Feasibility Studies of Virtual Laryngoscopy by CT and MRI—from data acquisition, image segmentation, to interactive visualization

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Abstract

Virtual endoscopy concept has been applied to study the larynx, as well as other hollow organs in recent years, assuming a clean lumen. In this work, we investigated the feasibility of virtual laryngoscopy by (1) studying currently available imaging protocols, (2) developing a suitable image segmentation method, and (3) constructing an efficient visualization system. By utilizing helical computed tomography (CT), the images for laryngeal volume can be obtained during a breath hold with 0.3mm resolution. A fast pulse sequence using 1.5T magnetic resonance (MR) imager can achieve 1mm resolution within few minutes. The gain in tissue contrast on MR images is at the cost of resolution, and motion artifacts must be considered during image segmentation. A first-order Lagrange interpolation was applied to mitigate the reduced resolution, as well as partial volume effect and noise on the MR images. An automatic segmentation algorithm was adapted to extract the wall volume of the larynx. The algorithm considers local voxel property and classifies voxels based on the local property in the KL (Karhunen-Loève) space. A visualization system was constructed for examining the mucosa and wall geometry with anatomical references in three dimensions. It navigates inside the lumen, as well as outside the larynx interactively with capability of inspecting and zooming into the regions of interest. It can also cut the larynx in any orientation to open the whole volume for viewing the entire inner surface. The procedure was tested on 2 volunteers and 2 patients. The segmentation performed consistently for all the studies and showed to be relatively insensitive to mild respiratory motion artifacts in the MR images. Image processing was accomplished within a few minutes on PC and low-end SGI platforms. These studies demonstrated the feasibility of virtual laryngoscopy for diagnosis of laryngeal abnormalities.

Key words: virtual laryngoscopy, adaptive segmentation, interactive visualization.

I. INTRODUCTION

Recently, several papers were published on the feasibility of virtual endoscopy [12, 16] in the evaluation of laryngeal diseases, this concept is referred to as virtual laryngoscopy [2, 8, 15]. This technology constructs a three-dimensional (3D) laryngeal model from computed tomography (CT) or magnetic resonance (MR) images and displays the 3D laryngeal structures by computer graphics tools. It is a non-invasive and safe diagnostic modality, as compared to conventional fiberoptic laryngoscopy, and is especially useful for patients who have a non-passable stenosis, or are at a high-risk of infection, inflammation, or congenital defects. Although previous studies [2, 8, 15] provided interesting results, there were limitations in their techniques, such as time, cost and quality of the reconstruction and navigation of the 3D laryngeal model. Since a clean lumen was assumed, they encountered a difficult task in image segmentation. Because of the lack of specific visualization tools for the laryngeal structures, they encountered another difficult task in achieving interactive navigation.

Both CT and MR provide useful images of the larynx, although different in some degree in spatial resolution and tissue contrast. Image segmentation of a clean airway lumen, as well as other different tissues within the neck, is necessary prior to surface or volume rendering [7]. Either surface or volume rendering will rely on the segmentation results to generate a mesh or reduce the rendering complexity [16]. For clinical applications, the accuracy of segmentation and rendering is essential in detecting abnormalities. The computing efficiency is another important factor. Efficient interactive navigation in the 3D laryngeal model of a high-resolution image is clinically desirable.

Fried et al. employed an adaptive segmentation method [17] in their preliminary studies [8]. Their segmentation method was based on a Markov random field (MRF) model of Gibbs function and utilized iterative calculation for the results. Since it was time consuming, the segmentation was implemented only in two dimensions. Furthermore, they reduced the higher resolution CT images from 512×512 to 256×256 matrix size to match that of lower resolution MR images (256×256) for image registration [18]. Other preliminary studies [2, 15] used a simple thresholding segmentation technique. It is expected that a 3D segmentation using the higher resolution images would generate a more accurate result. In this work, we will explore our previously proposed segmentation approach which considers the local image features as the MRF does, but with improved efficiency so that a 3D segmentation can be accomplished in the order of a few minutes [3].

Fried et al. adapted their visualization technique from an image-guided surgery application to virtual laryngoscopy [8]. The 3D airway lumen was modeled together with its associated tissues, such as the thyroid cartilage, for anatomical references. This integrated dataset was imported into their virtual endoscopy program [1]. This process took more than an hour for a single case without any interactive display functions [8]. They stated the limitations on time, cost of the procedure, and quality of the rendered mucosal surface. Other preliminary studies [2, 15] employed some basic visualization tools that were not optimized for this specific application. In this work, we will develop an efficient visualization system which utilizes our segmentation results and provides efficient interactive...

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navigation inside and outside the laryngeal model with 3D manipulation control. The key techniques in our visualization system are the organization of generated polygons in a data structure of binary space partitioning (BSP) tree and the application of level of details (LOD) technique which make the interactive visualization efficiently. By the LOD technique, a rough scene is displayed when manipulating the object, and a detailed scene is displayed when inspecting an area of the object. By the BSP tree structure, rendering the details of the limited scene is efficiently accomplished during navigation inside the hollow object.

In the following, we exam currently available CT and MR imaging protocols suitable to virtual laryngoscopy; and then describe our segmentation and visualization approach to achieve optimal and reliable results. Several clinical datasets were used to test the approach.

II. MATERIALS AND METHODS

Two patients and two volunteers were recruited into this preliminary study. Both patients are men of age 65. They were consented for the CT scan protocol, as described below. Volunteer 1 is a healthy female of age 37 and volunteer 2 is a healthy male of age 30. They were consented for the MR imaging protocol described below.

A. CT Scan Protocol

A GE/CTI spiral CT scanner was used. A routinely used protocol was employed for this study: 120 keV, 200 mA, 512x512 matrix size on 15cm field of view (FOV), and 3mm/2.0:1 collimation/pitch. The scan time was less than 30 seconds (within a single breath-holding). The data were reconstructed into 0.3mm thickness slice images, resulting in a total of 351 slices. Each image element is nearly a cubic voxel with a dimension of 0.3mm. Another protocol of 1mm/2.0:1 collimation/pitch could be used to achieve a better axial spatial resolution, at the cost of longer scanning time and higher radiation dose.

B. MR Imaging Protocol

A 1.5T Picker Edge whole-body scanner was used with body coil as the transceiver. A spoiled-GRASS pulse sequence was employed to collect T₁-weighted transverse volumetric images covering the spatial range of the whole larynx. This sequence generated a better result, in terms of higher signal-to-noise ratio (SNR) and less motion artifact, as compared to other pulse sequences available in the MR scanner. The scan protocol was: 5 ms TE, 20 ms TR, 30° flip angle, 24cm FOV, 1mm slice thickness, and 256x256 matrix size. The scan time was close to 7 minutes. Each image element is nearly a cubic voxel with a dimension of 1mm.

C. Self-Adaptive Segmentation Algorithm

Our previously proposed self-adaptive on-line vector quantization (SOVQ) algorithm [3] was adapted to classify voxels of both the CT and MR volume images, as described later. The reason for adapting this algorithm to this study is as follows. It is computationally efficient, so that a fully 3D implementation is feasible. It is adaptive to data features, so that a fully automatic segmentation is achievable. It considers the local voxel properties as the MRF model does; so that the assumption of piecewise contiguity of segmented ROIs (regions of interest) is realized.

For CT images with a higher in-plane resolution and better homogeneity across the FOV, the algorithm considered voxel neighbors up to the third order to catch the local density variation features. Since the MR image acquisition took a relatively longer time, motion artifacts due to swallowing, breathing, or coughing could not be avoided. In addition, the inhomogeneity in signal intensity across the FOV due to RF (radio frequency) field variation and the partial volume effect due to lower spatial resolution in the MR images have to be considered. The algorithm included only the first and second order neighbors after the MR images were interpolated to match the dimensions of the CT data. A pre-processing on the MR images for correction of the image inhomogeneity was performed prior to image segmentation [4]. It is expected that the high-resolution CT image typically has a better spatial resolution for detecting small morphological variation; while the high-contrast MR image is better in showing some degree of contrast variation in the soft tissues, for the purpose of identifying small lesions of the respiratory tract. Three-dimensional segmentation in an efficient manner is then desirable for the clinical diagnosis.

![Fig. 1. This chart shows the neighbors of a voxel for MR images (the left) and CT images (the right). The voxel marked by an asterisk is the fixed voxel. The center plane is the fixed slice.](image-url)
slice, as well as the whole image volume, have the same means and similar peaks; and (3) since the KL matrix is computed once and stored for all case studies, a noticeable computing time is saved because calculation of the KL matrix for each case is not necessary.

For the MR images, the histograms of voxel densities vary from slice to slice in each volunteer dataset due to the relatively lower spatial resolution, higher tissue contrast, and motion artifact as well as partial volume effect. A global choice of each or both volunteer datasets for the KL matrix is not adequate. Therefore, the KL matrix was generated from each slice respectively, rather than from all slices or two volume datasets simultaneously. Prior to forming the local density vectors, a first-order Lagrange interpolation [11] was applied to each slice from a matrix size of 256x256 to match the CT matrix size of 512x512. Then, the interpolation was used to generate new slices between each two adjacent original slices. The new slices were generated so that each interpolated voxel was a cube with a linear dimension of 0.5mm. The newly interpolated 512x512 image dataset was called an enlarged dataset. The interpolation reduces partial volume effect while performing a low-pass filtering on the image data to suppress noise. The local density vector of each voxel was formed by those neighbors as shown on the left picture of Fig. 1. The corresponding KL matrix was determined for each slice in the enlarged dataset, where two neighbor voxels from the closest slices were included for each voxel in that slice. Our experiments indicated that including more neighbor voxels or more slices would not improve the segmentation of the MR images.

By applying the KL transform matrix to the local density vectors, we obtained feature vectors for all the voxels in each volume image. Each feature vector of a voxel contains the local voxel density variation information. In the feature space, different tissue characteristics can be more easily recognized than in the image space. In other words, the feature vectors are more closely grouped into different clusters, so that a more accurate segmentation can be obtained as compared to the classification in the image space. Our SOVQ algorithm [3] was developed to separate the feature vectors into several clusters. It started by assigning a threshold parameter \( T \) which has a value equal to the maximum component variance of the feature vectors. This parameter encourages the least number of classes with distinct features or characteristics, because the maximum variance of the feature vectors provides an empirically optimal threshold for differentiating different classes. Let \( \text{dist}(x,y) \) be the Euclidean distance between two vectors \( x \) and \( y \). The algorithm scanned from the first voxel to the last one in the volume image. At the beginning, there was one class, whose representative vector was the feature vector of the first voxel. For each next voxel, the Euclidean distance, \( \text{dist}(\cdot, \cdot) \), between this feature vector and each representative vector of existing classes was calculated, respectively. If \( \text{dist}(\cdot, \cdot) < T \) for an existing class, the representative vector of this existing or current class was updated by including the feature vector of that voxel. If the requirement was not satisfied for all the existing classes, a new class was generated subject to the constraint of the maximum number of classes \( K \). This parameter \( K \) was assumed to be based on anatomical knowledge. After scanning over all the voxels, the representative vectors of all classes were generated. This self-adaptive on-line process is computationally efficient. Thereafter, all the voxels were classified accordingly based on a nearest neighbor rule between their feature vectors and the representative class vectors, respectively.

It is seen that the voxel classification depends on the choices of the local voxel density vector and the pre-set parameter \( K \). The choices of local density vector and value \( K \) varied from CT to MR datasets due to their characteristics. The local density vector had a larger size for CT than MR images, because the CT datasets had a higher spatial resolution and less image contrast, and need more neighbor voxels to detect the local density variation. A larger \( K \) value was chosen for the MR images (\( K=7 \)) than that of CT images (\( K=5 \)) based on the following reasons: there were approximately 6 and 4 tissue types that could be clearly distinguished visually from the MR and CT images, respectively. (The MR images showed more classes due to the contrast among soft tissues). A choice of a number larger or equal to that of the visual judgement in each dataset did not effect the segmentation results, since the segmentation is adaptive to the data characteristics. If a smaller number was assumed, the segmentation result would show less classes than the visual judgement. Therefore, it is better to assume the maximum number of classes greater than the visual judgement, so that extra classes can be assigned for the boundaries with a long dynamical range.

D. Extraction of Larynx Volume and Associated Tissues

The classified results were packed into a character format file with different voxel classes labeled by different integer values. With the aid of a 2D viewing tool in our visualization system, a seed point within the larynx was manually recorded. The laryngeal volume was then extracted by applying a region-growing algorithm from this seed point. If necessary, several seed points can be chosen for several segments of unconnected volumes for different types of tissue volumes.

E. 3D Interactive Rendering and Visualization System

Our goal is to develop an interactive visualization system under a fully 3D control for clinical applications of virtual laryngoscopy. The main technical barrier for efficient rendering of the larynx volume is the handling of a large amount of polygons. Several millions of polygons are usually required to depict the appearance of the larynx at the high spatial resolution. Rendering that large number of polygons at an interactive speed is a heavy burden even with a high performance graphical workstation (such as the high-end SGI/Onyx2 Infinite Reality systems). It is extremely challenging for low-end graphics computers. In order to
break down this barrier, the generated polygons were elaborately organized in a structure of BSP tree [6], and then a simplified LOD [10] technique was adapted to the rendering pipeline to achieve interactive visualization.

LOD is a technique that can improve rendering efficiency by reducing the complexity of a scene. A typical application of this technique can be described as follows. A low-level scene, or so called rough scene, is rendered to ensure interactive control or real time animation, while a high-level scene, or so called detailed scene, is obtained immediately after user stops manipulation for inspecting the details. The traditional implementation of this technique is to extract or merge polygons in a high level scene to interpolate a lower level one, subject to either smoothness and/or other criteria. The computation is very labor intensive. We took a different approach to the implementation of this LOD rendering concept.

We sampled the segmented binary volume image of 512×512×256 down size three times to a 64×64×32 bitmap of the patient anatomy by wavelet transform method. By appropriately modulating the wavelet transform coefficients, the low-level scene retained the main geometrical features of the high-level scene without boundary distortion artifacts which are usually seen by a simple shrinking or interpolation method. This multi-resolution decomposition of a volume image by wavelet transform is computationally efficient [14]. The polygons associated with both the high- and low-level volumes were then extracted respectively. The rendered low-level scene had a similar appearance as the high-level scene at a lower resolution. Obviously, fewer polygons were extracted from the low-resolution (64×64×32) bitmap than from the high-resolution (512×512×256) bitmap (Table 1). This two-level LOD rendering mode was applied to display the skeleton of larynx in an efficient interactive mode. While interacting with the object, such as rotation, shifting or any other change of viewing parameters, the polygons from the 64-sized dataset were rendered. Immediately after stopping the active interaction, a functional module was triggered to render polygons from the 512-sized dataset. When rendering the low-resolution larynx, a scale transformation must be applied to all generated polygons, so that there is no discontinuity in size when toggling. Since navigation inside the laryngeal lumen requires the details constantly within a limited viewing volume, the display mode of the navigation did not use the low-resolution polygon sets, here the BSP-tree organization of 512-sized polygons played a key role for efficient interactive control, as described below.

Traditional Marching Cubes method was employed to extract polygons to fit the surface of larynx [13]. Those polygons extracted from the 512-sized dataset were organized in a structure of BSP-tree [6]. The space of the original image volume was the root of the tree. The space was then partitioned into two subspaces so that each subspace contains approximately equal number of polygons (the size of the subspaces may be different). Such subdivision procedure was recursively performed on each subspace until the number of polygons in the latest subspaces was less than a given number. This given number was pre set based on the performance of the computer and algorithm, aiming to achieve the most efficient rendering. These latest subspaces were called leaf nodes of the tree. After the partitioning procedure, all polygons were stored in those leaf nodes. When navigating, polygon culling was applied by first culling those leaf nodes that were completely outside the viewing volume, and then accurately ordering and rendering the polygons in other subspaces that were not culled. The latter procedure was supported by the OpenGL functions which can provide the efficiency by hardware. Since the nodes have nearly the same number of polygons, the rendering efficiency was realized uniformly during the entire navigation.

<table>
<thead>
<tr>
<th>Patient</th>
<th>Volunteer</th>
<th>512-sized</th>
<th>64-sized</th>
<th>512-sized</th>
<th>64-sized</th>
</tr>
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<tr>
<td>Lumen</td>
<td>215,440</td>
<td>3,254</td>
<td>89,888</td>
<td>1,381</td>
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<tr>
<td>&quot;mucosa&quot;</td>
<td>472,952</td>
<td>6,138</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Cartilage</td>
<td>320,890</td>
<td>5,940</td>
<td>14,653</td>
<td>226</td>
<td></td>
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<tr>
<td>Total number</td>
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<td>13,332</td>
<td>104,541</td>
<td>1,607</td>
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</table>

Based on the BSP and LOD techniques, an interactive rendering and visualization system was constructed for applications of virtual laryngoscopy. It had three display modes: (a) skeleton display (solid, transparent, and mesh), (b) navigation, and (c) 2D slice image view. To achieve fully 3D interactive control, virtual trackball was implemented that the motion of a 2D interactive device, i.e., a mouse, was mapped to a 3D action to manipulate the objects in a 3D scene [5].

Fig. 2. The bull's-eye for navigation inside the lumen (left) and the navigation reference window (right).

No pre-calculated path was needed for navigation inside the larynx. A bull's-eye icon was attached at the center of the navigation scene. Pressing the mouse button with the cursor on different areas in the icon would lead to different actions that change the viewing parameters (left of Fig. 2), for example, moving forward and backward, rotating in clockwise and counter-clockwise, and etc. This kind of free navigation was feasible due to the relative simple structure of the laryngeal lumen. A reference window, where the skeleton was displayed transparently with both camera position and view direction, was presented as a navigation guide (right of Fig. 2). Some other auxiliary functions were also provided in the system, such as the management of image files, lights, materials, background color, as well as parameters setting for transparency control.
III. RESULTS AND DISCUSSION

After image acquisition, both CT and MR datasets were transferred, in DICOM format through the Ethernet, from the scanners to a SGI/Octane workstation. The transferring time was less than 5 minutes. The SGI computer has dual CPUs (195MHz MIPS RS10000), IMPACTSR graphics board, 890Mbytes RAM memory, and 56GB HD space. Pre-processing on data correction and interpolation, image segmentation, ROIs extraction, wavelet transform, and 3D visualization were implemented in this computer. The computing time for the 3D image segmentation (including ROI extraction) and polygon generation via the BSP-tree structure were listed in Table 2.

Table 2. Feature of dataset and implementation time in seconds. The sizes of enlarged MR images are used.

<table>
<thead>
<tr>
<th>Image modality</th>
<th>Volunteer 1</th>
<th>Volunteer 2</th>
<th>Patient 1</th>
<th>Patient 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matrix size</td>
<td>512x512</td>
<td>512x512</td>
<td>512x512</td>
<td>512x512</td>
</tr>
<tr>
<td>Number of slices</td>
<td>183</td>
<td>153</td>
<td>351</td>
<td>338</td>
</tr>
<tr>
<td>Segmentation (s)</td>
<td>56</td>
<td>48</td>
<td>387</td>
<td>365</td>
</tr>
<tr>
<td>Polygon generated (s)</td>
<td>13</td>
<td>12</td>
<td>28</td>
<td>26</td>
</tr>
</tbody>
</table>

The segmentation results for the CT images were satisfactory, based on visual judgement, see Fig. 3. The lumen and the “mucosa” (bright area) were clearly delineated from the CT images. From the segmentation results (left of Fig. 3), the “mucosa” appeared thickened. One possible cause of the apparent thickening of the “mucosa” may be due to the fact that the wall of larynx consists of thyroid cartilage and mucosa, both of which have the same density in the CT images. The combination of them was the “mucosa” that appeared in the segmentation results. Another possible reason for the cause may be due to the partial volume effect. In the case of partial volume effect, a volume rendering of the “mucosa” may be a better choice, as compared to a surface rendering. The thickened “mucosa” provides a natural range for calculating the volume rendering parameters, e.g., the degree of transparency. Figure 7a (in the last page) demonstrates both the “mucosa” and the thyroid cartilage around the lumen of the airway. The thyroid cartilage is indicated by the circular symbol. The hyoid bone is indicated by the cross symbol. The “mucosa” is shown in a transparency model enclosing the lumen. Figure 7b shows the same ROIs of Fig. 7a without the “mucosa”.

For the MR images, the lumen was clearly segmented even though the motion artifacts were present in both datasets of volunteers 1 and 2 (see the left of Fig. 4). Heavy ghosting artifacts were also seen in the last few slices toward the shoulder (see the right of Fig. 4). These ghost artifacts did not influence our virtual laryngoscopy, because these last few slices were close to the shoulder and did not contain useful information for the larynx reconstruction. In the TI-weighted images, although the associated tissues around the larynx were distinct from each other, the boundary of different tissues was not clear due to noise and partial volume effect. It is a very challenging task to extract those tissues accurately (see Fig. 5). The thyroid cartilage was extracted approximately. In Fig. 7(c), the cartilage and the larynx are showed together with different grayscale. The cartilage is indicated by the circular symbol. The trachea is indicated by the arrow symbol. The hyoid bone could not be delineated separately in the MR datasets.
Fig. 6. The interface of a pseudo 3D slice display in our virtual laryngoscopy system is shown in the pictures. In the display window, the segmented lumen and/or lumen contours can be displayed within the slice images. Picture (a) shows the CT image and (b) shows the MR image. This display mode provides an efficient means for inspecting both the raw data and the segmented ROIs.

Fig. 7. The extracted volumes of interest are compared to the anatomical chart (d). Picture (a) and (b) are the larynx volume extracted from the patient 1 CT dataset. The thyroid cartilage is indicated by the circular symbol and the hyoid bone by the cross symbol. The “mucosa” (transparency) surrounds the lumen is displayed in (a), and is removed in (b). Picture (c) is the larynx volume extracted from volunteer 1 MRI data set. This display model provides a global view of the entire larynx volume.

Fig. 8. The top panel is the navigation views inside the larynx lumen of the volunteer 1 (MRI) and the bottom panel is the navigation views inside the larynx lumen of the patient 1 (CT). The vocal cords (arrowed) and the epiglottis (crossed) are clearly seen.
In all 4 cases, the entire lumen was screened with the interactive navigation system. The camera could move along either the ascending or the descending direction. The vocal cord and epiglottis were clearly viewed (see Fig. 8). If the lumen has a stenosis, the navigation view might be restricted. At that location, the cut view of the lumen would be very helpful. Since the CT images possessed higher spatial resolution, the surface of the lumen looked much smoother than the MR images, as shown by Fig. 8. Navigation of the laryngeal anatomy was facilitated by providing the reviewer with reference images, as mentioned before. In our system, we provided two kinds of references. One is a smaller scale larynx volume which was rendered transparently with the camera location and the viewing field marked inside (see the right panel of Fig. 2). Another was the cartilage volumes which were extracted and displayed around the larynx in both CT and MR images, as shown in Figs. 7(a)-(c). Figure 7(d) can also be used as a reference. The system could provide a color display of the external view with cartilage surrounded the larynx, where different tissues could be coded with different colors in both solid and transparency rendering modes (see Fig. 7). This overview together with Fig. 6 prior to detailed inspection has proved to be of great help in grasping the anatomy of the larynx, especially when navigating inside the laryngeal lumen of Fig. 8.

As mentioned in the previous work [8] that virtual laryngoscopy, unlike fiberoptic laryngoscopy, could not be used for biopsy. However, the flexible interactive 3D display provides the physician a helpful tool to inspect the larynx. Furthermore, it provides a means for virtual surgical planning.

IV. CONCLUSION

A self-adaptive automated image segmentation, feature extraction, and efficient visualization system was developed to achieve interactive virtual laryngoscopy. The technology was tested on two patients and two volunteers for feasibility studies on both CT and MR imaging protocols. It took less than 8 minutes for data preprocessing in all cases, respectively, prior to visualization on a SGI/Octane graphics workstation. The technology appears promising for interactively visualizing the entire larynx by both inside navigation and outside global view. It is especially useful for patients who are poor candidates for fiberoptic endoscopy. Further refining of the system is needed for clinical use, such as including virtual biopsy on the suspected area with volume rendering on the 3D raw data and navigation inside the lumen of both CT and MR images simultaneously from the same patient.

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VI. REFERENCES