Quality Enhancement of Direct Volume Rendered Images

Ming-Yuen Chan, Yingcai Wu, and Huamin Qu

The Hong Kong University of Science and Technology

Abstract

In this paper, we propose a new method for enhancing the quality of direct volume rendered images. Unlike the typical image enhancement techniques which perform transformations in the image domain, we take the volume data into account and enhance the presentation of the volume in the rendered image by adjusting the rendering parameters. Our objective is not only to deliver a pleasing image with better color contrast or enhanced features, but also generate a faithful image with the information in the volume presented in the image. An image quality measurement is proposed to quantitatively evaluate image quality based on the information obtained from the image as well as the volumetric data. The parameter adjustment process is driven by the evaluation result using a genetic algorithm. More informative and comprehensible results are therefore delivered, compared with the typical image-based approaches.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism

1. Introduction

The rendered images of 3D volumetric data using typical *direct volume rendering* (DVR) techniques can provide useful information about the dataset. By specifying a proper transfer function, voxels are assigned with certain optical properties and different structures are revealed in the rendered image. The images of DVR are useful for various kinds of scientific visualization, like medical diagnosis and life science research.

Similar to typical images, the quality of the rendered images is critical for effective visual analysis on the images. Certain enhancement operations are always necessary in order to obtain better images for further analysis. In the image processing perspective, it is an operation which forms a new image with a certain mapping of pixel values, in the hope that a more visually pleasing result will be generated. More importantly, the information in the image should be more easily interpreted by viewers for quantitative analysis. For a *direct volume rendered image* (DVRI), the structures embedded in the volumetric data should be presented faithfully in the final image.

Although numerous image processing techniques have been proposed to tackle the problem of image enhancement, most of them are post-processing algorithms focusing on the image domain. Useful information in the image can be improved by increasing the contrast and emphasizing the features. However, such improvement is limited by the original image in which some essential information may be hidden in the rendering process due to poor lighting or rendering settings.

We propose a new enhancement method tailored for DVRIs which takes volumetric data into consideration. By analyzing the formation of the image during the ray-casting process and the constituent sample points along the rays, hidden information can be discovered. An image measurement is proposed to quantitatively evaluate the effectiveness of the DVRIs in conveying information in the volume. The image is then enhanced to reveal those information by adjusting various rendering parameters in the transfer function, lighting and reflection models using a genetic algorithm. Our objectives are to deliver DVRIs which have satisfactory contrast and to allow the existing information in the volumetric data to be more effectively presented in the rendered images.

The rest of the paper is organized as follows. We introduce the previous work related to image enhancement in Section 2. Some issues on the image quality of typical DVRIs are discussed in Section 3. A proposed image quality assessment scheme is described in Section 4. The image refinement method is then explained in Section 5. Several suggested adaptive and interactive approaches are introduced in Section 6. Experimental results will be presented in Section 7 and conclusions are drawn in Section 8.

2. Previous Work

Image enhancement is a fundamental image processing procedure in computer vision and pattern recognition. To meet various subjective visualization expectations, different spatial or frequency domain methods may be applied. In practice, convolution is performed on the image with certain filtering kernels or filtering is carried out in the frequency domain. Various effects like smoothing, sharpening and feature enhancement can be achieved. Contrast enhancement is a critical issue as it can improve the image for visual interpretation. Some techniques like contrast stretching and histogram equalization [GW02] are commonly used in typical applications. As global histogram equalization cannot deal with the possible variation of contrast in different parts of the image, local and adaptive methods [PAA*87] have been proposed to tackle the problem. Different from classical histogram equalization, histograms are computed from the context within a small window and different mappings are applied to the pixels in different parts of the image.

Cromartie and Pizer [CP91] first proposed an edge-based enhancement approach and Caselles et al. [CLMS99] suggested a shape-preserving local histogram modification technique. These works indicate the importance of the topological meaning in the enhancement process. Neighborhood metrics in [EM05] provide further refinement on histogram equalization by considering the local image properties. More specific enhancements based on features [BlN89] [Leu92] were also proposed. As over- and under-enhancement are the common drawbacks of local histogram equalization, Cheng et al. [CXS03] developed a homogeneity measurement to define and control the contrast. More variations on contrast enhancement can be found in [Sta00] [DJT93].

Besides the grey scale image enhancement approaches, more works have been done on color images [PNS03] [SMCD03] [NM03]. Gooch et al. [GGSC98] on the other hand suggested a non-photorealistic lighting model and demonstrated the importance of shape information and clear visual distinctions in technical illustrations. However, as different distinct colors are always assigned to different structures in transfer functions for typical DVRIs, the color changes in the lighting model may affect the visual perception of viewers. Entropy-based methods have been proposed in [Gum02] [VFSH01] to refine such parameters to obtain better results.

The limitation of the existing image-based enhancement approaches is that they can neither recover the missing details due to poor rendering parameters nor enhance the structures with respect to their topology and shape in the volumetric data. Based on the observation that image contrast is a determinant psychological factor [TM99] to the cognitive ability of the viewers, we propose a new enhancement method for effective visualization of DVRIs and the corresponding volumetric data, by considering the existing structures in the volume.

3. Typical Problems in DVRIs

Direct volume rendered images can be generated using the volumetric ray-casting method. A ray is generated for each pixel and is casted from the eye to the volume. Each pixel in the image is the composite value along the ray where points are sampled in the volumetric data. The image pixel values are attributed to voxels of different structures and the overall image should depict the presence of the structures.

However, the structures may not be clearly shown in the rendered images. Due to various reasons like poor lighting and reflection parameters, the pixel values cannot give any implication on the existence of the structures. For example, a homogenous region in the image may represent the fine details of a structure. The image should have a variation to indicate this. Typical image-based enhancement algorithms cannot solve this problem as they are merely transformations of images and do not have any idea on the actual scene/volumetric data and the image synthesis process. Besides, conventional methods only improve the quality of an image based on the existing features in the image. The basic philosophy is that no information should be created or destroyed. However, with the help of the volumetric data and the knowledge of the rendering process of DVRIs, we can further improve the image quality accordingly and reinforce the hidden details about the volume in the image.

Fig. 1 demonstrates the limitation of existing image-based solutions by using the CT engine dataset. The shape and details of the engine are not clearly shown in the original image. By equalizing the image using image-based techniques, we can obtain an image with better contrast and edges are emphasized. However, the overall color is distorted and some fine details are suppressed in the dark regions. Further improvement can be achieved in the manually enhanced image using various filtering techniques. Compared to these results, our method can deliver a more promising image with clearer details and shapes. It shows that a significant enhancement cannot be achieved without considering the structures and their shapes, while lighting and other rendering parameters play an important role in the process. The improvement in image-based methods is limited by the missing information in the original images.

Typical enhancement methods attempt to strengthen the subtle features in the images and make them visible to the viewers. Our method, on the other hand, enhances the images based on existing information in the volume. The objective is to detect the possible existence of structures by analyzing the variations involved in the ray composition. To

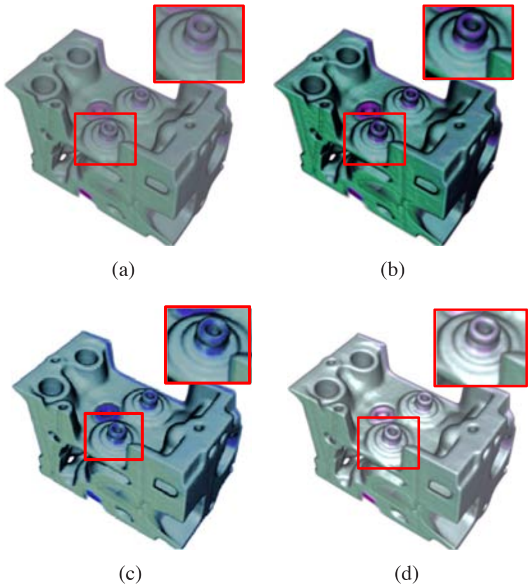


Figure 1: *An example using the CT engine dataset: (a) shows the original image with a poor contrast; (b) and (c) are the images enhanced by Photoshop and manual adjustment using various image filters; (d) is the result generated by adjusting the rendering parameters.*

reveal such information in the image, the final DVRI should also demonstrate certain degree of variation in terms of pixel intensity.

4. Image Quality Assessment

The quality of DVRIs is defined as the effectiveness of the rendered images in presenting the information in the volumetric data. The basic idea is to determine whether the image can show a significant variation in regions where the rays carry different information (e.g., passing through different structures in the volume or varying in the composition of the rays). To quantitatively analyze a DVRI, we establish several measurements for both image and volume data information.

4.1. Image Measure

The variation in an image can be interpreted as contrast and the overall contrast of an image can be estimated by the Lyapounov functional suggested in [CLMS99] [SC95]:

$$\begin{aligned} E(v) &= \frac{|\Omega|}{2(b-a)}\int_{\Omega}(v(x)-\frac{b-a}{2})^2dx \\ &\quad -\frac{1}{4}\int_{\Omega}\int_{\Omega}|v(y)-v(z)|dydz \end{aligned} \tag{1}$$

where Ω is the image and the intensity range is from a to b and v is the mapping function of pixel values. It can indicate the variation of pixel value in an image. A homogeneous region should have a low energy value. We define pixel difference Δv in color images in terms of luminance L, which is an effective metric to indicate the visual variation to viewers' perception:

$$\begin{cases} |\Delta v| = |v(x_1)-v(x_2)| = |L(x_1)-L(x_2)| \\ L(x) = 0.3x_R + 0.59x_G + 0.11x_B \end{cases} \tag{2}$$

Energy function E in Eq. 1 indicates the variations in the image and the utilization of colors for visual presentation. It provides useful information for better transfer function design. Furthermore, we estimate the local variation in the image with a window of size ω using standard deviation σ (Eq. 3) and entropy h (Eq. 4) [CXS03]:

$$\sigma(x) = \sqrt{\frac{1}{|\omega|}\sum_{\omega}(v(i)-\mu_x)^2} \tag{3}$$

$$h(x) = -\frac{1}{log|\omega|}\sum_i p_i log p_i \tag{4}$$

where p_i is the probability of having a pixel value of i and μ is the mean pixel value in the window. These two terms can be used to estimate visual information and we generalize them into an image measure M_I as

$$M_I(x) = \sigma(x) \times h(x) \tag{5}$$

4.2. Ray Measure

Voxels in the volume are assigned with different opacities based on the transfer function specified by users for revealing different structures. In the ray-casting process, the pixel intensity is the composite value of the sample points along the ray's paths traversing from the viewpoint to the volumetric data. This allows different layers of structures to be visible in the final image. The compositing equations can be described as:

$$\begin{cases} c_{accum} = c_s\alpha_s(1-\alpha_{accum}) + c_{accum} \\ \alpha_{accum} = \alpha_s(1-\alpha_{accum}) + \alpha_{accum} \end{cases} \tag{6}$$

where c and α are the color and opacity values. Each sample point contributes to the final image in different degrees and their contribution can be estimated by $\alpha(1-\alpha_{accum})$. The sample points with zero or insignificant contribution become invisible.

We therefore estimate the information carried by the rays and their variations by considering those visible sample points along the rays. As the mutual information (Eq. 7) is an effective metric for image similarity measure and the entropy term (Eq. 8) is commonly used to represent the dependence of information contents,

$$I(R_1,R_2) = H(R_1) + H(R_2) - H(R_1,R_2) \tag{7}$$

$$H(R) = -\sum_i p_i log p_i \tag{8}$$

we follow this approach to design a ray information measure. The ray measure is represented as

$$M_R(R) = -\sum_i p_i \sum_j p_i(j) log p_i(j) \quad (9)$$

where j represents the position along the ray R and $p_i(j)$ is the probability that a sample point is located at j given intensity i. Ray measure H_R estimates the dependance among the rays by considering both the intensity and position of the sample points along the rays. By using this measure, we can estimate the variations in the intensity distribution and profile as well as the position of the sample points on a ray with the context. As the probability terms are computed from all the neighboring rays within the windows, the entropy term can signify the information variation among the rays. As noise may introduce undesired information, it has to be suppressed in the volumetric data.

4.3. Composite Measure

By considering the information in the image and ray domains, which are represented as image measure M_I and ray measure M_R, we can derive a composite measure on image quality. The value of M_I and M_R are normalized to $[-1..1]$. Composite measure M_C is given by

$$M_C = (1 + exp(-\frac{-M_I + M_R}{s}))^{-1} \quad (10)$$

where s is the steepness of the curve. This composite measure indicates the deviation between the image and ray information at each pixel in the image. It produces a high response when ray measure M_R is high but image measure M_I is low (i.e., large variation in ray information and small variation in the image). Based on this measure, we can optimize the rendering parameters to achieve a better result by minimizing the overall information deviation - preserving the information of the volume in the image domain.

5. Parameter Refinement

From the example in Section 3 (see Fig. 1), we know that a better result can be obtained by adjusting different parameters involved in the rendering process. It can be a difficult and tedious task for non-experts to adjust several parameters simultaneously. Therefore, we propose a framework using a genetic algorithm to automatically optimize the parameters. The aforementioned image measures are also incorporated into the process. The framework of the iterative enhancement process is shown in Fig. 2. In this section, we will cover the rendering parameters involved in our enhancement process and the details of the refinement process will be explained.

5.1. Reflection/Illumination Model

Recall that the lighting effect has a major impact on the visual perception of an image while it cannot be easily restored or improved by typical image-based enhancement approaches. Therefore, we should directly adjust lighting configuration. In typical shading models, the visual result is determined by the reflection model and its parameter settings. The lighting effect can be indirectly controlled by the ambient, diffuse and specular coefficients. In a condition with sufficient lighting, shape perception and also the overall contrast can be improved. Therefore, these parameters have to be adjusted in our framework.

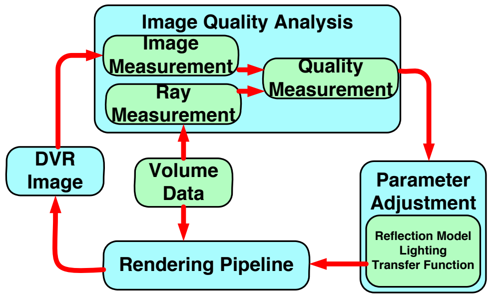


Figure 2: *A flow-chart demonstrating the image enhancement process.*

Different from typical rendering approaches that a global setting is applied to all the voxels, our refinement method allows different reflectance values to be assigned to voxels of different intensities. It is similar to a transfer function on reflectance. Therefore, the lighting effect on structures with different intensities can be adjusted individually and this makes the structures more visually distinguishable in the image.

5.2. Transfer Function

In DVR, users first define a transfer function for the volumetric data to specify different optical properties for different structures. Color is an important property subject to refinement. However, as mentioned in many previous literature [NM03] on image enhancement, the color of the image should not be distorted in order to preserve the original meaning of the image. Most researchers agree that hue must remain unchanged during the enhancement process. Usually, only the brightness and saturation in HSV or luma information in YIQ are modified. For volume rendering, this property is ultimately important as each class of structures is assigned a specific color. Any inconsistence in color may lead to misinterpretation in visual inspection. We can preserve this property by transforming the transfer function space from original RGB to HSV or YIQ color space and manipulating only on the "safe" channels during the refinement process. To tackle the gamut problem in the transformation, clipping techniques [YR96] can be used. By adjusting the brightness of structures, different structures can demonstrate a more noticeable difference in appearance without any severe changes to the original colors assigned by the transfer function. This can help preserve the original meaning of the DVRI during the enhancement process.

5.3. Genetic Algorithm

The adjustment of the parameters is a combinatorial optimization problem with a huge solution space. To efficiently search for an optimal solution in the parameter space, we employ the *genetic algorithm* (GA) [HHKP96]. This method has been used in scientific visualization [WQZC06]. In the GA, the candidate solutions are encoded as *genomes*, in which the parameters are evenly sampled at different intensities in the transfer function of the solution and are represented as an array. The image quality measure is treated as the objective function to calculate the fitness measure. The GA is driven by the fitness measure and the genomes changes during the evolution process to obtain a better result. The GA terminates when the results converge. The final result is considered as the optimal setting with the best image quality.

The advantages of the GA are that the stochastic search can avoid local optima and the computation time is not directly related to the number of parameters used. A tradeoff can be made between the performance and quality by changing the GA's parameters. The process terminates when the result becomes stable, with an optimal image quality.

Although a better result can also be obtained by manual adjustment on the parameters, the process may be time-consuming. The GA provides an automatic method to refine the parameters with respect to image quality. A more detailed adjustment on different parameters is performed and voxels of different intensities are assigned with different optimal values. This is difficult to achieve manually.

6. Adaptive Enhancement and User Interactions

Although global parameter adjustment can help deliver an improved configuration with a better overall image quality, adaptive enhancement can also be exerted to different parts of the image. Following the same argument for conventional adaptive image enhancement approaches, small details may be under-enhanced in the global configuration and certain structures in the image may have to be further enhanced for specific purposes. A flexible adaptive enhancement method with user interactions is necessary to achieve various visualization goals.

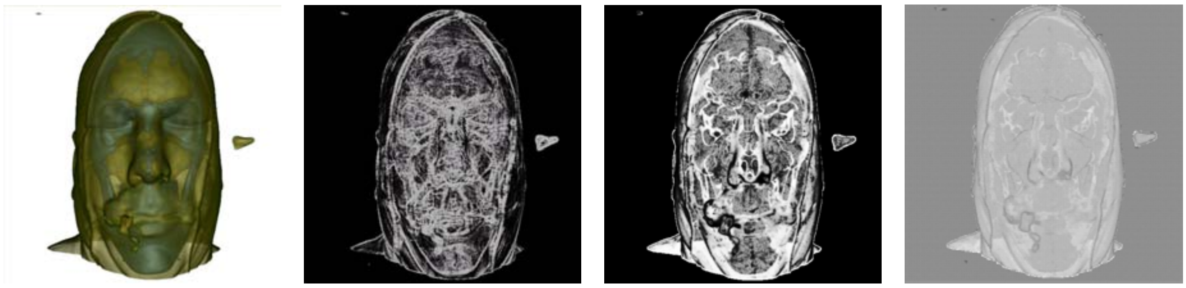
In our image enhancement framework, user manipulations are supported and the regions for further enhancement can be specified in the image and/or data domain. By manually highlighting in the image, the rays in the selected regions are analyzed and refined together. This allows more accurate refinement to recover those fine details which are insignificant and may be easily ignored in the overall image enhancement process. Similarly, users can select certain classes of structures at an intensity level using the histogram or transfer function, and perform enhancement on the corresponding structures in the image. The sample points that fall within the selected intensity range will be further preserved or improved in the process. Moreover, users can refer to the response image of the measures (Fig. 3) to locate the regions where information exists and can be improved. For example, with reference to the composite measure response, users can determine regions with strong response where the information in the volume is not preserved well in the DVRI and select them for further enhancement.

7. Experimental Results

To evaluate our proposed method, experiments have been conducted on several volumetric datasets and the performance and effectiveness of the results are discussed. The experiments were carried out on a standard PC machine (Pentium Core2Duo 6300, 2GB RAM) equipped with an NVIDIA GeForce 8800GTS graphics card.

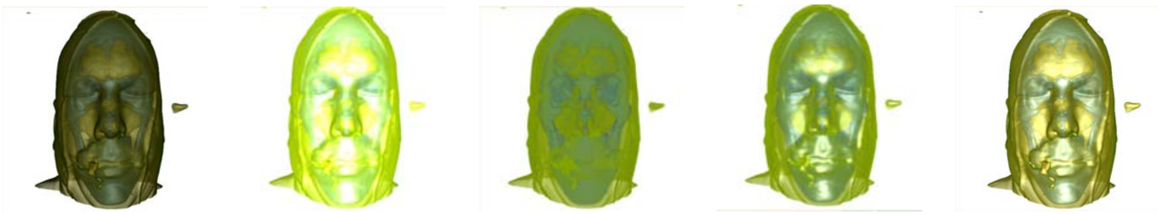
To evaluate the quality of a DVRI, image and ray measure responses are first computed based on the proposed quality measurements (Eq. 5 and 9). Fig. 3 shows the response images generated from a CT head dataset. The image measure response (Fig. 3(b)) represents the variation of the pixel values in terms of entropy and standard deviation. It captures the features (e.g., edges and silhouettes) and color intensity variations in the image. A high response value implies a better visual awareness of the image information to viewers. The ray measure response (Fig. 3(c)) on the other hand captures the variation of the rays. Such variation can reveal the structural information in the volumetric data, which should be clearly shown in the rendered image. By analyzing the image and ray measure responses, we can derive a composite measure response (Fig. 3(d)) using the sigmoid function (Eq. 10). The quality of the image is determined by whether the information present in the volumetric data (i.e., ray information) can be effectively presented in the image. A high response indicates that the variation in the volume cannot be reflected in the DVRI. Therefore, we have to minimize the overall response in order to obtain a DVRI with more information preserved. In this example, several features on the face are not clearly shown and they result in a relatively high response in the response image.

The genetic algorithm is then applied and the rendering parameters are continuously refined and different DVRIs are generated in the evolution process. Some intermediate results are shown in Fig. 4. During the evolution process, the intermediate results are evaluated using our image measure and only good results are selected for further processing. Fig. 5 shows the final result generated by our method. Compared with the original DVRI, the overall image measure response is higher and this implies that the image variation on features are improved. This can be reflected in our enhanced DVRI, in which features on the face are better preserved. This con-



(a) (b) (c) (d)

Figure 3: *An experiment on a CT head dataset: The features in the original DVRI (a) is not clear and the contrast is not satisfactory. These are reflected in the image measure responses of the DVRI (b). (c) is the ray measure response image which indicates the presence of information in the volume. (d) is the composite measure response which shows a high response at the regions where information in the volume is not preserved well in the DVRI.*



(a) (b) (c) (d) (e)

Figure 4: *Results generated in the evolution process using the genetic algorithm: (a) original DVRI; (b)-(d) intermediate results and (e) final result.*

forms with the result that the composite measure response is reduced. A result enhanced by the image processing tools in Photoshop is also shown for comparison. Our result can preserve the fine details to a larger extent.

The performance of the process depends on various factors. As the DVRIs are repeatedly generated and analyzed, the rendering speed and the image measurement computation become the critical factors. However, as the commodity graphics hardware nowadays can obtain a sufficiently high frame-rate (about 20-30 FPS), the rendering speed issue becomes less significant. In the image measurement, the ray information measure has to be computed only once. Although the image information measure has to be re-computed for every intermediate DVRI, it only takes about 0.3 second for a 512×512 DVRI with a window size of 3.

Under the GA framework, we can always make a tradeoff between the DVRI quality and the performance. By lowering the gene population, mutation and crossing rate, the result converges in a shorter time. This may, however, deteriorate the optimality of the final result if the complexity of the problem is high. In our experiment, an optimal result is delivered in about 60 seconds by setting the population to 5 and the mutation and crossing rate to 0.2 and 0.3, respectively. The quality of the result is similar even with higher value GA parameters.

Fig. 6 shows a comparison between our results with those of image-based enhancement. It can be found that the fine details are better preserved in our results. The improvement of the image-based enhancement approaches is limited by the original image, in which the details may be hidden or unrecognizable due to the insignificant variation in color. Our method takes both the image and volumetric data into account and, therefore, can reveal more hidden features. Moreover, with a proper rendering setting, not only are the variations in color of the image emphasized, the variations due to the structure shapes in the volume are also amplified. The perception of 3D shapes and layers is better preserved as a result in the final image.

8. Conclusion

This paper presented a new enhancement method tailored for DVRIs. Different from the typical image-based transformation approaches, the proposed enhancement method is driven by the existing information in both the image and the volume. We are not only seeking for aesthetic results, but also delivering faithful DVRIs which can effectively convey

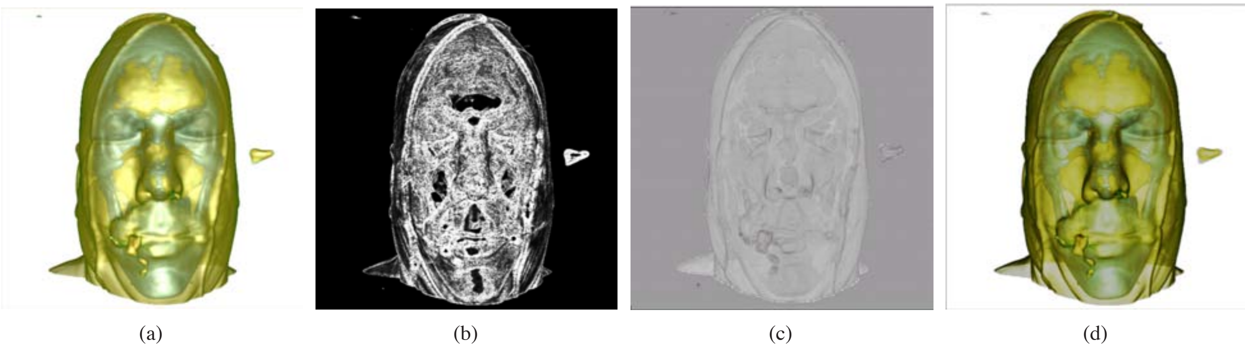


Figure 5: *Final results of the CT head experiment: (a) is an enhanced DVRI using our method. As shown in the image measure response (b), the overall contrast is improved and the details are better preserved on the face. The composite measure response (c) is reduced as a result. (d) is the enhanced result using various image processing tools in Photoshop.*

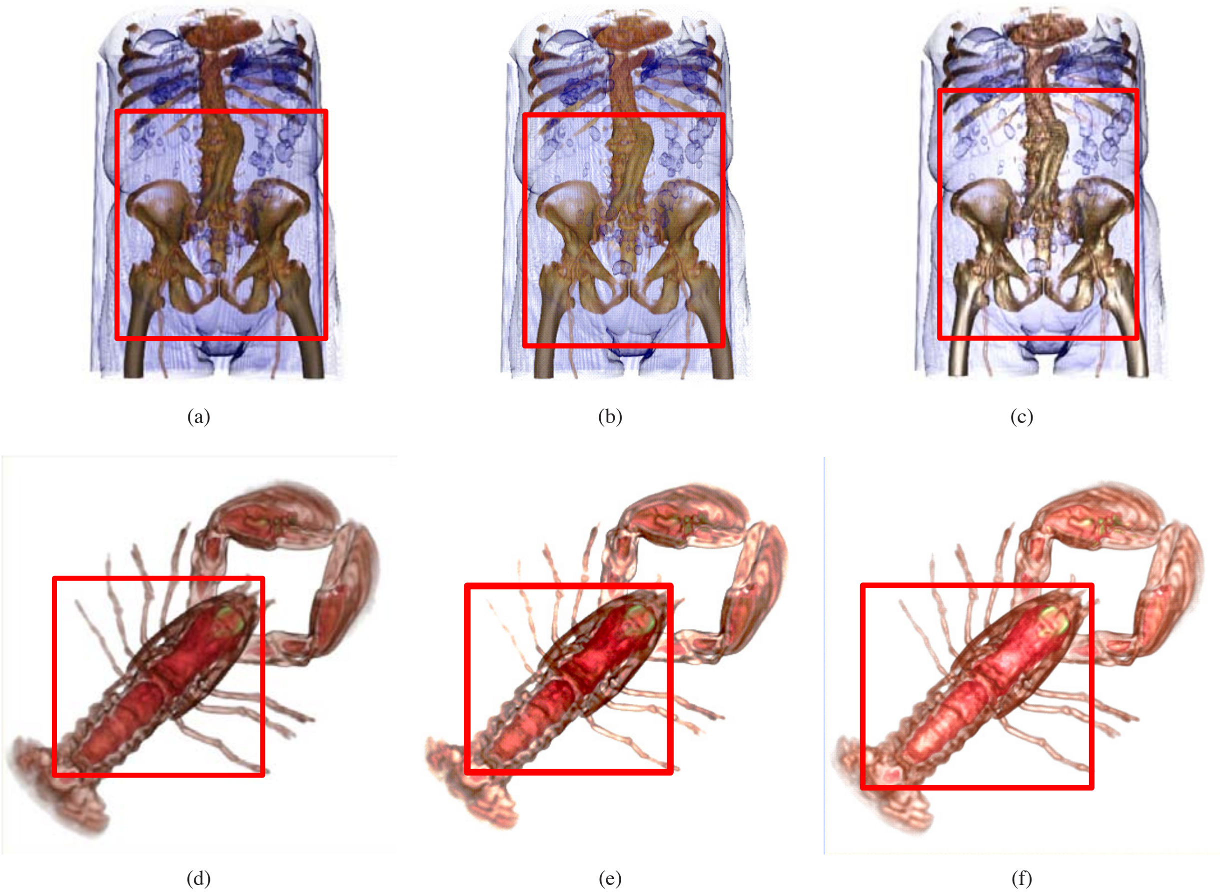


Figure 6: *Experiments on different datasets: (a) (d) original DVRIs; (b) (e) enhanced images using Photoshop; (c) (f) our results. Features are better presented in our results, as shown in the red boxes.*

the information in the volume. We proposed an image quality assessment scheme with regard to the information in the rendered image and volumetric data. It measures the effectiveness of the image in conveying the information about the volumetric data. By adjusting the rendering parameters using genetic algorithm, a more pleasing and informative result is delivered. The GA efficiently solves this parameter optimization problem and provides an optimal rendering setting and thus the best DVRI quality. The proposed measurement can also assist users in performing adaptive and interactive enhancement on DVRIs to achieve different visualization purposes. Although the computation is more complicated comparing with the typical image-based enhancement approaches, the performance can be improved by adjusting the GA parameters and optimizing the rendering pipeline using GPU.

Acknowledgement

We would like to thank Ms Denise Tong for proofreading the paper and the anonymous reviewers for their valuable comments. This work was partially supported by RGC grant CERG 618705.

References

[BlN89] BEGHDADI A., LE NEGRATE A.: Contrast enhancement technique based on local detection of edges. *Comput. Vision Graph. Image Process. 46*, 2 (1989), 162–174.

[CLMS99] CASELLES V., LISANI J. L., MOREL J.-M., SAPIRO G.: Shape preserving local histogram modification. *IEEE Transactions on Image Processing 8*, 2 (1999), 220–230.

[CP91] CROMARTIE R., PIZER S. M.: Edge-affected context for adaptive contrast enhancement. In *IPMI '91: Proceedings of the 12th International Conference on Information Processing in Medical Imaging* (1991), pp. 374–485.

[CXS03] CHENG H. D., XUE M., SHI X. J.: Contrast enhancement based on a novel homogeneity measurement. *Pattern Recognition 36*, 11 (2003), 2687–2697.

[DJT93] DALE-JONES R., TJAHJADI T.: A study and modification of the local histogram equalization algorithm. *Pattern Recognition 26*, 9 (1993), 1373–1381.

[EM05] ERAMIAN M., MOULD D.: Histogram equalization using neighborhood metrics. In *CRV '05: Proceedings of the The 2nd Canadian Conference on Computer and Robot Vision* (2005), pp. 397–404.

[GGSC98] GOOCH A., GOOCH B., SHIRLEY P., COHEN E.: A non-photorealistic lighting model for automatic technical illustration. In *SIGGRAPH* (1998), pp. 447–452.

[Gum02] GUMHOLD S.: Maximum entropy light source placement. In *Proceedings of IEEE Visualization* (2002), pp. 275–282.

[GW02] GONZALEZ R. C., WOODS R. E.: *Digital Image Processing*. Prentice Hall, 2002.

[HHKP96] HE T., HONG L., KAUFMAN A., PFISTER H.: Generation of transfer functions with stochastic search techniques. In *Proceedings of IEEE Visualization* (1996), pp. 227–234.

[Leu92] LEU J.-G.: Image contrast enhancement based on the intensities of edge pixels. *CVGIP: Graphical Model and Image Processing 54*, 6 (1992), 497–506.

[NM03] NAIK S. K., MURTHY C. A.: Hue-preserving color image enhancement without gamut problem. *IEEE Transactions on Image Processing 12*, 12 (2003), 1591–1598.

[PAA*87] PIZER S. M., AMBURN E. P., AUSTIN J. D., CROMARTIE R., GESELOWITZ A., GREER T., ROMENY B. T. H., ZIMMERMAN J. B.: Adaptive histogram equalization and its variations. *Comput. Vision Graph. Image Process. 39*, 3 (1987), 355–368.

[PNS03] PICHON E., NIETHAMMER M., SAPIRO G.: Color histogram equalization through mesh deformation. In *Internation Conference on Image Processing (Vol.2)* (2003), pp. 117–120.

[SC95] SAPIRO G., CASELLES V.: Histogram modification via partial differential equations. In *ICIP '95: Proceedings of the 1995 International Conference on Image Processing (Vol. 3)* (1995), p. 3632.

[SMCD03] STARCK J.-L., MURTAGH F., CANDÈS E. J., DONOHO D. L.: Gray and color image contrast enhancement by the curvelet transform. *IEEE Transactions on Image Processing 12*, 6 (2003), 706–717.

[Sta00] STARK J. A.: Adaptive image contrast enhancement using generalizations of histogram equalization. *IEEE Transactions on Image Processing 9*, 5 (2000), 889–896.

[TM99] TIZHOOSH H. R., MICHAELIS B.: Subjectivity, psychology and fuzzy techniques: a new approach to image enhancement. In *Proceedings of 18th Int. Conf. of NAFIPS* (1999), pp. 522–526.

[VFSH01] VAZQUEZ P., FEIXAS M., SBERT M., HEIDRICH W.: Viewpoint selection using viewpoint entropy. In *Proceedings of the Vision Modeling and Visualization Conference* (2001), pp. 273–280.

[WQZC06] WU Y., QU H., ZHOU H., CHAN M.-Y.: Fusing features in direct volume rendered images. In *International Symposium on Visual Computing* (2006), pp. 273–282.

[YR96] YANG C. C., RODRIGUEZ J. J.: Saturation clipping in the LHS and YIQ color spaces. In *Internation Symposium on Electronic Imaging* (1996), pp. 297–307.