Occlusion and Slice-based Volume Rendering Augmentation for PET-CT

Younhyun Jung, Jinman Kim, Member, IEEE, Dagan Feng, Fellow, IEEE, and Michael Fulham

Abstract—Dual-modality positron emission tomography and computed tomography (PET-CT) depicts pathophysiological function with PET in an anatomical context provided by CT. Three-dimensional volume rendering approaches enable visualization of a two-dimensional slice of interest (SOI) from PET combined with direct volume rendering (DVR) from CT. However, because DVR depicts the whole volume, it may occlude a region of interest, such as a tumor in the SOI. Volume clipping can eliminate this occlusion by cutting away parts of the volume, but it requires intensive user involvement in deciding on the appropriate depth to clip. Transfer functions that are currently available can make the regions of interest visible, but this often requires complex parameter tuning and coupled pre-processing of the data to define the regions. Hence, we propose a new visualization algorithm where a SOI from PET is augmented by volumetric contextual information from a DVR of the counterpart CT so that the obtrusiveness from the CT in the SOI is minimized. Our approach automatically calculates an augmentation depth parameter by considering the occlusion information derived from the voxels of the CT in front of the PET SOI. The depth parameter is then used to generate an opacity weight function that controls the amount of contextual information visible from the DVR. We outline the improvements with our visualization approach compared to other slice-based and our previous approaches. We present the preliminary clinical evaluation of our visualization in a series of PET-CT studies from patients with non-small cell lung cancer.

Index Terms—Dual-modality PET-CT Visualization, Direct Volume Rendering, Transfer Function, Occlusion

I. INTRODUCTION

The advent of efficient volume rendering algorithms and powerful graphics processing units has enabled direct volume rendering (DVR) of medical imaging data. This volume rendering approach provides three-dimensional (3D) views of data and an ability to interactively manipulate the image volumes. DVR has been used for clinical diagnosis, surgical and radiotherapy planning, and training [1-3]. Most clinical image interpretation, however, still relies on reading two-dimensional (2D) cross-sectional image slices that are analyzed slice-by-slice in transaxial/coronal/sagittal planes, and this approach is referred to as cross-sectional view planes. Figure 1 shows an example of a positron emission tomography (PET) and computed tomography (CT) dataset in cross-sectional view planes. PET-CT is a dual-modality imaging technology where PET is combined with CT in a single device. PET-CT is routinely used in the evaluation of malignancy, in particular, in the staging disease and assessment of response to treatment [4]. PET-CT allows the visualization of pathophysiological function with PET on an anatomical template provided by CT. Importantly PET can detect sites of disease in structures that do not appear abnormal on CT. Ideally for PET-CT visualization, a region of interest on PET, such as a tumor, is shown while the underlying anatomy from CT is preserved, without compromising the focus of interest, to provide precise localization of the tumor. Although it may seem counter-intuitive, the effective assimilation and visualization of these two large data volumes are non-trivial. DVR can display the entire volumetric dataset across multiple dimensions and a specific region of interest such as a tumor in a PET volume can be more readily discerned relative to surrounding structures. The reasons for the lack of a more generalized use of volume rendered images in routine clinical image reading are complex and they relate to the established habits of image reading.
regions of interest. Conventional one-dimensional (1D) or 2D transfer functions can control the visualization of the structures that occlude the voxels belonging to these structures. The transfer function can be visualized by manipulating the opacity and color of the objects, which makes it difficult to localize the regions of interest within the lung PET slice (see arrows).

An alternative approach to rendering the PET and CT volumes simultaneously is to augment a DVR of the CT volume onto a slice of interest (SOI) of the PET volume, which we refer to as slice-based volume rendering. This can localize 2D pathophysiological information within a 3D anatomical context, and thus provide additional visual cues, for the localization of the critical lesions and their relationship to adjacent structures, as shown in Figure 2(b). This slice-based volume rendering, however, inherently occludes the regions of interest, e.g., in Figure 2(b) the skull on CT is occluding lesions in the lung PET slice (see arrows).

A common approach to reduce occlusion in DVR is to apply a transfer function that allows the user to specify structures to be visualized by manipulating the opacity and color of the voxels belonging to these structures. The transfer function can control the visualization of the structures that occlude the regions of interest. Conventional one-dimensional (1D) or multi-dimensional transfer functions [5-8], however, can only be applied to the entire volume and not to individual structures, which makes it difficult to localize the regions of interest within a volumetric context.

An alternative to manipulating the transfer functions involves the removal of occlusion by identifying and enhancing the most important elements of the volume to be rendered during volume ray-casting using approaches such as maximum intensity difference accumulation [9] and depth-based feature enhancement [10]. These ray-casting based DVR approaches, however, are also applied to the entire volume and so cannot ensure that the regions of interest remain visible.

Volume clipping is another approach to address the occlusion challenges inherent in DVR. The clipping cuts away the obstructing elements of the volume [11-14]. Its major drawbacks, however, are the time taken to select the right depth to cut and information loss from the clipped volume that may result in the removal of valuable contextual cues.

Our work was motivated by the need to present complex clinical imaging data, such as PET-CT, in a format that is more intuitive and easy to assimilate by the medical imaging specialist, other clinicians involved in patient management, and by patients themselves. Hence, we propose a new visualization approach that augments the SOI from a PET volume with volumetric contextual information derived from the DVR of the CT. Our approach uses the occlusion information derived from the CT voxels in front of the PET slice to automatically calculate an augmentation depth parameter. We refer to our approach as Occlusion and Slice-based Volume Rendering Augmentation (OSVRA). Our approach enables the occlusion information of voxels to be analyzed at a structure-level rather than at a voxel-level by grouping the voxels belonging to the same CT structure during depth computation. We preserve the view of all regions of interest in the SOI by using a depth parameter to control the amount of augmentation produced by the CT DVR, which provides 3D contextual cues of relevant structures that are adjacent to the SOI without occluding the view of the SOI. Figure 2(c) shows a visualization created using OSVRA, in which the SOI is clearly visible and unnecessary structures, e.g. skull, brain, and spine, are removed when compared to Figure 2(b).

In our earlier work, we used occlusion information for estimating a depth parameter for volume clipping and showed its potential in examples of PET-CT studies [15]. In this work we have further enhanced the approach with the inclusion of histogram analysis, improvements to the visual quality through the flexible application of varying transfer functions and incorporation of a context preserving weight function to the
depth computation. We evaluated the approach in a larger group of patients with non-small cell lung cancer (NSCLC) of varying stages and complexity, and lymphoma. We also conducted an evaluation of its performance when compared to two ray-casting based DVR approaches that rely on occlusion information in the rendering, maximum intensity difference accumulation [9] and depth-based feature enhancement [10].

II. RELATED WORK

A. Volume Clipping

Rectangular planes are typically used in volume clipping but more complex clipping geometries may be applied as reported by Weiskopf et al. [11] and Islam et al. [12]. Other approaches have improved the usability of volume clipping by incorporating additional information from an anatomical atlas, to allow the user to adaptively place axis-aligned clipping planes [13] and editable clipping planes to create custom cross-sectional views [14]. Although these approaches employ sophisticated methods to select the clipping plane, they require complex human interaction and may result in information loss from the clipped volume, as described previously.

Birkeland et al. [16] recently used an elastic membrane to clip the volume to reduce the visual loss of contextual information. The membrane was guided by the definition of a potential field and adapted to the anatomical structures in the neighborhood of a clipping plane. This approach, however, required that boundaries of the structures were well-defined and the indirect manipulation of a complex deformable membrane plane was carried out through non-intuitive and time-consuming parameter tweaking, which required intensive user involvement.

B. Volume Ray-casting

The key strength of volume rendering is attributed to volume ray-casting, which allows a visualization to depict an entire volume at once. In this way, the optical contributions of every voxel along the viewing rays are accumulated in the final visualization, subject to the optical mapping by the transfer function. Recently, Bruckner et al. [9] proposed an adaptive method of the opacity accumulation to improve the regional context nearer to a structure of interest; the structure of interest of each ray corresponded to its maximum intensity. They achieved this by adaptively controlling the opacity accumulation of voxels in each ray according to their distance to the structure of interest. Adaptations to this method used multiple local maxima [17] and gradient-based relevance functions [18] to define structures of interest. Tang et al. [10] proposed a depth-based feature enhancement approach that assigned a distance-based opacity function (weight) to voxels in the ray such that the occlusion of the voxels closer to the view point were reduced; this enabled all the voxels in the ray to contribute to the final rendering. These DVR approaches modified the opacity accumulation from conventional volume ray-casting to allow multiple regions of interest to be displayed in a single visualization. Nevertheless, they cannot ensure that the visualization of the regions of interest are retained since the optical contributions of regions of interest localized further along the viewing ray may be attenuated by the less important structures that precede them.

C. Volume Visualization of Multi-modality Imaging Data

In pioneering work, Cai and Sakas [19] reported a data intermixing algorithm to fuse multiple volumes in volume rendering. Hauser et al. [20] proposed a two-level volume rendering where structures from each volume were visualized individually by using different volume rendering algorithms and the visualizations were then combined into a single scene. Kim et al. [8] used a pair of 1D transfer functions for PET and CT volumes, in which the resultant visualizations of the two volumes were intermixed. Jung et al. [21] suggested an automated transfer function optimization approach in which any initial CT transfer function was optimized to maximally depict the CT anatomy without compromising the visibility of the PET regions of interest. Bramon et al. [22] improved convergence to optimal solutions by incorporating several information theoretical strategies to the optimization equation. Unfortunately, the transfer functions in these approaches were applied to the entire volume and it was often difficult to obtain an appropriate transfer function to visualize a specific region of interest while maintaining the details of surrounding structures. Furthermore, such approaches relied on the identification of the region of interest, which usually involved pre-processed segmentation of the regions of interest.

III. APPROACH

A. Overview

Our approach has six steps as shown in Figure 3. In Figure 3(a) in the initial step, a SOI (255th slice) from a PET volume is selected by the user. Using the concept of opacity accumulation in volume ray-casting, we compute the occlusion distance of each sample in the slice (see the red arrows in Figure 3(b)), which is the distance where CT information relevant to each sample is maximally visible without impairing its visibility; here, the CT volume is represented by a cube. Pre-defined transfer functions for the PET and CT volumes are used: in PET, the transfer function reveals the functional activities, including brain, kidneys, bladder, and abnormal regions and in CT, the transfer function depicts the anatomical structures. The same transfer functions as shown in Figure 2(a) were applied but any pre-defined transfer functions may be applied instead. In Figure 3(c), we constructed a map to represent the occlusion distances of every sample in the slice (rendered in green). Prior to the mapping, the background samples are removed. In Figure 3(d) the creation of a histogram for the occlusion distance map, which is then used to calculate the augmentation depth parameter (D), is shown. This parameter controls the amount of DVR from CT to be rendered while avoiding the occlusion to the slice. As a default, the first peak of the histogram is used; in Figure 3(d) it is set to D = 33 slices. We then generated an opacity weight curve with shape of a logistic function using D as its inflection point as in Figure 3(e). This curve is used with the CT transfer function to improve the contextual cues from
the DVR of the CT in a way that emphasizes the relevant anatomy before $D$ as well as de-emphasizing other structures occurring after $D$. The CT volume is then rendered with the CT transfer function and the derived opacity weight curve and is then fused onto the PET slice. In Figure 3(f) the resulting visualization is shown; it enables augmentation of the lung tissues and bony structures in the form of the 3D spatial cues while minimizing the obtrusiveness to the visibility of the slice (see lesions in the lung and pelvis).

During fusion, we allocated an equal opacity value of 0.5 (where 1.0 is the full opacity) to the PET SOI and CT DVR, ensuring that the DVR and SOI contributed equally to the final visualization. This is commonly referred to as the 50:50 fusion ratio and is consistent with the default value used in PET-CT image fusion. This ratio can be adjusted by the user, who could assign different ‘opacity limits’ to the DVR and the SOI, e.g., fusion ratio of 30:70 (DVR:SOI) meaning that 30% of the opacity is from the DVR and 70% of the opacity is from the SOI. For consistency, we used the 50:50 fusion ratio for all PET-CT studies used in this paper.

B. Occlusion Distance Histogram Generation and Augmentation Depth Computation

We adopted the concept of opacity accumulation in back-to-front volume ray-casting for computation of the depth $D$. Each sample from a PET SOI casts a ray to the viewpoint. The opacities of CT voxels along these rays are then accumulated according to:

$$a_i = (1.0 - a(s(i))) a_{i-1} + a(s(i)) \quad (1)$$

where $a_{i-1}$ is the accumulated opacity, $s(i)$ is the intensity value of the $i$th voxel of the CT volume along the viewing ray, and $a(s(i))$ is the opacity value of the $i$th voxel, defined by a transfer function.

Once the accumulated opacity’s contribution reaches the opacity limit of CT DVR, the ray is terminated. The occlusion distance is calculated as the Euclidean distance from the terminated ray to its sample location. The voxels belonging to the same structure (specified by the transfer function) are expected to have consistent values (intensity and opacity), meaning that the occlusion distances of rays casted from the structure should have similar values. This permits grouping of these voxels for structure-level analysis, rather than voxel-level analysis. The voxels are then used to compute an occlusion distance histogram.

Figure 4 shows the construction of the occlusion distance histogram for structure-level depth analysis. Here, all voxels belong to one of 3 structures $S_1, S_2,$ and $S_3$, and we consider $S_1$ to be a region of interest. The voxels are then used to compute the occlusion distance histogram with three peaks representing different distances $D_1$ to $D_3$. Different structures are emphasized in the final visualizations depending on the selection of the $D$. In $D_1$ (first peak), structure $S_1$ is rendered fully while $S_2$ is rendered partially. With $D_2$ (second peak), $S_1$ and $S_2$ are fully visualized while some of the renderings from $S_3$ are visualized thereby partially occluding $S_1$ and $S_2$. Although $D_3$ (third peak) allows all the structures to be visualized, the rendering of $S_1$ prevents the other structures from being visible. Our computation will automatically select $D_i$, which typically corresponds to the group of voxels that are identified as belonging to the same CT structure and have the closest distance to the SOI. We integrated a user interface into our visualization to enable users to select other peaks from the occlusion distance histogram (see Figure 8).

C. Dynamic Generation of Opacity Weight Curve

An opacity weight curve was generated based on the calculated $D$ with a logistic function as illustrated in Figure 5. We adopted a logistic function [23], which is a sigmoid S shape where the initial stage of growth is approximately exponential and as saturation begins, the growth slows; at the end, the growth stops. We used Y-axis inverted logistic function as the opacity weight curve, $w$, which enabled the preservation of the contextual information by adding the information further from $D$ as a compensation for the loss of the information prior to $D$. The location of $D$ is used as the inflection point ($I$) and used to calculate the curve:
where \( d_i \) is the Euclidean distance of the \( i^{th} \) voxel to a SOI, \( A \) and \( C \) represent the opacity weight range, and \( B \) is calculated as \((\ln A)/D\). We empirically set \( A \) to 0.0001 (the minimum weight value) and \( C \) to 1.0 (the maximum weight value) to ensure that all structures could contribute to the final visualization depending on the distance from the SOI.

### D. Fusion of SOI of PET and DVR of CT

We integrated the opacity weight curve (Equation 2) in back-to-front volume ray-casting to adjust the optical contributions of the voxels from a CT volume, based on the distance to a SOI of its counterpart PET volume as follows:

\[
\begin{align*}
    c_i &= (1.0 - a(s(i))w(d_i))c_{i-1} + c(s(i))a(s(i))w(d_i) \\
    a_i &= (1.0 - a(s(i))w(d_i))a_{i-1} + a(s(i))w(d_i)
\end{align*}
\]

(3)

(4)

where \( c_{i-1} \) is the accumulated color and \( c(s(i)) \) is the color value of the \( i^{th} \) voxel (defined by a transfer function). Ray-casting of the CT volume was performed in the same way as in the occlusion distance computation, together with the derived opacity weight curve. The resulting CT rendering was augmented onto the PET SOI by applying voxel-level intermixing (fusion) [19].

### IV. IMPLEMENTATION

Real-time performance for our approach was achieved by using the programmability and massive parallelism of the modern graphics processing unit within volume rendering engine (Voreen) [24]. Voreen is an open source texture-based volume rendering library that allows interactive visualization of volumetric datasets and it has high flexibility for integrating new algorithms and optimizations. In the following sections and Figure 6, we explain how our proposed occlusion distance map and histogram can be computed efficiently using a two-pass execution in graphics processing unit to avoid the computer intensive execution on the central processing unit. All renderings in this study were performed on a PC with nVIDIA GTX 590 1.5G GPU; Intel i7 CPU @3.20 GHz; running 64-bit Windows 7.

A. Occlusion Distance Map Generation

A PET SOI was used as a back-face for volume ray-casting. In the fragment shader, samples from this back-face cast rays to the front-face of the view-point with the opacity values of the CT voxels along the rays being accumulated according to Equation 1. Once the accumulated opacity reached the opacity limit of CT DVR, ray-traversing was terminated (see circles in Figure 6). The occlusion distances of the terminated rays to the back-face were then transferred to their corresponding pixel in a 2D graphical render buffer that was read back to the central processing unit.

![Figure 6. Efficient computation of the occlusion distance map and resulting histogram, using parallel graphics processing unit architecture.](image)

B. Occlusion Distance Histogram Generation

We exploited the texture fetch and scattering operation which were reported by Scheuermann and Hensley [25]. Here, the occlusion distance map was initially loaded as a 2D texture. Point primitives were generated by the vertex shader (one per pixel texture) and then translated in a 1D graphical render buffer, according to the corresponding occlusion distance values. Using the hardware-supported fusion operation of the fragment shader, we could count up all the primitives, and the resulting histogram was transferred to the central processing unit.

### V. DATASETS AND PRE-PROCESSING

All PET-CT studies were acquired with a Siemens Biograph TruePoint PET-CT scanner (Siemens Medical Solution, Hoffman Estates, IL, USA) in the Department of Molecular Imaging, Royal Prince Alfred Hospital, Sydney. Each PET-CT study had 410 slices with slice thickness of 3 mm, extending from the top of the head to the upper thighs. PET image slices were reconstructed to 168 x 168 pixels at 4.07 mm² / pixel, and CT slices were reconstructed to 512 x 512 pixels at 0.98 mm². The hardware co-aligned PET was then resampled to the CT dimensions. For the CT scans the background and bed/linen artifacts were removed via adaptive thresholding and image subtraction from a bed template [26]. The voxel intensity of the CT was in Hounsfield units with the intensity range of -1000 (air) to about +2000 (bone/contrast media); this was mapped to 0 to 4095 (12 bits) for rendering. For PET, a linear intensity normalization was applied to match the 12 bits intensity range of the CT. All patients were scanned supine so the right side of the patients appears on the left of the corresponding renderings (mirror image).

We applied our approach to 7 patient studies, where the underlying diagnosis was NSCLC and lymphoma, to render the visualizations presented in this paper (including studies in the appendix). For the clinical domain expert review, we used another set of 46 patient studies with NSCLC; the patients had varying stage of disease that included regional nodal disease in thorax and more widespread metastatic disease outside the thorax. NSCLC was chosen because of the importance of accurate staging on patient management. Stage I and II disease, where mediastinal lymph nodes are not involved, can be treated effectively with surgery. Stage III is generally treated with a combination of chemotherapy and radiotherapy or chemotherapy and then surgery, if the mediastinal nodal disease...
is confined to the thorax and is on the same side of the chest as the primary tumor. In Stage III the accurate delineation of the regional nodal disease is critical for surgical and radiotherapy planning. The depiction of the sites of disease on PET relative to the adjacent anatomy offered a preliminary opportunity to assess the utility of our approach.

In Section VI, all DVRs were made with a single default CT transfer function definition, (as in Figure 2(a)) in which the lungs and the bony skeleton were emphasized more than the skin, soft tissues and the lung boundaries; the transfer function setting could be readily adjusted, either in one- or multi-dimensional variants [6, 7], by manipulating the opacity values corresponding to each of the structures for emphasis, as consistent with the process in existing literatures [5, 27, 28].

VI. RESULTS

A. Occlusion and Slice-based Volume Rendering (OSVAR) Visualization

Figure 7 shows our OSVAR when compared to conventional slice-based volume rendering with manual volume clipping at various depth levels. The objective in this example was to accurately visualize the tumor and its surrounding anatomy. Figure 7(a) shows the visualization of a tumor on the 263rd PET slice and Figure 7(b) shows the visualization of anatomical structures on the corresponding CT slice without any volumetric augmentation. Figure 7(c) shows the visualization with OSVAR using the automatically derived depth \(D = 43\) and the opacity weight curve. In comparison, (d) shows the visualization with a clipped slice-based volume rendering with a thinner depth \(D = 30\) from the slice in which the details of the lungs and also the trachea (indicated by red arrows) were less visible, suggesting that too much volume was clipped. In Figure 7(e) the slice-based volume rendering was set to the same depth \(D\) calculated by the OSVAR as in Figure 7(c); and Figure 7(f) shows that the thicker depth \(D = 61\) produced strong occlusion from the outer parts of the lungs and it subsequently occluded the view of the tumor and the lung parenchyma adjacent to the midline representing respiratory bronchioles and bronchi, (indicated by red arrows). The resulting visualization also rendered irrelevant sub-diaphragmatic bowel, overlying the kidneys, to the slice (indicated by blue arrows). In Figure 7(e), we note that simply using the \(D\) was able to produce relatively good visualization when compared to Figure 7(d) and Figure 7(f) but the overall shape of the lungs was not clearly outlined when compared to OSVAR (see arrows indicating the parts of the volume that were clipped). This also demonstrates the importance of automatic generation of the weight function that was applied in the OSVAR, which, in this example, allowed only the adjacent structures to be depicted in the resulting visualization. This illustrates the importance of selecting the right depth for volume clipping. Selection of the correct depth relies on tedious tweaking of the depth (slice) position until a desired visualization is found e.g., several minutes as measured in a single-modality tooth CT data with volume dimension of 256³ [29].

Figure 7. An example of our OSVAR and conventional slice-based volume rendering with manual clipings at various depths. A PET-CT study with a large tumor in the right lower lobe of the lung was visualized using both approaches. 2D PET and CT renderings ((a) to (b)) are shown as the reference functional and anatomical information for the patient study.

Figure 8 shows the impact of depth \(D\) on the amount of augmentation of volumetric context. In the transaxial view of Figure 8(a), the OSVAR visualization with the depth \(D = 42\) derived from the first occurring peak in the occlusion distance histogram (fourth row) revealed the details of the lung parenchyma. Further lung detail was introduced in the depth \(D = 61\) from the second peak in Figure 8(d). In Figure 8(g) with the entire depth \(D = 164\), irrelevant structures, such as the skull outline, were introduced causing unnecessary occlusions to the slice. Note that the histogram and the depth \(D\) were re-computed based on the viewing angles. Consistent with the transaxial views, we can see that the \(D\) selections in the other two views were an influential parameter that controlled the level of augmentation from the DVR. In all our visualizations, including this example, we found that the \(D\) derived from the first occurring peak in the histograms was an appropriate depth to augment relevant structures onto each slice without impairing its visibility.

Figure 9 shows the typical coronal view planes used for PET-CT imaging interpretation when compared to OSVAR. The patient had bone marrow involvement in the proximal humeri (see red arrows in Figure 9(a)). Typical coronal view planes show Figure 9(a) the PET, Figure 9(b) the CT, where it is notable that there are no obvious abnormalities on the CT, and Figure 9(c) the fused PET-CT, which are commonly used in routine clinical practice. In Figure 9(c), a color-scale transfer function ranging from red to white color was applied to the PET and then was fused onto the CT so that colored regions reflect areas of abnormality on the PET. Since the PET and CT were typically rendered using two individual grey-scale transfer functions, the information from the PET and CT are problematic to interpret. It is important to note that these 2D visualizations do not provide 3D anatomical contextual cues; clinical experts rely on scrolling through multiple coronal slices and their expertise and experience to mentally reconstruct the
Figure 8. OSVRA results from using various \( D \) values. The first three rows correspond to the cross-sectional views of PET-CT data at different depth augmentation and the fourth row is the occlusion histograms of the data. In the first row, \( D \) was derived from the first peak from the histograms; the second row from the second peak; and the third row from the last peak. Each column depicts different views: transaxial in left column, then coronal in middle column, and sagittal views in right column. Note a gradual increase in the occlusion of the DVR as the value of \( D \) increases.

3D information. Our visualization in Figure 9(d) augments the anatomical structures onto the 2D slice in a more readily assimilated package than the individual coronal planes and the fused plane.

Figure 10 shows OSVRA visualizations applied to different slices of the same PET-CT patient study used in Figure 9. The result shows that the \( D \) and the opacity weight curve in OSVRA were dynamically calculated during the slice-by-slice volume navigation. This allowed different structures to be augmented on different slices, e.g., the proximal humeri in Figure 10(b), and the lung parenchyma and the bronchial tree in Figure 10(d). These anatomical cues were not available in the coronal view plane equivalents in Figure 10(a) and Figure 10(c).

Figure 11 compares OSVRA with maximum intensity difference accumulation [9] and depth-based feature enhancement [10] approaches. For this comparison, the volume rendered images from the two approaches were combined with the SOI using the same fusion way as with OSVRA. Furthermore, the volume rendered images were computed only for the structures between the slice and the same depth as derived from OSVRA. In this example, we note that the two approaches could visualize all the structures in front of the slice, via manipulation of the opacity values. However, the visibility of structures which were distant from the slice, e.g., the skull (see the red arrows), were dominant and this compromised the visibility of the most relevant structures to the slice, including the lungs and vertebral column. Our approach emphasized only the relevant structures and thus preserved the contextual cues between the slice and its surrounding structures. Such visual improvements from OSVRA were more evident when the default full volume renderings (without depth computation) of the two approaches were applied.

B. Computational Performance of OSVRA

We measured the computation time of our approach for interactive visualization, in frames per second (FPS). All measures were calculated during typical user volume manipulations that involved rotation, panning, and transfer function manipulations. Four different rendering sizes were used for the evaluation, ranging from \( 128 \times 128 \) to \( 1024 \times 1024 \). Even in the higher resolution (1024×1024) rendering, OSVRA achieved an interactive rate of > 10 FPS under 1D transfer function. Due to greater computation demand when applying 2D transfer functions, there was an expected FPS reduction.
from 28.11 FPS to 11.84 FPS in 512×512 rendering; this was still an interactive rate.

C. An Expert Review Using Clinical PET-CT Studies of Patients with Lung Cancer

We conducted an expert review to investigate the clinical utility of OSVRA applied to clinical PET-CT lung cancer patient studies. Our expert reviewer was a senior medical imaging specialist who has read over 63,000 PET-CT studies; he is an author of this paper. We followed an evaluation procedure based on multi-dimensional in-depth long term case studies [30-32] in which a senior physician’s experience and expertise formed the basis for the evaluation of clinical utility. Forty-six patient studies were examined.

For the expert review, we developed a viewing software with three view panes: (i) OSVRA visualization of each patient; (ii) corresponding diagnostic report; and (iii) semi-quantitative questions and general feedback. For the visualization, we rendered the PET-CT patient study in the coronal and the sagittal views at three depth levels: the first, second, and last peaks of the occlusion distance histogram. The software allowed for slice-by-slice navigation of the PET-CT renderings and also adjustment to the window level of the PET data (via the transfer function). The imaging specialist was asked to interpret the patient study with OSVRA visualizations and to provide feedback on three aspects: (i) the most appropriate depth level (peak from the occlusion distance histogram) for assimilating the PET-CT data; (ii) the benefits provided by OSVRA which are not available with conventional 2D vendor software for PET-CT data; and (iii) general comments about the visualization.

(i) Depth Level: In 42 (91%) studies, the first peak was preferred as most appropriate visualization of PET-CT data, reflecting that the minimum depiction from DVR (like silhouette) was the preferred visualization for PET-CT image interpretation as it did not greatly impair the view of the SOI. The second and third peaks meanwhile produced renderings that occluded important contextual details and were the preferred peaks in only 4 (9%) studies. In these studies, the abnormal regions of interest did not have anatomical structures in front of them and therefore did not require occlusion distance analysis. As expected, for these cases, the structures visible from the peaks were not relevant to the regions of interest and therefore preferences were given to peaks that visualize additional structures.

(ii) Benefits: In the 42 cases, the key clinical feedback was that the contextual information derived from the CT (visualized in DVR) was useful in accurately localizing the PET abnormalities (visualized in SOI), in particular, where there was regional nodal disease and where the tumor was more central. Central tumors make a surgical approach more problematic as a pneumonectomy may need to be considered to entirely remove the tumor and a pneumonectomy has significant morbidity and mortality. The involvement of regional, in particular, mediastinal nodes, affects surgical options and the radiation planning treatment fields. The imaging specialist provided a free-hand schematic (see Figure 12(a)) to explain the varying degrees of the complexity in the expression of NSCLC and the importance of the localization of the PET abnormalities in determining the disease stage and treatment options. We prefer to show the expert’s free-hand drawing rather than an artist’s professional interpretation of sites of disease as it reflects how a clinician emphasizes the importance of adjacent critical structures for diagnosis and management. Figure 12 (b) and Figure 12(d) show that the OSVRA visualization better outlines the primary tumor and its relationship to the mediastinum and trachea and the lymph node involvement relative to the hilum and the carina when compared to the 2D fusion equivalent of Figure 12(c).

(iii) General Comments: The imaging specialist suggested that OSVRA visualization could supplement the current clinical practice as a rapid overview visualization where the OSVRA could be used as a fly through the PET-CT data to quickly identify important regions of the imaging study for further detailed interpretation using conventional 2D view planes. Furthermore, the imaging specialist suggested using OSVRA visualization in the context of the multi-disciplinary team (MDT) meetings. In MDTs all the various clinicians (imaging specialists, thoracic surgeons, pulmonologists, medical oncologists, radiation oncologists, nurse specialists, palliative care clinicians, pathologists) involved in a patient’s care contribute to the discussion about the best plan of management for the patient [33, 34]. The expert suggested that the OSVRA would provide a much simpler and rapid display of the relevant data for the non-imaging specialists in the MDT and this would enhance communication and understanding of the imaging findings. Although the trachea is augmented using OSVRA, due to the limitation of the transfer function it cannot...
be distinctively identified and our imaging specialist recommended the inclusion of a segmentation label of the trachea and the proximal bronchial tree (shown in Figure 12 (d)) given the important impact of central sites of disease on management decisions.

VII. DISCUSSIONS AND FUTURE WORK

Our approach offers a multi-dimensional adjunct to conventional slice-based volume rendering approaches. Slice-based volume rendering approaches require manual volume clipping with each slice or viewpoint change. A key feature of our approach is the automated depth computation to produce visualizations that enhance manual volume clipping. Our approach, which resulted in contextual information from DVR (CT) and the retention of the visibility of the SOI (PET), was consistently better than conventional slice-based volume rendering. We suggest that our approach can be applied to a clinical imaging workflow for lung cancer PET-CT patient studies. Although our approach was only applied to PET-CT lung cancer patient studies, it does not require any modality-specific parameter settings and so we suggest that it can be applied to any dual-modality data that can be visualized in slice-based volume rendering, for example, PET-MR and SPECT-CT; this will be the subject of further work. It is also feasible to use our approach with single-modality data such as angiography volumes (in this case, the DVR and SOI are from the same volume).

The value of the depth $D$ parameter in our approach was derived by analyzing our proposed occlusion distance histogram. The histogram grouped voxels, which exhibited similar values (intensity and opacity), together into structures for structure-level analysis. Intensity is the most basic visual yet robust attribute of a voxel and has been widely used in image processing applications, including CT [35, 36]. Our approach, however, is not limited to any particular voxel attribute and can be adapted to use modality-specific attributes, for example, texture attribute in brain MR imaging [7]. Image segmentation approaches can also be used to construct labels for the structures in defining the transfer function in our approach. An occlusion distance histogram for each segmented structure label can be generated and used to assign individual depth parameters. We incorporated a segmented structural label to outline the trachea. The trachea was semi-automatically segmented using an active contour approach [37] that uses spatial neighboring information of the voxels in addition to its intensity attribute. The segmentation label allowed the differentiation of the trachea from the lung tissue, which was not possible with a transfer function alone in 1D or 2D variants. It also aids localization of the tumor region of interest. Such segmentation labels can be particularly useful when applied to MR data where there is inherent intensity inhomogeneity, i.e., the intensity of the same tissue varies with the location of the tissue within a volume [38], which often prohibits transfer function from depicting adequate labels.

In all of our visualizations, we avoided potential bias from transfer function manipulations when comparing our approach to slice-based volume rendering by using a set of default transfer functions for both PET and CT volumes. For a similar reason, we set the fusion ratio between the two volumes to 50:50. The value of the depth $D$ parameter was derived using the first peak from occlusion distance histogram and was used for all the visualizations. Subtle variations ($\pm$10 slices) from the peak did not greatly affect the resulting visualization. Nevertheless, this parameter can be manually adjusted for user-specific optimizations. Complex cases, in which a large number of structures exist, would have occlusion distance histograms with multiple peaks; this could raise the challenge in separating the peaks. For such cases, adjacent minor peaks could be merged to reduce the number of peaks. The use of the dynamic weight curve in OSVRA, estimated from the automatic computation of the depth $D$, resulted in a gradual decline in the occlusion of the DVR as its distance from the SOI increased. A static curve function without the depth $D$ could be applied to the manually clipped volume but this will mandate the adjustment of the transfer function whenever the clipping depth changed and would add further complications to the clipping process. Although we only showed the use of cross-sectional rectangular-shape SOI in computing $D$ and producing the subsequent augmentation of volumetric context, any arbitrary shape could be applied to our OSVRA approach; for clarity, visualizations with polygonal-shape SOI can be found in the appendix.

In all the renderings, we employed a transfer function that was defined to best depict the thorax – soft tissues, the lung fields, and the bony skeleton from CT. This setting was optimized for lung cancer studies but for diseases which may involve other anatomical structures, a different transfer function can be employed and this is not unusual for medical imaging where a disease specific transfer function is a common requirement. Advanced multi-dimensional transfer functions [5-8, 39] can be integrated into our approach for enhanced medical image visualizations; as an example, the visualizations in Figure 12 (b) and Figure 12(d) show the applicability of a 2D transfer function that enhances the boundaries of structures [5]; for clarity, visualizations using either a 1D and 2D TF can be found in the appendix.

Our expert review, a co-author of this paper, identified a number of potential clinical applications with our approach. We are now actively pursuing clinical evaluation of our approach through collaboration with two other clinical imaging centers. We also intend to explore our approach in other diseases including soft tissue sarcomas and the lymphomas.

VIII. CONCLUSIONS

We present a new visualization approach that automatically augments 2D SOI with the relevant 3D contextual information. The contextual information is calculated based on estimating the occlusion from the voxels (structures) residing in front of the SOI and rendered by incorporating DVR with an opacity weight curve derived from the occlusion estimation. Our experiments with PET-CT volumes show that our approach was able to augment the 3D structural context onto the PET SOI...
and avoid occlusion of the PET SOI, thereby leading to improved visualization when compared to the conventional slice-based volume rendering approaches together with volume clipping.

ACKNOWLEDGMENT

This research was funded in part by ARC grants.

REFERENCES


