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Perceptual analysis of distance sampling and transmittance estimation techniques in biomedical volume visualization

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Abstract: In volumetric path tracer, distance sampling and transmittance estimation techniques play a vital role in producing high-quality final rendered images. Previously, these techniques were implemented for production volume rendering, and were analyzed for faster convergence. In this article, we have augmented additional transmittance estimators including ratio tracking, residual ratio tracking and unbiased ray marcher in a GPU-based volumetric path tracer (Exposure Render) for biomedical datasets. We have also analyzed distance sampling methods and transmittance estimators perceptually using CIEDE2000 and Structural Similarity Index (SSIM). It was found that ratio and residual ratio tracking estimators performed close to each other and were better than unbiased ray marching perceptually. In addition, ray marching was observed to be better than delta tracking for distance sampling. We also validated these results by conducting a user study where different users were shown rendered images using varied distance samplers and transmittance estimators. Although, as expected, datasets had an impact on the rendering result for each technique, the perceptual differences did exist between distance samplers and transmittance estimators. As a major contribution of this work, we have found that distance sampling and transmittance estimation techniques have a crucial role for biomedical visualization due to having a direct impact on the final rendered image which is used in the diagnosis and prognosis of disease.

Key words: Monte Carlo, volume rendering, biomedical visualization

1. Introduction

Volume visualization of biomedical datasets plays a crucial role in diagnosis and prognosis of a disease. One of the most crucial features in the biomedical volume visualization is clarity of structures, which depends on the samples taken from the volume datasets and the light sources. For visualization of biomedical datasets, volumetric light transport is used, which explains the light ray traversal from sensor to the light source, and the interaction of light ray with the medium. There are two important computations involved in the volumetric light transport, 1) distance sampling and 2) transmittance estimation. In distance sampling, samples of distance travelled by the photon before it interacts with the medium are taken, whereas transmittance is defined as the estimation of amount of light that reaches the sensor after the volume traversal [1].

The distance sampling techniques decide which sample/s to take, number of samples and the number of significant samples (i.e. samples which have part of the medium, not air) from the dataset. Similarly, transmittance estimation techniques play a role in the calculation of light samples. These samples mainly contribute towards the quality of final rendered image, which affects the quality of diagnosis and prognosis

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of a disease in the biomedical visualization. Various distance sampling techniques exist in the literature, like ray marching [2], delta tracking [3], spectral tracking [4], decomposition tracking [4], etc., which have been implemented for production volume rendering. Similarly, transmittance estimation techniques like ratio tracking [5], residual ratio tracking [5], unbiased ray marching [6], etc., are also implemented for production volume rendering. These techniques have mainly been developed and analyzed to ensure faster convergence and accuracy. However, none of these techniques have yet been implemented for biomedical datasets. Furthermore, perceptual analysis has also not been performed which may provide structural clarity in a given image. The user studies detailing human perceptions for comparison of rendered images with ground truth have also not been conducted in the past. Hence, a gap has been identified to investigate the existing distance sampling and transmittance estimation techniques for biomedical data sets. In addition, user studies for perceptual analysis are required that may help identify the image attributes relevant for biomedical visualization.

Volumetric path tracers such as Exposure Render [7] (which is a graphic processing unit (GPU) based volumetric path tracer) are available for innovative visualization applications. Earlier extensions to Exposure Render include MeVis path tracer [8]. Promising visualization result is also presented in Ospray CPU based ray tracer [9], etc. In this work, we have extended the Exposure Render framework by including additional transmittance estimation techniques including ratio tracking [5], residual ratio tracking [5] and unbiased ray marching [6]. Our sole reason for augmenting these newer transmittance estimators is to investigate each of these for biomedical datasets and also, to analyze them perceptually using SSIM [10] and CIEDE2000 [11]; SSIM reveals the clarity of structures in the images, whereas CIEDE2000 is a measure used for comparing the color intensity. We used three existing datasets, that are available within Exposure Render, i.e. Manix, Artifix and Macoessix, by taking multiple views for each. Furthermore, we have also analyzed the distance sampling techniques (ray marching and delta tracking) perceptually.

The major contributions of this work are as follows:

- We have extended the GPU-based Monte Carlo path tracer, Exposure Render by implementing additional transmittance estimators: ratio tracking, residual ratio tracking and unbiased ray marcher.
- We have analyzed the transmission estimation techniques (ratio tracking, residual ratio tracking and unbiased ray marcher) and distance sampling techniques (ray marching and delta tracking) for biomedical datasets perceptually using SSIM and CIEDE2000.
- We have conducted a user study to validate the results of perceptual analysis using three different datasets by taking multiple views for each in order to investigate the impact of dataset on the behavior of distance sampling and transmission estimation techniques.

The rest of this paper is organized as follows: Section 2 details the relevant literature; Section 3 summarizes the implementation details; Section 4 presents experimental results and finally, Section 5 concludes the paper and offers directions for future research.

2. Previous work

This section discusses existing distance sampling and transmittance estimation techniques.

2.1. Distance sampling

Initial distance sampling methods such as the regular tracking [12] and ray marching [2] resorted to fixed step sampling to approximate the volume rendering integral. However, these methods required significantly large number of samples to produce acceptable results. In addition, banding artifacts were produced in ray marching due to aliasing, which could be minimized by random perturbation of rays. In regular tracking, on each interaction/collision with a medium, there is check if the ray has crossed the boundary of another medium. In case if ray enters from one medium to another, path length calculation is restarted using the crosssection based on the new material [13].

In order to reduce random samples and still obtain acceptable results, delta tracking [3] method was integrated with Monte Carlo path tracing [7]. Delta tracking introduced the idea of homogenizing the medium by adding fictitious particles so that a path length is calculated using a single global majorant. However, there are certain shortcomings, associated with this technique. First, a large value of majorant may reduce sampling efficiency. Second, in low density regions/void regions, delta tracking becomes inefficient because, chances of real collision decreases and a lot of collisions are rejected. Third, delta tracking is a binary estimator, which leads to high variance in the result. Fourth, the probability distribution function (PDF) is unknown. Therefore, this technique may not be merged with any other sampling technique via multiple importance sampling (MIS).

To reduce the value of majorant and improve the sampling efficiency, Kalos et al. [14] introduced the concept of defining the local constant and polynomial majorants in the form of super voxels instead of using a single global majorant. The efficiency of this algorithm is dependent on the super voxel resolution. Behlouli et al. [15] applied a similar technique in simulations for medical applications. Delta tracking may become inefficient in some applications such as heavy absorbing materials due to high majorant value, [16] suggested using an arbitrary majorant value instead of using maximum crosssection as majorant. This technique results in collisions with negative weights, which represents backward scattering. There is an overall gain in efficiency, but the efficiency is dependent on the sampling efficiency, sampling probability and location of interaction.

Decomposition tracking was introduced in [4], which accelerates the conventional delta tracking by decomposing the medium into control medium and residual medium. Control medium is calculated analytically whereas, residual medium is calculated numerically, which reduces the expensive look up. Decomposition tracking minimizes the per-sample cost. For heterogeneous medium, the efficiency of the decomposition tracking is dependent on the extinction coefficient. [4] also extended this work for chromatic media, and the technique is known as spectral decomposition tracking. Since these techniques use rejection based sampling, therefore exact PDF computation is still not possible.

Rejection sampling in existing delta tracking makes the technique inefficient when acceptance rate of sampling is low, [17] introduced the idea of weighted delta tracking for Monte Carlo based light transport algorithms. In this work, the rejection sampling is replaced by a statistical weight and only absorption model for the participating media was considered. Later, this work was extended by [18]. One of the limiting factors of rejection based samplers is the accurate estimation of PDF, which is addressed in [19]. A generalized null scattering volumetric path integral framework which allows accurate estimation of PDF is presented. Moreover, a technique known as spectral MIS is also presented for distance sampling which uses MIS to combine various sampling techniques and in addition, it can handle chromatic medium. While combining various techniques, care has to be taken as the risk of degrading efficiency may increase.

2.2. Transmittance estimation

Existing Monte Carlo based path tracers [7, 20] used ray marching for transmittance estimation. Delta tracking may be used for transmittance estimation. The shortcomings of ray marching and delta tracking are already discussed in detail in the previous section. In order to reduce the value of majorant and improve the efficiency for transmittance estimation, [21] provided an integral formulation of null collisions which accepts negative value of null collisions. Since, the value of majorant is reduced by accepting negative collisions, therefore expensive collisions are also minimized. However, overall convergence is hampered due to the acceptance of negative collisions.

Novak et al. [5] introduced ratio tracking, which replaced the Russian roulette based ray termination by a statistical weight which is equal to the probability of interacting with a fictitious particle. To improve the sampling efficiency, residual ratio tracking was introduced which decomposes the extinction coefficient into control extinction (evaluated analytically) and residual extinction coefficient (evaluated numerically). In this technique, the overall sampling efficiency is improved, but the variance is dependent on controlled extinction coefficient.

The concept of unbiased transmittance estimation without involving null collisions was introduced in [22]. In this work, several formulations are presented including Volterra integral formulation, power series formulations comprising of iterative power series, recursive power-series and hypercube. To minimize the variance in new formulations, control variate for null collisions was introduced. However, it may not be accommodating for diverse rendering scenarios. Later, Eon et al. [23], extended the Volterra integral formulation for transmittance estimation and applied zero variance theory to reduce variance.

Jonsson et al. [24] presented a Taylor expansion of the exponential for transmittance estimation. Two new transmittance estimators, i.e. dependent Poisson and independent Poisson, were presented. Dependent Poisson estimator suffers from a small bias as it reuses existing samples and thus it requires additional data structures for storage. On the other hand, independent Poisson estimator lowers variance, and it is independent of expensive auxiliary data structures. The error in independent Poisson, however, is dependent on the value of the control coefficient. Ketunen et al. [6] investigated the existing transmittance estimation for sources of variance and named them Y variance and roulette variance. In this work, U statistics power series transmittance estimator is presented which minimizes Y variance. This transmitter is dependent on a pivot value. Negative value of optical depth when used as a pivot value reduces variance, whereas majorant based pivot value does not improve variance. Existing transmittance techniques approximate the exponential transmittance function, which leads to silhouette bloating and light leaking artifacts. A model for transmittance is developed in [25] which provides more accurate appearance of opaque surfaces. The model improves the accuracy, but is dependent on the approximation of the phase function.

We have reviewed in detail the existing state-of-the-art work done in the field of distance sampling and transmittance estimation. In this work, we intend to extend state-of-the-art Monte Carlo based path tracer, Exposure Render with various transmittance estimation techniques. We also intend to investigate distance sampling and transmittance estimators on different biomedical datasets to identify their impact on clarity of structures.

3. Implementation details

Our work is implemented by extending an open source GPU-based Monte Carlo volume path tracer, the Exposure Render [7]. The aim is to evaluate a complete volume rendering integral which incorporates absorption, emission and scattering.

In order to provide a more standard visualization pipeline, the Visualization Toolkit (VTK) library, and its volume rendering modules were used. Once data is loaded, view rays are initialized and the Compute Unified Device Architecture (CUDA) kernel for rendering technique (single scattering or multiple scattering) is launched dynamically based on the user selection from the user interface (UI). For multiple scattering technique, the single scattering steps are executed N times where N is the total number of bounces of the secondary ray. This was controlled through the UI slider. The single scattering kernel starts by tracing a ray (R_0) from eye into the scene. This eye ray is intersected with the volume dataset bounding box to get the ray intersection parameters t_{min} and t_{max} for obtaining the near and far ray intersection parameters, respectively. Subsequently, from the intersected ray position (t_{min}), the user may dynamically select the distance sampling technique (ray marching or delta tracking). Based on the technique, the dataset is sampled and point of intersection is calculated. The choice of distance sampling is also given to the user through an appropriate UI radio button.

At the point of intersection, material properties are calculated dynamically based on either bidirectional scattering distribution function (BSDF), isotropic phase function or hybrid phase function. The BSDF material uses local illumination, calculating the gradient at the point of intersection. The phase function material uses a simple isotropic phase function that traces random rays, which are importance sampled using MIS to obtain the output ray direction (ω_0). The hybrid material probabilistically switches between BSDF and phase function. For the light rays calculation, i.e. transmittance estimation, user may select dynamically between, ratio, residual ratio or unbiased ray marching through UI radio buttons. The contributions of all random samples are integrated to obtain the contribution of the current pixel. Since Monte Carlo integration uses random samples, noise is inevitable. This requires a denoising step which is carried out using a separate CUDA kernel. K-nearest neighbour (k-NN) [26] noise reduction filter was used as a denoiser. The denoised rendered output is then tone mapped from high dynamic range (HDR) image to low dynamic range (LDR) image using a tone mapping kernel which implements Reinhard tone mapper [27]. Finally, the LDR image is rendered on the screen.

Since Monte Carlo ray tracing is inherently parallel, there are a lot of stages where shared memory optimizations may be introduced. In particular, the ray entry/exit parameters (t_{min}, t_{max}) can be cached in shared memory for all of our distance sampling and transmittance estimation kernels. Moreover, CUDA symbols were employed for storage of per-kernel constants, for example, scene parameters like camera position, light positions, light type, etc. This allows notifications of all scene parameter changes to be broadcasted to all threads, providing a performance boost. In addition, we required the ability to toggle the used distance samplers (ray marching or delta tracking) and transmittance estimators (ray marching, ratio tracking, residual ratio tracking or unbiased ray marching). Due to the pluggable nature of our scattering technique, distance sampling and transmittance estimation CUDA kernels, we were able to swap the desired components on demand using the UI. This capability was unfortunately missing from the existing framework provided by Exposure Render which is limited to a fixed set of kernels supporting only delta tracking with single scattering. Our modified pipeline is presented in Figure. 1.

All GPU-based methods are unfortunately limited to within-core data that is the requirement of the entire volume dataset to be in GPU memory therefore, we tested our implementation on small datasets. This makes handling of out-of-core datasets a challenge, which are better handled on the CPU. In the following subsections, we present the implementation details of the distance sampling (ray marching, delta tracking) and transmittance estimation techniques (ratio tracking, residual ratio tracking and unbiased ray marching). For all our kernels, the scene, the volume data properties and the ray are passed as kernel parameters. As an added optimization, all distance sampling and transmittance estimators check if the current ray intersects the volume bounding box and continue only if the intersection exists.

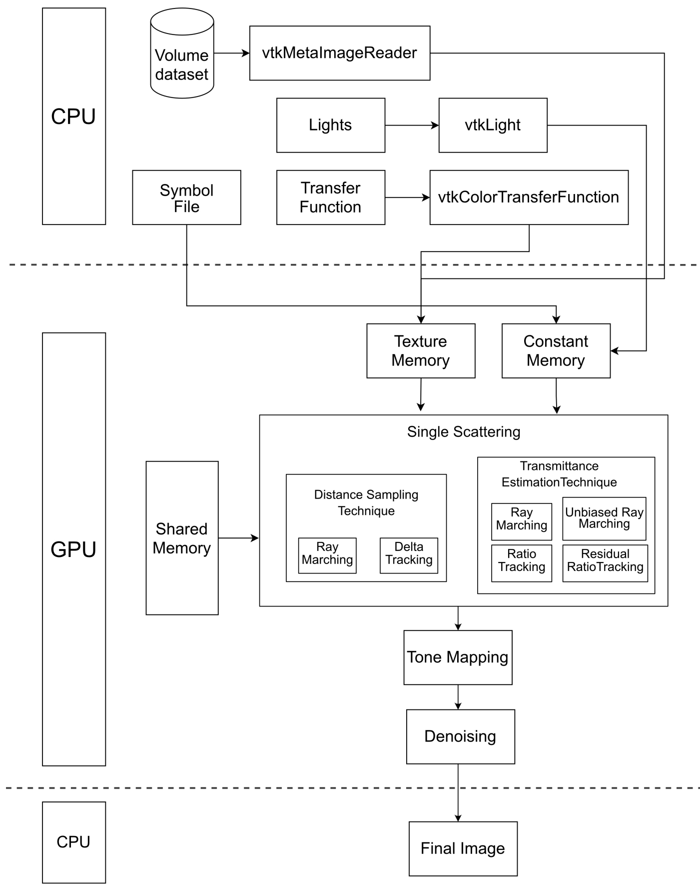

Figure 1. The control flow diagram.

3.1. Ray marching

In the ray marching kernel, the ray is progressed at equal step size starting from the ray position at parametric ray intersection t_{min}. The intersection point is calculated where the ray hits the medium. Material properties and transmittance are evaluated at the intersection point, x_s and the sampling continues until the complete volume is traversed. We made a separate device function for ray marching transmittance estimator because it required caching of transmittance estimations which are returned to the caller for use later. The ray continues using a fixed step size, and light sampling continues until the ray exits the dataset. Note, however, that ray marching is costly for distance sampling if a sufficiently large number of samples are used.

3.2. Delta tracking

In the delta tracking kernel, the ray is progressed using random step sizes, which are determined on the outcome of a random number generator. The intersection point is calculated where the ray hits the medium. Material properties and transmittance are evaluated at the intersection point x_s. The ray propagation is terminated probabilistically using a Russian roulette. We continue distance sampling till the random number ξ is greater than the ratio of extinction value $\sigma_t(x_s)$ and the majorant value σ_{maj} at the current ray position. This is interpreted as a fictitious collision. The distance sampling stops in two cases, if a real collision occurs or if the ray reaches the end of the volume. Transmittance is a binary estimate which could be 1 or 0 depending on if we had a real or fictitious collision. This binary estimation when used as transmittance estimation manifests itself as noise in the final rendered image.

3.3. Ratio tracking

The ratio tracking kernel is used for transmittance estimation only. It calculates transmittance estimate for light rays only. We terminate the ray propagation based on a probabilistic decaying factor. The light sampling continues until either the end of the volume is reached or the transmittance reaches a saturation threshold. On each interaction, the ratio of extinction value $\sigma_t(x_s)$ and the majorant value σ_{maj} at the current ray position are decayed and transmittance is updated. The ray progresses forward similar to the delta tracking kernel.

3.4. Residual ratio tracking

Similar to the ratio tracking kernel, the residual ratio tracking is also used for transmittance estimation only. The control and analytical transmittance are calculated first. The control transmittance is dependent on the μ_c value. This value is provided by the user through the UI. Light sampling continues until the ray exits the volume or energy of the photon is diminished. Final transmittance is calculated as a product of controlled and analytical transmittance. The ray progresses forward similar to the delta tracking kernel.

3.5. Unbiased ray marching

The unbiased ray marcher is used for distance sampling as well as transmittance estimation. It requires the tuple size, i.e. the number of densities to be evaluated for each optical thickness. Subsequently, we determine the highest order of power series using the modified BK roulette [6]. The ray progresses by taking a fix number of steps, similar to how the ray marching kernel progresses. Finally, the elementary mean is taken to approximate the transmittance or the sampling distance.

4. Experimental results

The distance sampling and transmittance estimation methods discussed in this paper are implemented on a workstation with NVIDIA® GPU (TITAN X) with 12 GB graphics memory and Intel® Core™ i7-8700 CPU @ 3.20 GHz with 16 GB of RAM. The operating system used was Microsoft® Windows™ 10 64-bit. The output resolution used in all these experiments has 1024×768. In our case, the ground truth image is a fully converged image over 500 iterations using delta tracking as distance sampling and ray marching as transmittance estimation. The images used in comparisons are generated without the denoising step.

We have analyzed the existing distance sampling and transmittance estimation techniques using a perceptual analysis through various experiments. We have taken various views of the datasets in order to investigate the dependency between distance sampling, transmittance estimation techniques and datasets on the viewing directions. We have used three datasets[1], the Manix, the Macoessix and the Artifix dataset. The Manix has the most material in it, therefore we have taken three different views of the Manix dataset, showing front on view (View 1), view from side on (View 2) and view from bottom up (View 3). The Artifix has a medium amount of material, bones and some flesh, therefore it is suited to check the dependency on nature of dataset. For transmittance estimation technique, we have taken two views of the Artifix dataset, front on view (View 1)

[1]Datasets courtesy of http://www.osirix-viewer.com.

and side on view (View 2). In the Macoessix dataset, the amount of material is the least, and we have taken two different views of the Macoessix dataset, the oblique view (View 1) and side on view (View 2).

In the first set of experiments, we evaluated distance sampling techniques perceptually. We highlighted the color differences of the rendered images using CIEDE2000[11]. It may be seen in Figure. 2 that CIEDE2000 results have predominantly white areas, which indicates differences in colors. In CIEDE2000, if the image is more black, it implies that it is more similar in colors to the ground truth. Figure. 2 implies that there is a significant difference in the final rendered images using ray marching and delta tracking.

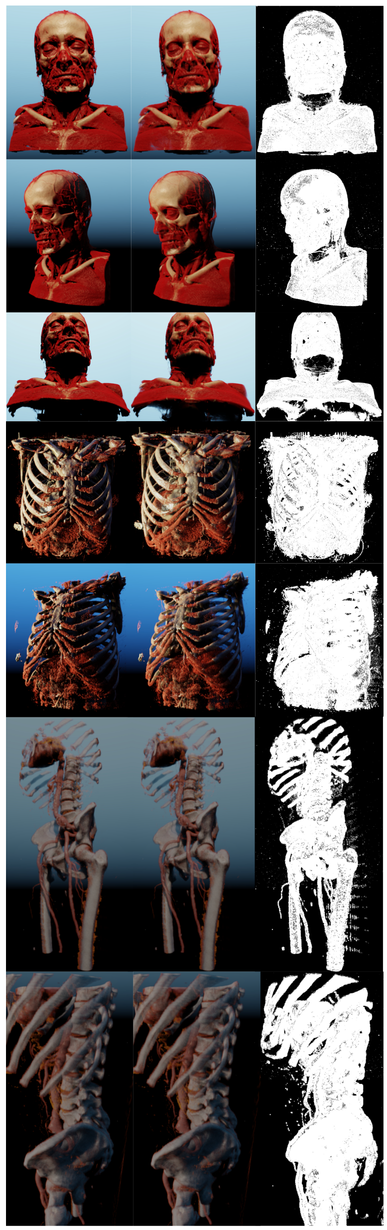

Figure 2. Distance sampling techniques applied on various datasets showing the Manix dataset in the top three rows, the Artifix dataset in the middle two rows and the Macoessix dataset in the bottom two rows.

To further validate the results of CIEDE2000 evaluations, we conducted a user study in which fully converged images of ray marching and delta tracking for different datasets were presented and users were asked to select images with the most visible structures. The user study had 3 options: a) ray marching, b) delta tracking, and c) no visible changes. The user study was filled by 50 different participants belonging to diverse demographics and professions, including doctors. The results of user study are presented in Figure 3. The majority of users selected ray marching for the most visible structures. Although delta tracking had been widely used over ray marching for its faster convergence [5], the perceptual side is mostly overlooked. From our experiments, it may be inferred that there is a major difference in the visual aspects for different transmittance estimators. This visual difference in the rendered images is due to the quantity and selection of sample points, which depends on the distance sampling technique being used.

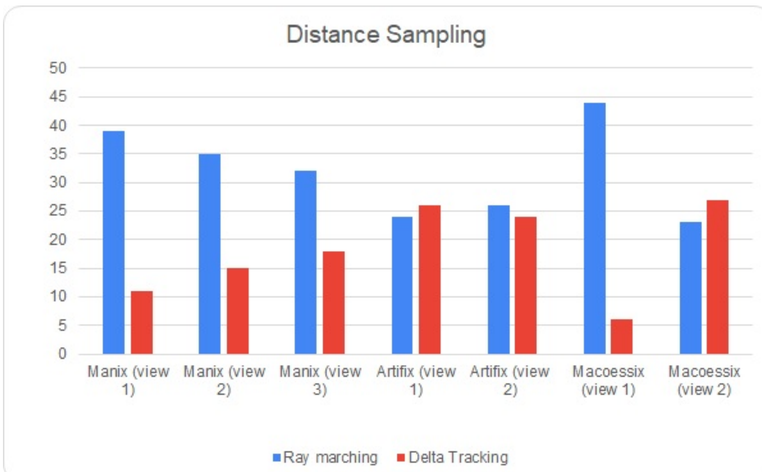

Figure 3. User study results of distance sampling techniques applied on various datasets.

In the next set of experiments, we evaluated transmittance estimators perceptually. We present the color differences among the rendered images using CIEDE2000 [11] in Figure 4. It is quite visible in Figure 4 that CIEDE2000 for ratio and residual ratio tracking has more black areas, which implies that they are more close to the ground truth. Another important observation worth mentioning is that the results of CIEDE2000 for ratio and residual ratio tracking are quite similar to each other. These observations support the results extracted from the user study that no visible changes are evident in ratio and residual ratio tracking. On the other hand, unbiased ray marching has more white areas, which indicates that images rendered using unbiased ray marching are perceptually different from the ground truth. However, users still selected no visible change for unbiased ray marching indicating that CIEDE2000 was able to detect perceptual changes in the renderings of unbiased ray marching technique, but those changes were not obvious to many users in the user study.

We further investigated using another perceptual metric, SSIM [10] which highlights the structural differences and degradation among the images. In Figure 5, we present SSIM analysis for various transmittance estimation techniques on different datasets. SSIM should be equal to one when the rendered image is structurally similar to the ground truth image. A similar trend is visible in Figure 5 where ratio and residual ratio are found to be much closer to each other and the ground truth, whereas there is a difference in the unbiased ray marching. It may be seen in Figure 5 that for the same dataset and fixed iteration numbers, the SSIM value varies for each transmittance technique, which implies that the selection of transmittance estimation technique is dependent on the density distribution of the dataset.

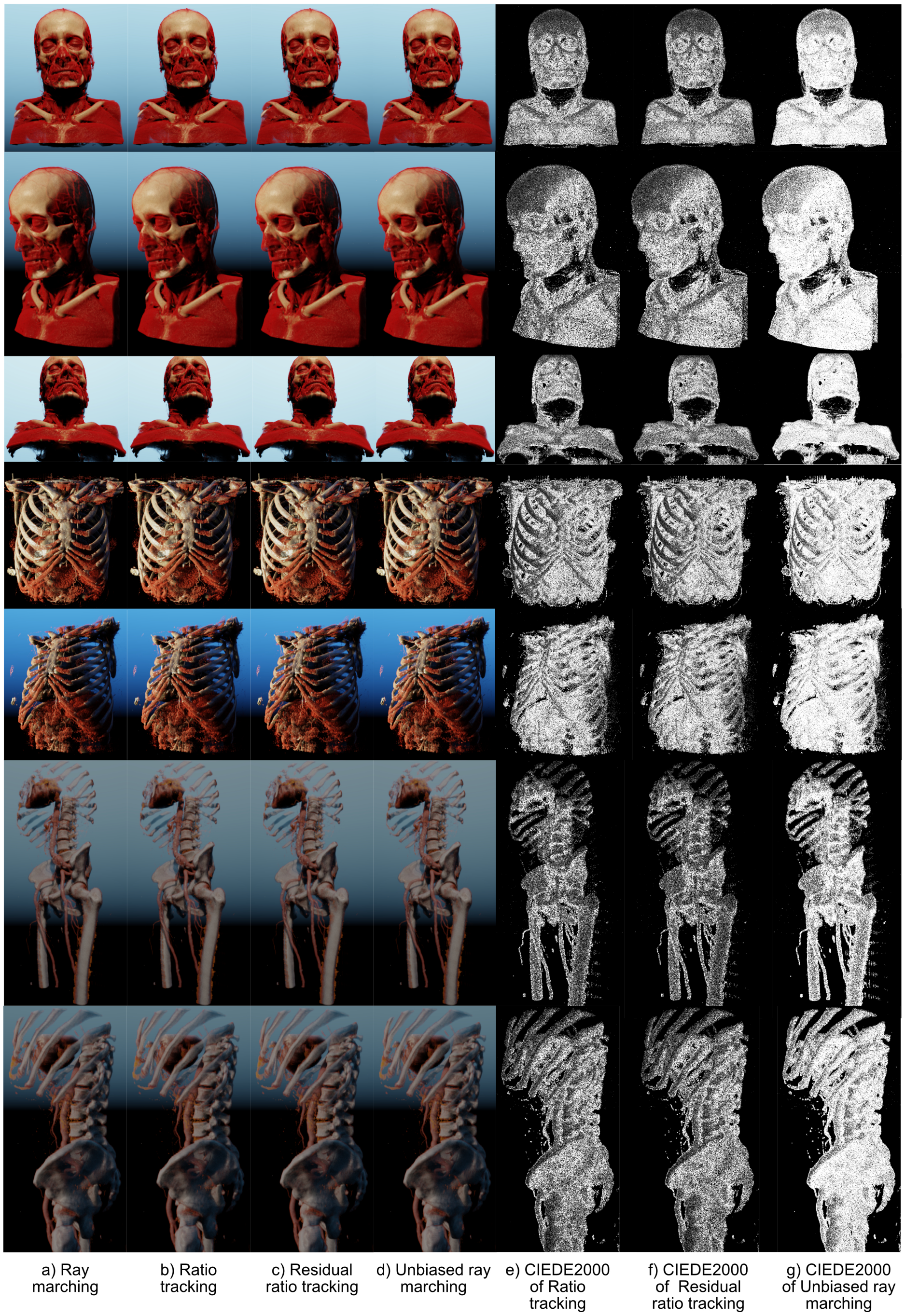

Figure 4. CIEDE2000 of transmittance estimation techniques applied on various datasets showing the Manix dataset in the top three rows, the Artifix dataset in the middle two rows and the Macoessix dataset in the bottom two rows.

To support the results of CIEDE2000 and SSIM evaluations, we extended the user study, and presented fully converged images over 500 iterations of various transmittance estimators. The user study offered 5 options to select from: a) ray marching, b) ratio Tracking, c) residual ratio tracking, d) unbiased ray marching, and e) no visible change. The names of technique were not shared with the participants, to avoid bias. Participants

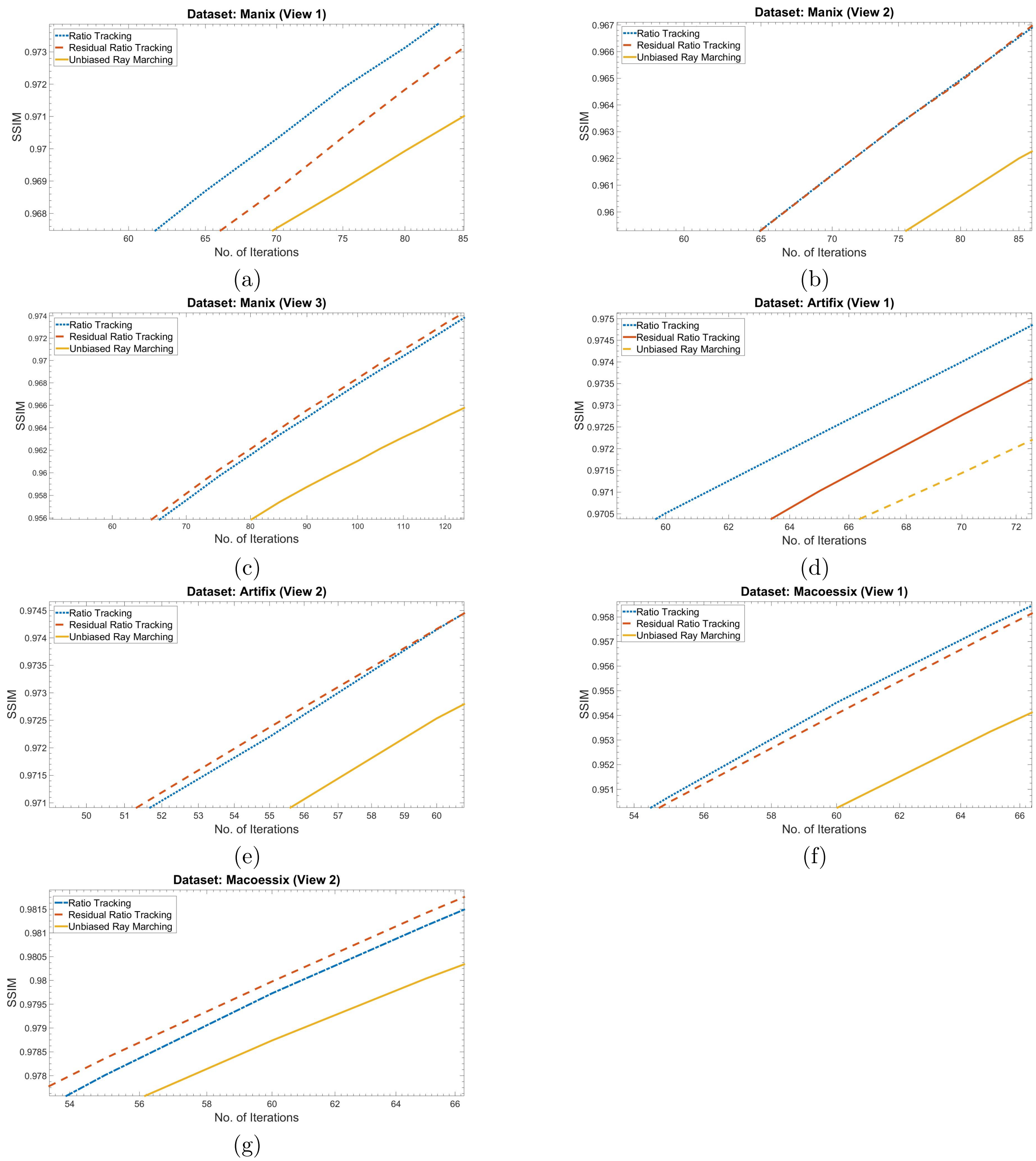

Figure 5. SSIM of transmittance estimation techniques applied on various datasets using single scattering. (a) For Manix View 1, (b) For Manix View 2, (c) For Manix View 3, (d) For Artifix View 1, (e) For Artifix View 2, (f) For Macoessix View 1, (g) For Macoessix View 2.

were asked to select the image which has the most visible structures in their opinion; the results are presented in Figure 6. Majority of users selected the option that all the images looked similar. Therefore, from visual perspective, users were not able to identify any major difference in the rendered images. The rendered images using various transmittance estimation techniques are presented in Figure 4.

To further compare our perceptual analysis against the performance of transmittance estimation techniques, we calculated the root mean square error (RMSE), which is presented in Figure 7. It is quite evident from Figure 7 that ratio tracking and residual ratio tracking perform better than unbiased ray marching. This implies that ratio and residual ratio tracking are not only closer to the ground truth visually, but are also better in performance. This finding is in agreement with the results reported by previous studies [5]. The reason for ray marching to offer more visible structures is that it takes samples at equal intervals and traverses the whole dataset. On the other hand, delta tracking takes random samples and does not traverse the whole dataset. Therefore, for biomedical visualization, as visual aspect plays a very critical role for diagnosis of a disease, ray marching may be a better choice. From the perspective of performance, delta tracking appears to be better as it takes fewer samples and does not traverse the whole dataset [3]. On the contrary, ray marching not only traverses the whole dataset but also takes more samples at fixed intervals, which results in increased processing time and computations [2].

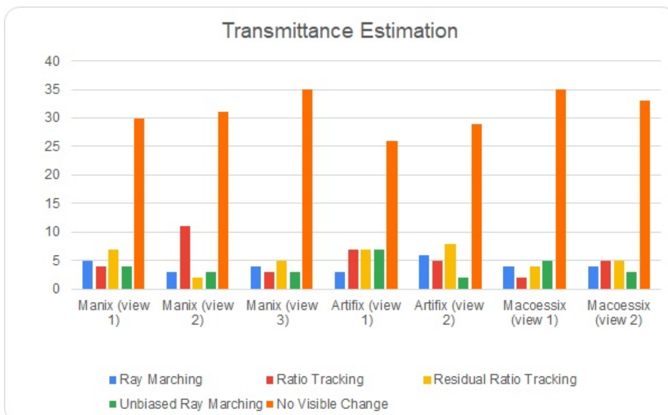

Figure 6. User study results of transmittance estimation techniques applied on various datasets.

5. Conclusion and future work

This paper presented a novel investigation of distance sampling and transmission estimation techniques for biomedical datasets from a perceptual lens. In the past, these techniques were mainly used for production volume rendering, which led to gap identification for this article. We extended Monte Carlo based path tracer, Exposure Render to include transmittance estimation techniques of ratio tracking, residual ratio tracking and unbiased ray marching. We conducted a perceptual analysis of distance sampling and transmittance estimation techniques to study the depth perceptions and color intensities of the biomedical images. In addition, a user study was also conducted to validate our experimental findings in relation to human perceptions. Performance analysis was also presented for transmittance estimation techniques.

For biomedical visualization, distance sampling technique plays a pivotal role in clarity of structures, as it affects the number and selection of samples. Furthermore, selection of appropriate transmittance estimation techniques is also crucial for governing the performance of biomedical visualization. Unlike previous studies which reported that for distance sampling, delta tracking converges faster than ray marching, we have found that ray marching is perceptually better than delta tracking as presented in CIEDE2000 results. This is mainly because ray marching traverses the complete datasets using a constant step size unlike delta tracking in which random samples are taken, and traversal is dependent on the value of majorant. Moreover, for transmittance estimation, previous studies reported that unbiased ray marcher converges better whereas, we have found that ratio and residual ratio tracking were perceptually better than unbiased ray marching as shown in CIEDE2000 analysis, due to the dependency on optical depth and number of densities to traverse. It was also revealed that values of SSIM are dataset dependent, as the values varied for the same dataset while we investigated different views. Finally, the user perceptions collected via structured survey also agree with our experimental findings.

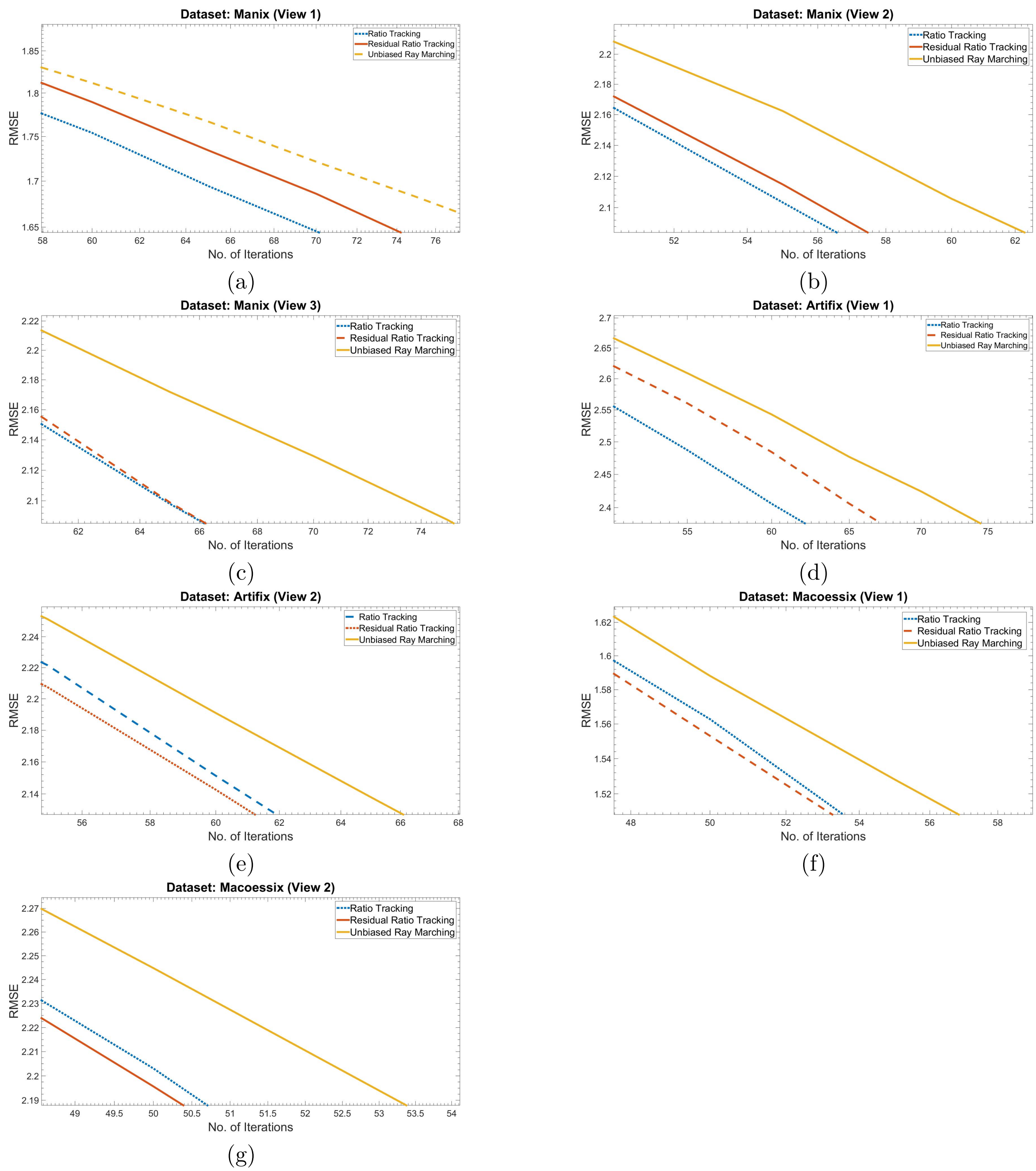

Figure 7. RMSE of transmittance estimation techniques applied on various datasets using single scattering. (a) For Manix View 1, (b) For Manix View 2, (c) For Manix View 3, (d) For Artifix View 1, (e) For Artifix View 2, (f) For Macoessix View 1, (g) For Macoessix View 2.

We believe that the perceptual analysis presented in this article would help in diagnosis and prognosis of diseases like cancer where surgical margins have to be delineated. Since the perceptual differences are the key in identifying varied structures, the same may assist in detecting cancerous regions from noncancerous regions. Further investigation needs to be carried out in this area.

In future, we plan to integrate the distance sampling and transmittance estimation techniques studied in this article into existing state-of-the-art rendering frameworks such as Intel OSPRay and Paraview. Furthermore, we also plan to investigate these techniques for more biomedical datasets while using more parameters, which could further highlight the accuracy and efficiency of the rendering process. Finally, the detailed user study with the help of unstructured questionnaires can also be conducted, particularly for the medical professionals as it would facilitate crossdisciplinary research opportunities.

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