_A \\
&C_2 = m_1 C_A + (1 - m_1) C_C; \quad I_2 = max(I_A, I_C) = I_C \\
&C_3 = m_2(m_1 C_A + (1 - m_1) C_C) + (1 - m_2) C_B \\
&I_3 = \max(I_C, I_B) = I_B
\end{aligned} \tag{5}
$$

By the definition of the modulation factor m (Equation 2), and recalling that accumulated opacities are one for opaque samples, the above requirement turns into $1 - vis(I_A, I_B) = (1 - vis(I_A, I_C) \times (1 - vis(I_C, I_B)$, which is fulfilled by the visibility function of Equation 3. Note that if we set importance to zero for all samples the modulation factor m will be one, which leads to the conventional DVR, where visibility depends solely on the chosen transfer function.

After choosing the visibility function we need to generalize the composition of importance for translucent samples. The opacity obtained from the transfer function is also a measure of sample relevance. For instance, zero opacity volume samples must have absolutely no effect on the visualization. Therefore, for a meaningful update of accumulated importance during composition, the impact of a sample on the accumulated importance must be dependent on the contribution of this sample to the ray integration.

B. Updating Accumulated Importance

We generalized the importance update equation based on the analysis of the composition of a sequence of samples with the same importance, after having accumulated high opacity, lower importance samples. In such situation the first sample S_J of the sequence of higher importance samples causes modulation of the previously accumulated color and opacity to guarantee the visibility required by its importance. The desired behavior is that this modulation, followed by the composition of sample S_J, also produces the exact visibility required by the next, equally important sample S_K of the sequence. Such requirement corresponds to Equation 6a. α_{i+1} and I_{i+1} are, respectively, the accumulated opacity and importance after the composition of sample S_J. We payed special attention to sequences of samples of same importance because most volumes present spatial coherence.

$$
1 - \alpha_{i+1} = vis(I_K, I_{i+1}) \qquad \Longrightarrow \tag{6a}
$$

$$
\alpha_J + (1 - \alpha_J) \exp(I_i - I_J) = \exp(I_{i+1} - I_K) \tag{6b}
$$

Using Equations 2, 3 and 4b we developed Equation 6a into Equation 6b, where α_J is the opacity of S_J, and I_J and I_K are the importances of samples S_J and S_K. Considering $I_J = I_K$ (the samples have the same importance as stated above) we can solve Equation 6b for I_{i+1}. This leads to Equation 7, which is the update of the accumulated importance based on its previous value (I_i) and the current sample's importance and opacity (I_s and α_s). The *max* operator ensures that the accumulated importance never decreases. Note that a fully transparent sample does not affect the accumulated importance and a fully opaque sample makes the accumulated importance equal to its importance.

$$
I_{i+1} = \max\left(I_i, \ln(\alpha_s + (1 - \alpha_s)\exp(I_i - I_s)) + I_s\right) \tag{7}
$$

At this point, one last issue remains: the composition of a low opacity, high importance sample followed by high opacity, low importance samples might lead to undesired results. The low opacity, high importance sample could scale down the previously accumulated color and opacity, ensuring high visibility for subsequent samples but introducing a very small contribution to the ray integration. The contribution of these low importance samples would dominate the accumulated color because of their high visibility. Their contribution might be even greater than that from previous higher importance samples. We solve this problem by scaling up accumulated color and opacity at the end of each composition step in order to make the opacity equal to the one obtained from the original composition equation (Equation 1b). This modification leads to the complete importance-aware composition, formalized in Equation 8.

$$
C'_{i+1} = mC_i + (1 - m\alpha_i)C_s \tag{8a}
$$

$$
\alpha'_{i+1} = m\alpha_i(1 - \alpha_s) + \alpha_s \tag{8b}
$$

$$
\alpha_{i+1} = \alpha_i(1 - \alpha_s) + \alpha_s \tag{8c}
$$

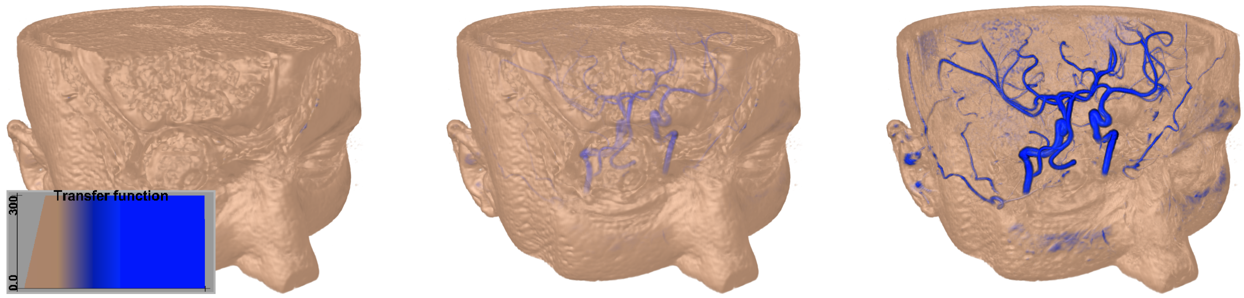
$$
C_{i+1} = \begin{cases} 0 & \text{if } \alpha'_{i+1} = 0, \\ \frac{\alpha_{i+1}\ C'_{i+1}}{\alpha'_{i+1}} & \text{otherwise.} \end{cases} \tag{8d}
$$

$$
I_{i+1} = \max\left(I_i, \ln(\alpha_s + (1 - \alpha_s)\exp(I_i - I_s)) + I_s\right) \tag{8e}
$$

Opacity α_{i+1} results from the typical composition scheme. It is used to scale up the accumulated color in Equation 8d. C_s,α_s and I_s are the properties of the current sample, and C'_{i+1} and α'_{i+1} are auxiliary variables. Our importance-aware composition equation requires more floating point operations than the typical composition but can be efficiently and easily implemented and optimized in coding level. Next section presents several ways of calculating sample importance on the fly to get compelling illustrative effects using the composition scheme presented herein.

IV. Importance Assignment and Results

The importance-aware composition equation provides visibility control based on samples' importance. In order to create meaningful illustrations, we need to derive importance



(a) (b) (c)

Figure 3. Effect of using intensity as importance. The depicted transfer function (bottom left) is used for the three visualizations. The horizontal axis is intensity and the vertical axis is the extinction coefficient. Weight equal to zero results in the conventional DVR of an angiography dataset (a). A moderate weight makes regions with high intensities visible (b). A high value for the weight results in a visualization practically identical to colored MIP (c).

according to the emphasis that we want to give to specific features. As a general approach to calculating sample importance during rendering, several properties of the scalar field at the sample position can be evaluated and combined in a weighted sum to produce the actual importance value. The following subsections describe the importance measures we experimented and the achieved illustrative effects. We used simple one-dimensional transfer functions (TFs) to assign color and opacity to volume samples.

A. Importance Measures

1) Intensity: By making the importance proportional to the samples' intensity ($I_S = W_{intensity} \times intensity$) we ensure visibility of samples with highest intensities. Varying the weight $W_{intensity}$ produces visualizations smoothly ranging from typical DVR to MIP. A color transfer function may be used to apply sophisticated volume coloring, while the opacity transfer function restricts the visualization to interesting materials only. The effect is roughly similar to Bruckner and Gröller's MIDA [14], which also blends MIP and DVR. Figure 3 shows three visualizations of an angiography dataset using a simple color and opacity transfer function and different weights for the intensity in the importance calculation.

2) Extinction Coefficient: In the emission-absorption illumination model [1], sample opacity is calculated as $1 - \exp(-\tau d)$, where τ is the extinction coefficient and d is the sampling step. We use $\ln(1 + \tau)$ as an importance measure to make the extinction coefficient transfer function also play the role of a visibility TF. We use the logarithm because the effect of the extinction coefficient on the visualization is non-linear. As discussed by Correa and Ma [6], it would be convenient for the user to think of the TF as a means of directly controlling the visibility of structures in volume visualization. By deriving an importance measure from the outcome of the transfer function ($I_S = W_\tau \times \ln(1 + \tau)$) we allow a more direct user control over the visibility of specific structures. Figure 4 provides and example of using this importance measure.

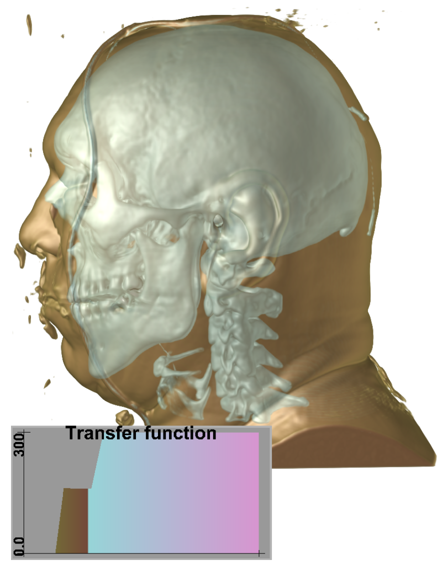
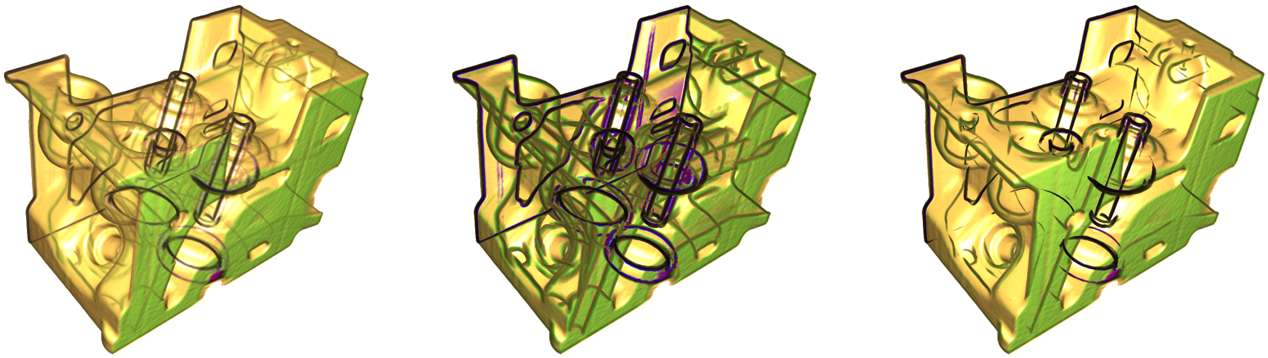


Figure 4. A visualization of the Vismale Head produced by deriving importance from the extinction coefficient, and the corresponding TF. The skin would occlude the skull without importance-aware composition.

3) Gradient Magnitude: Gradient magnitude can be used as an importance measure ($I_S = W_{gradient} \times |gradient|$) to provide visibility control based on boundary strength. High gradient regions are often structures of interest because they are typically interfaces between different materials. By adjusting the weight of the gradient in samples' importance one can ensure visibility of the strongest boundaries, as shown in Figure 1a. The noisy Foot dataset has well-defined boundaries, with high gradient, on the surface of bones. Weighting the gradient magnitude with a high value in the importance calculation ensures visibility of such boundaries.

4) Silhouetteness: Silhouetteness measures how much a sample belongs to the silhouette of an important boundary. We empirically developed an expression for *silhouetteness* (Equation 9) that is similar to other well-known definitions [15], [2]. It depends on the normalized viewing vector V, the normalized gradient N, and the gradient magnitude



(a) (b) (c)

Figure 5. Effect of using *silhouetteness* as importance. A low weight for *silhouetteness* is used in (a), and a high weight is used in (b), where silhouettes are much more visible. The silhouette emphasis can be made superficial, as shown in (c), by adding the *unocclusion* measure to the importance calculation.

m_G, which is globally normalized to the interval $[0, 1]$. The exponent p controls the influence of the gradient magnitude, parameters s_1 and s_2 define the start and the end of the slope of the $smoothstep$ function, which is available in shading languages, and the abs function yields the absolute value of the dot product between V and N, which is the core of most silhouette detection techniques. The following values are used for the mentioned parameters: $p = 1.7$, $s_1 = 0.4$, and $s_2 = 1.0$. These values work well for most datasets.

$$sil = m_G^p \times smoothstep(s_1, s_2, (1.0 - abs(V \cdot N))) \quad (9)$$

The sample color is scaled by the empirically chosen factor $\exp(-4 \times sil)$, becoming darker as *silhouetteness* increases. This makes silhouettes distinguishable but does not ensure their visibility. However, by making importance proportional to *silhouetteness* ($I_S = W_{sil} \times sil$) one can achieve the illustrative effect shown in Figure 5 (a) and (b).

5) Unocclusion: Our importance-aware composition scheme can make visible important structures that are otherwise occluded, even if they are far from the viewer. This omission of depth cues can be controlled by reducing the importance of samples according to the amount of occluding material in front of them. We calculate the amount of occluding material by integrating the extinction coefficient along the viewing ray. This simple integration can be performed as samples are collected in front-to-back order by summation of $\tau \times d$, where τ is the extinction coefficient from the TF and d is the ray integration step.

We define *unocclusion* as a positive constant (we use 20) minus the amount of occluding material. The constant must be large enough to ensure a positive value. Adding *unocclusion* to the importance calculation ($I_S = W_1 I_1 + ... + W_n I_n + W_{unocclusion} \times unocclusion$) causes the importance-based illustrative effects to be applied only superficially, i. e, near the observer, as shown in Figure 5c.

6) Lighting: Bruckner et al.'s work [12] suppresses volume structures according to illumination. Inspired by this idea, we developed the importance measure from Equation 10 to assign greater importance to samples where the Phong illumination is weak. H is the normalized half-angle vector, L is the normalized light incidence vector, and N and m_G have the same definition as in Subsection IV-A4. Parameters p_1, p_2 and p_3 control the influence of specular, diffuse and gradient terms, respectively. The best settings are data dependent, but the values 50, 5 and 30 led to good results for most tested datasets. The gradient term penalizes regions of low gradient magnitude, which may have ill-defined surface orientation for illumination.

$$I_S = 3 - (N \cdot H)^{p_1} - (N \cdot L)^{p_2} - (1.0 - m_G)^{p_3} \quad (10)$$

The achieved effect is roughly similar to that obtained by Bruckner et al., as shown in Figure 1b, which illustrates a CT scan of a hand. Lower importance values are assigned to more illuminated volume samples.

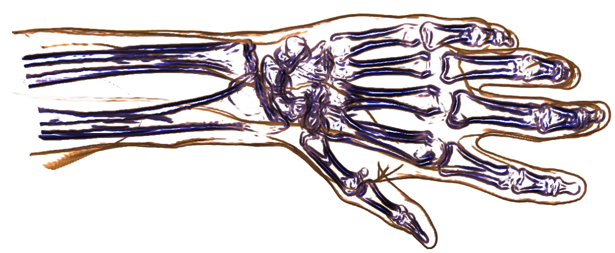


Figure 6. A silhouette rendering of the Hand dataset achieved by assigning high importance to the background and silhouettes. Low importance regions are automatically suppressed to make the background visible.

B. Combining Importance Measures

Although discussed individually, the presented importance measures can be combined in a weighted sum to produce more elaborated visualizations. The visualization reproduced in Figure 1c was obtained by adjusting the weights of the following importance measures: intensity and extinction coefficient for emphasizing the skull; gradient and *silhouetteness* for emphasizing contours; and *unocclusion* to restrict such emphases to low-depth regions. Note that only bones and contours near the skin surface are visible.

We also propose a global weight to smoothly control the impact of importance on visualizations. It scales the weighted sum of importance measures leading to the general expression for sample importance: $I_S = W_{global} \times (W_1 I_1 + ... + W_n I_n)$. When W_{global} is zero, importance is zero, resulting in traditional DVR, as discussed in Subsection III-A.

C. Suppressing Structures

We have shown how to use importance-aware composition to emphasize important structures that would be otherwise occluded. However, it is also possible to use our method to suppress unimportant regions. To accomplish this we consider the background as a layer of completely opaque samples having the background color, and assign an adjustable importance to them. The composition of the background with the rendered volume can then be used to fade less important regions. An example is presented in Figure 6.

D. Focus plus Context

Instead of using a global weight to scale importance, one can define a different weight per viewing ray. These weights would then be "global" only in the scope of individual rays. This way we can give specific image regions a more prominent illustrative aspect. Focus-plus-context visualization is the obvious application of this strategy. The context can be visualized with traditional DVR – per-ray-global weight equal to zero – while the focus is represented with strong illustrative characteristics using a chosen maximum global weight. A smooth transition between focus and context can be obtained by varying the per-ray-global weight.

In our implementation the focus is defined by dragging and resizing a circular area on the image plane. We implemented three types of focus representation: *circular*, *Gaussian* and *screendoor*, shown in Figure 7. Global weights for viewing rays (pixels) are respectively given by a step function and a Gaussian function of the distance to the focus center for the circular and the Gaussian focus. The screendoor focus uses a binary function of pixel coordinates to produce the weights, and the local sparseness of the screendoor depends on a Gaussian curve.

V. Discussion and Implementation

The proposed method for importance-based visibility control requires setting extra parameters – the importance weights. On the other hand, designing transfer functions – one of the most difficult tasks in volume visualization – becomes simpler since we provide extra, more intuitive degrees of freedom to control emphasis and visibility.

We observed that our composition method has a very low impact on performance, and since it does not require two-pass rendering nor data segmentation – unlike previous approaches – it can be easily implemented in most interactive DVR tools. Calculating samples' importance on the fly also contributes to performance reduction. Notwithstanding, we still achieve high quality rendering at interactive rates using the combined importance measures described in Section IV. The tests ran on a PC with an Intel Core2 Quad Q6600 2.40GHz CPU, 4GB of RAM, and an NVIDIA GeForce 9600GT graphics card.

A limitation of our method was found in illustrating MRI data due to noise and contrast issues, which make some importance measures less reliable, specially lighting and *silhouetteness*. To better illustrate MRI data it may be necessary to use different importance measures. Statistical signatures [16] are strong candidates.

A slice-based volume visualizer implemented in OpenGL and GLSL was used in this work. The dataset and the corresponding gradient field are stored as a 3D texture which is sampled in front-to-back order. Our interface for importance assignment is a collection of sliders corresponding to weights for each importance measure described in Subsection IV-A, besides the sliders for the *background* weight and the global weight.

Accurate silhouette rendering requires high-quality gradient estimation. We used the regression technique by Neumann et al. [17]. We employed OpenGL *framebuffer objects* and multiple render targets (MRT) to manage the buffers that store intermediate results during slice composition. Two floating point textures were used as buffers: one for accumulating RGBA pixel colors, and another for accumulating the importance value and the amount of occluding material (see Subsection IV-A5), and storing the per-pixel-defined global importance weight when using-focus-plus context illustration (see Subsection IV-D).

VI. Conclusions and Future Work

We presented a composition method for front-to-back ray integration in direct volume rendering that directly takes into account a measure of samples' importance to control their visibility. Unlike previous approaches to incorporating importance into volume visualization ours allows single-pass rendering and does not depend on segmented datasets. Moreover, our importance-aware composition scheme can be implemented in existent DVR applications in a minimally intrusive way and with low performance penalty.

Visibility is a crucial issue in volume illustration. We demonstrated that direct and precise visibility control in DVR can be provided through an importance-guided visibility function incorporated into the composition equation. Additionally, we provided a detailed justification of the proposed composition method. Our proposal is strongly based on modulating accumulated color and opacity in front-to-back composition, a mainly unexplored degree of freedom.

We suggested a collection of illustrative effects obtained by just setting importance weights. By controlling a global importance weight we can produce visualizations smoothly

(a) Circular focus (b) Gaussian focus (c) Screendoor focus

Figure 7. Illustrations with different focus styles. Center and size are interactively defined. Per-pixel-global importance weights are defined according to the distance in image plane to the focus center. The visualizations were produced using non-zero weights for intensity, *silhouetteness* and background.

ranging from tradition DVR to flat rendering, which means drawing volume layers on top of each other ordered by importance. As future work we want to widen the collection of illustrative effects that our approach allows by creating new meaningful importance measures. We will also experiment with importance-aware composition in illustrating segmented volume data as well as in other scenarios where importance-based layer composition is required.

Acknowledgment

The authors thank CNPq (Conselho Nacional de Desenvolvimento Cientfico e Tecnolgico) for financial support.

References

[1] N. Max, "Optical models for direct volume rendering," *IEEE Transactions on Visualization and Computer Graphics*, vol. 1, no. 2, pp. 99–108, 1995.

[2] P. Rheingans and D. Ebert, "Volume illustration: Nonphotorealistic rendering of volume models," *IEEE Transactions on Visualization and Computer Graphics*, vol. 7, no. 3, pp. 253–264, 2001.

[3] S. M. F. Treavett and M. Chen, "Pen-and-ink rendering in volume visualisation," in *Proceedings of the 11th IEEE Visualization Conference*, 2000, pp. 203–210.

[4] I. Viola and M. E. Gröller, "Smart visibility in visualization," in *Proceedings of EG Workshop on Computational Aesthetics Computational Aesthetics in Graphics, Visualization and Imaging*, 2005, pp. 209–216.

[5] I. Viola, A. Kanitsar, and M. E. Gröller, "Importance-driven feature enhancement in volume visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 11, no. 4, pp. 408–418, 2005.

[6] C. D. Correa and K.-L. Ma, "Visibility-driven transfer functions," in *Proceedings of the 2009 IEEE Pacific Visualization Symposium*. IEEE Computer Society, 2009, pp. 177–184.

[7] H. Pfister, B. Lorensen, C. Bajaj, G. Kindlmann, W. Schroeder, L. S. Avila, K. Martin, R. Machiraju, and J. Lee, "The transfer function bake-off," *IEEE Comput. Graph. Appl.*, vol. 21, no. 3, pp. 16–22, 2001.

[8] M. Kraus, "Scale-invariant volume rendering," in *Proceedings of the 16th IEEE Visualization Conference*. IEEE Computer Society, 2005, pp. 295–302.

[9] I. Viola, A. Kanitsar, and M. E. Groller, "Importance-driven volume rendering," in *Proceedings of the 15th IEEE Visualization Conference*. IEEE Computer Society, 2004, pp. 139–146.

[10] M. Levoy, "Display of surfaces from volume data," *IEEE Computer Graphics and Applications*, vol. 8, no. 3, pp. 29–37, 1988. [Online]. Available: citeseer.ist.psu.edu/levoy88display.html

[11] J. Krüger, J. Schneider, and R. Westermann, "Clearview: An interactive context preserving hotspot visualization technique," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 941–948, 2006.

[12] S. Bruckner, S. Grimm, A. Kanitsar, and M. E. Gröller, "Illustrative context-preserving exploration of volume data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 6, pp. 1559–1569, 2006. [Online]. Available: http://www.cg.tuwien.ac.at/research/publications/2006/bruckner-2006-ICE/

[13] P. Rautek, S. Bruckner, and M. E. Gröller, "Interaction-dependent semantics for illustrative volume rendering," *Computer Graphics Forum*, vol. 27, no. 3, pp. 847–854, 2008.

[14] S. Bruckner and M. E. Gröller, "Instant volume visualization using maximum intensity difference accumulation," *Computer Graphics Forum (Eurovis 2009)*, vol. 28, no. 3, pp. 775–782, 2009.

[15] B. Csbfalvi, L. Mroz, H. Hauser, A. Knig, and M. E. Grller, "Fast visualization of object contours by non-photorealistic volume rendering," *Computer Graphics Forum*, vol. 20, pp. 452–460, 2001.

[16] S. Tenginakai, J. Lee, and R. Machiraju, "Salient iso-surface detection with model-independent statistical signatures," in *Proceedings of the 12th IEEE Visualization Conference*, 2001, pp. 231–238.

[17] L. Neumann, B. Csébfalvi, A. König, and E. Gröller, "Gradient estimation in volume data using 4d linear regression," *Computer Graphics Forum (Eurographics 2000)*, vol. 19, no. 3, pp. 351–358, 2000.