A Level Set Based Algorithm to Reconstruct the Urinary Bladder from Multiple Views

Zhen Ma\textsuperscript{a}, Renato Natal Jorge\textsuperscript{a}, T. Mascarenhas\textsuperscript{b}, João Manuel R. S. Tavares\textsuperscript{a}

\textsuperscript{a} Faculdade de Engenharia, Universidade do Porto
Rua Dr. Roberto Frias, s/n, 4200-465 PORTO - PORTUGAL
Email: \{zhen.ma, rnatal, tavares\}@fe.up.pt

\textsuperscript{b} Hospital de São João, Faculdade de Medicina, Universidade do Porto
Al. Prof. Hernâni Monteiro, s/n, 4200-319 PORTO - PORTUGAL
Email: tqc@sapo.pt

Name and Address for Correspondence:

Prof. João Manuel R. S. Tavares
Faculdade de Engenharia da Universidade do Porto (FEUP)
Departamento de Engenharia Mecânica (DEMec)
Rua Dr. Roberto Frias, s/n, 4200-465 PORTO - PORTUGAL
Telf.: +315 22 5081487, Fax: +315 22 5081445
Email: tavares@fe.up.pt Url: www.fe.up.pt/~tavares
A Level Set Based Algorithm to Reconstruct the Urinary Bladder from Multiple Views

Abstract: The urinary bladder can be visualized from different views by imaging facilities such as Computerized Tomography and Magnetic Resonance Imaging. Multi-view imaging can present more details of this pelvic organ and contribute to a more reliable reconstruction. Based on the information from multi-view planes, a level set based algorithm is proposed to reconstruct the 3D shape of the bladder using the cross-sectional boundaries. The algorithm provides a flexible solution to handle the discrepancies from different view planes and can obtain an accurate bladder surface with more geometric details.

Keywords: Biomedical Engineering; Medical Imaging; Image Analysis; Deformable Model; 3D Reconstruction.
1. Introduction

A normal bladder has a thin smooth muscular wall that is mainly composed of the detrusor muscle. Dysfunction of the urinary bladder can cause various urological conditions such as cystocele, urinary incontinence (UI), overactive bladder (OAB), and underactive bladder. Nowadays, the prevalence of these diseases affects a large number of populations; for example, it was estimated that in the United States 16.0% of men and 16.9% of women have OAB and overall 38% of women have symptoms of UI \(^1,\,^2\). The negative impacts of the bladder-related conditions can considerably influence the patients' physical and social lives, and need to be treated properly. The diagnosis requires an in-depth understanding of the functionalities of the urinary bladder and its relationship with the involved structures. The modern imaging modalities play an important role in this process \(^3\)-\(^8\). For instance, computerized tomography (CT) and magnetic resonance (MR) imaging have been used as the non-invasive ways to follow the extension of bladder tumors and to stage bladder cancer.\(^3\), \(^4\) Details of the urinary bladder on the cross-sectional plans can be presented clearly; however, information from these two-dimensional image slices is neither continuous nor intuitive due to the slice gaps. In order to carry on further analysis such as biomechanical simulation and quantitative analysis, the three-dimensional (3D) surface model of the urinary bladder needs to be reconstructed.

Usually, using the imaging facilities provided by modern CT and MR imaging systems, the urinary bladder can be visualized from three spatial views: axial, sagittal, and coronal. Unlike the multi-view stereo reconstruction, the medical image series contain little redundant information because the cross-sectional imaging planes are parallel in the same spatial view and intersectional (in many cases also orthogonal) between different spatial views. The joint information from different views can benefit the 3D reconstruction of the urinary bladder and provide more details to the surface model. In this paper, a level set based algorithm is proposed that combines the information from the multiple views to reconstruct the urinary bladder. The level set method \(^9\) is used to track the surface evolution, and the moving equation is defined based on the weighted distance to the cross-sectional boundaries. The proposed algorithm provides a flexible method for reconstruction and can obtain a reliable bladder surface with more geometric details.
2. Background

A common procedure for 3D reconstruction is to use the cross-sectional regions of the bladder segmented on the images: a rough profile of the bladder can be sketched through stacking the sequential boundaries from the same spatial view; then, the 3D surface model can be reconstructed using, for example, the marching cubes algorithm. Therefore, the reliability of a 3D model depends on two critical factors: the accuracy of the segmented regions and the spatial interpolation between neighbouring slices. Regarding the first factor, effective segmentation algorithms have been proposed based on the appearances of the bladder. Although some aspects of these algorithms still need to be improved, in most cases correct results can be obtained; hence, segmentation accuracy is not the focus in this paper. For the second factor, the spatial interpolation is used to recover the missing information at the slice gap. The slice gap is a parameter determined at the imaging phase: the smaller this value, the more information acquired. If the gaps between neighbouring images are small enough, a realistic 3D surface model can be obtained. High quality multiplanar reconstruction can be rendered precisely through isotropic or near-isotropic scanning provided in the CT urography (CTU) and MR urography. In particular, CTU has become the practice in studying conditions of urinary tract. Compared with the MR imaging, isotropic imaging using CT is easier to achieve and less time-consuming; nevertheless, MR imaging can provide better tissue contrast and does not involve radiation exposure, which is a critical feature for selected patients like children and pregnant women. Besides, T2-weighted MR imaging is considered as a suitable modality for imaging the urinary bladder especially for the bladder wall. Based on these features, MR imaging is an alternative with great potential for diagnosing urological conditions. However, the acquisition time of an isotropic MR scanning is long. As such, in order to decrease the scanning time and increase the contrast and signal-to-noise ratios, a common practice for MR imaging is to adopt a low through-plane resolution and a high in-plane resolution; consequently, surface model built from a single view may not be accurate for the lack of information at the large slice gaps. Besides, the imaging appearance of the urinary bladder can be influenced by the neighbouring structures under a certain view so that some geometric properties of the bladder are hard to be observed. Image series acquired from multiple views can considerably improve these situations, for the missing information in one view can be
compensated by the contents from other views; accordingly, reconstruction based on multiple view planes can obtain a bladder surface model with more and comprehensive details.

If all the images are segmented accurately, the cross-sectional boundaries of the bladder from different views should intersect with each other. Nevertheless, this feature barely holds in practical cases, as incorrect segmentation is sometimes inevitable due to the fact that the imaging appearance of the bladder can be easily distorted by noise or influenced by neighbouring organs and artefacts. A case in point can be seen in Fig. 1: the posterior part of the bladder in the axial image is unclear due to the partial volume effect caused by the anterior parts of the vagina; and the bladder boundary in the sagittal image is blurry because the image is acquired at the lateral side of the bladder; consequently, the accuracy of segmentation at these parts cannot be assured. When the boundaries from different view planes are aligned, the correct positions at some parts of the bladder become confused. Fig. 2 illustrates two surface models built by the marching cubes algorithm using the axial and sagittal boundaries respectively, from which the discrepancies at the lateral and upper sides of the urinary bladder can be clearly identified. Then, reconstruction with the cross-sectional boundaries from multiple view planes becomes an ill-posed problem; if all the boundaries are treated equally in reconstruction, the 3D model built may approach to the wrong positions at the parts with discrepancies. Registration of the intersection points between two intersectional boundaries seems to be a proper way to eliminate the discrepancies and establish the correspondence; however, modification of the boundary points can change the local continuity and smoothness and lead to new discordance at other parts of the boundary. Given the number of cross-sectional boundaries, registration requires high computational complexity to find the correspondence matching among boundaries, and is not appropriate for this application. Therefore, the way to build a reliable surface of the urinary bladder based on the information from multi-view planes becomes an interesting topic to explore.

For the urinary bladder, its lateral boundary can be better identified on axial plane while the dome and the base are more clearly observed on sagittal and coronal planes. Hence, the positions defined by the upper and lower parts of the sagittal boundaries should be more reliable than the ones defined by the axial boundaries; the lateral sides of the bladder are more accurately defined by the axial boundaries. Though these conclusions are not definitive, the reliability of the segmented boundaries can be a
useful criterion for handling the confusions in the reconstruction: the surface should approach to the positions defined by the parts with higher reliabilities. With these ideas, a 3D reconstruction algorithm is proposed that, even though the urinary bladder is concerned here, can be used to reconstruct efficiently organs with multi-view imaging planes.

3. Algorithm

According to the accuracy of segmentation, the boundary of the urinary bladder on each image can be divided into several parts with each one assigned with a confidence level. The bladder surface should have the minimal distance to the cross-sectional boundaries. Given the discrepancies of segmentation from multiple view planes, the distance should approach to zero. To facilitate the discussion, supposing there are $N \geq 1$ confidence levels and the parts of a boundary with $i$-th confidence level have higher reliability than the ones with the $j$-th confidence level when $i < j$; consequently, the energy functional for reconstruction is proposed as:

$$E(\Gamma) = \sum_{i=1}^{M} \omega_i \int_{\Gamma_i} d_i(\bar{x}) ds + \left(1 - \sum_{i=1}^{M} \omega_i \right) \int_{\Gamma} d(\bar{x}) ds,$$

where $\Gamma$ is the surface, $d_i(\bar{x})$ is the distance of the surface segment to the parts of boundaries with the $i$-th confidence level, $d(\bar{x})$ is the distance of the surface segment to all the boundaries, $ds$ is the surface area, $M$ is an integer that satisfies $1 \leq M \leq N$, and $\omega_i > 0$ is the weight of each distance with $0 \leq \sum_{i=1}^{M} \omega_i \leq 1$ and $\omega_i \geq \omega_j$ if $i < j$.

The first item at the right side of Eq. (1) emphasizes the importance of the parts with the fore $M$-highest confidence levels to the reconstruction; and the definition of the distance weights $\omega_i$ assures that the parts with high confidence levels have larger influences than the ones with low confidence levels. Thus, the surface obtained will be attracted to the positions defined by the boundaries that are more reliable when there are discrepancies. The second item is a distance measure of the surface to all parts of the boundaries and was used in applications such as the point cloud reconstruction 21; it is added here so that the information from the parts with low confidence levels will not be discarded in reconstruction, and the surface has an overall small distance to all the segmented boundaries. Hence, the bladder surface
defined by the proposed energy functional is the one that has the minimal weighted
distance to the cross-sectional boundaries.

The Euler-Lagrange equation of Eq. (1) can be derived as:

\[
\left( \sum_{i=1}^{M} \omega_i \nabla d_i (\bar{x}) + \left( 1 - \sum_{i=1}^{M} \omega_i \right) \nabla d (\bar{x}) \right) \cdot \vec{N} + \left( \sum_{i=1}^{M} \omega_i d_i (\bar{x}) + \left( 1 - \sum_{i=1}^{M} \omega_i \right) d (\bar{x}) \right) \kappa = 0,
\]

where \( \vec{N} \) is the external normal vector and \( \kappa \) is the curvature of the surface.

Correspondingly, the moving equation to find the minimal surface is proposed as:

\[
\frac{\partial \phi}{\partial t} = \left( \sum_{i=1}^{M} \omega_i \nabla d_i + \left( 1 - \sum_{i=1}^{M} \omega_i \right) \nabla d \right) \cdot \nabla \phi + \lambda \left( \sum_{i=1}^{M} \omega_i d_i + \left( 1 - \sum_{i=1}^{M} \omega_i \right) d \right) \nabla \cdot \nabla \phi \left| \nabla \phi \right|,
\]

where \( \phi \) is the level set function \( \phi(x,y,z,t) = 0 \). The implicit tracking of the surface by the level set method can facilitate the calculations of the surface changes and decrease the computational complexity. The values of the initial level set function \( \phi(x,y,z,0) \) are defined as the signed distance function to the initial surface, with positive (negative) signs inside (outside).

In the right side of Eq. (3), the first part acts as the external force that defines the direction of movement, following which the surface is attracted to the positions defined by the cross-sectional boundaries; the force is composed of two parts: the first one, \( \sum_{i=1}^{M} \omega_i \nabla d_i \), is derived from the \( M \) subsets of the boundary parts that defines and influences the moving direction of the surface when there are discrepancies; and the second item, \( \left( 1 - \sum_{i=1}^{M} \omega_i \right) \nabla d (\bar{x}) \), is derived from all the boundary parts that drives the surface approaching to the correct positions and assures that no information is missed.

The second part, \( \left( \sum_{i=1}^{M} \omega_i d_i + \left( 1 - \sum_{i=1}^{M} \omega_i \right) d \right) \kappa \), acts as an internal force to keep the smoothness of the surface through the influence of curvature; the smoothing effect is controlled by the parameter \( \lambda \): a larger \( \lambda \) can lead to a smoother surface.

Furthermore, the distance between a surface segment \( S \) and a contour \( L \) is defined as:

\[
D(S,L) = \min_{p \in S} \left( \min_{p' \in L} \left( d(p, p') \right) \right),
\]

(4)
where \( d(p, p') \) is the Euclidean distance between the points \( p \) and \( p' \). Meanwhile, the assignment of the confidence levels to different parts of the boundaries can be done through sampling the boundaries to discrete points and evaluating these points based on their positions and reliabilities. Accordingly, the calculation of \( d(\bar{x}) \) and \( d_i(\bar{x}) \) at a segment \( \Gamma' \) on the surface \( \Gamma \) can be easily carried out by finding the minimal Euclidean distances between the surface points and the sampled boundary points as:

\[
d(\bar{x}) = \min_{p \in \Gamma} \left( \min_{p' \in P} (d(p, p')) \right),
\]

\[
d_i(\bar{x}) = \min_{p \in \Gamma} \left( \min_{p' \in P_i} (d(p, p')) \right),
\]

where \( P \) is the point set composed by all the sampled boundary points and \( P_i \) stands for its subset in which the points have the \( i \)-th confidence level.

The proposed algorithm is based on the cross-sectional boundaries from the multi-view planes using the criterion that the surface should approach to the positions defined by the more reliable segmentations when discrepancy happens. Following Eq. (3), the bladder surface can be obtained through surface evolution, and the reconstruction process is flexible and naturally handles the multi-view discrepancies. The procedure of the proposed algorithm can be summarized as the following steps:

- Step 0: Segment the boundaries of the urinary bladder on the images acquired from each view; align them to the same coordinate system according to the orientation and imaging attributes of each image.
- Step 1: Sample the boundaries into discrete boundary points and assign these points with different confidence levels based on their reliabilities.
- Step 2: Define the initial surface and initialize the values of the level set function using the signed distance.
- Step 3: The initial surface evolves according to Eq. (3) until it becomes stable.

4. Results and Discussions

In order to better explain the procedures and show the influences of the weighted distance, the 3D reconstruction of the urinary bladder from a T2-weighted MR image series is addressed here. The image series used was acquired from a 26-year-old woman under a turbo-spin echo (TSE) sequence with the following parameters:
patient position: head first-supine (HFS), field strength: 1.5 T, echo time (TE): 103 ms, repetition time (TR): 5440 ms, bandwidth: 130 Hz/pixel, FOV: 220×220 mm², acquisition matrix: 272×320, flip angle: 150°, and the spatial resolution is 0.69×0.69×5.40 mm³ for the axial plane, 4.20×0.81×0.81 mm³ for the sagittal plane, 0.69×5.40×0.69 mm³ for the coronal plane. The coordinates of the upper left voxel on each image is recorded following the LPS (Left-Posterior-Superior) system, and the orientation of each view plane can be accessed from the DICOM tags contained in the image series.

4.1 Reconstruction Process

Segmentation and alignment: in the image series, the bladder can be clearly identified in 16 axial images, 23 sagittal images, and 8 coronal images; correspondingly, the segmentation was carried out on these images. The segmented boundaries were aligned to the same coordinate system based on the positions and orientations of the imaging planes, Fig. 3(a). As a comparison, the profile of the bladder from the sagittal view is shown in Fig. 3(b). One can see that the lacking information at the slice gap in the sagittal view is compensated by the contents from the axial and coronal planes; the sketched profile of the bladder from multiple views is more complete and its laterals can be identified clearly.

Sampling and assignment: the cross-sectional boundaries were sampled to discrete points, Fig. 3(c); among them, 4673 points are from the axial boundaries, 4806 from the sagittal boundaries, and 2259 from the coronal boundaries. Only two confidence levels were considered so that the influence of the distance weights can be shown in a clear way. Accordingly, the sampled points were classified into two groups, and the ones that are more reliable were assigned with high confidence level and highlighted with the red color in Fig. 3(c) (among them 4382 points are from the axial plane, 3309 from the sagittal plane, and 2206 from the coronal plane).

Initialization: The initial surface was placed completely in the bladder lumen, Fig. 3(c); hence, for this experiment, the final surface was obtained through expansion. The level set value \( \phi(x, y, z, 0) \) was initialized as the signed distance to the initial surface; the distances of the initial surface to the cross-sectional boundaries and to the boundary parts with high confidence level were calculated using Eq. (5).

Evolution: since only two confidence levels were considered, the moving equation becomes:
\[
\frac{\partial \phi}{\partial t} = \left( \omega \nabla d_i + (1 - \omega) \nabla d \right) \frac{\nabla \phi}{\| \nabla \phi \|} + \lambda \left( \omega d_i + (1 - \omega) d \right) \nabla \cdot \left( \frac{\nabla \phi}{\| \nabla \phi \|} \right) \| \nabla \phi \|, \tag{6}
\]

where \( \phi \) is the level set function, \( d_i \) is the distance function of the surface to the boundary points with high confidence level, \( d \) is the distance function of the surface to all the sampled boundary points, \( 0 \leq \omega < 1 \) is the weight that controls the influence of the points with high confidence level, and \( \lambda \) controls the smoothing effect. Following this equation, the surface evolves and the level set function is updated until it achieves a stable status. The reconstruction attained can be seen in Fig. 3(d).

4.2 Discussion

The weighted distance to the cross-sectional boundaries makes the obtained surface no longer the one that has the minimal average distance to the boundaries; consequently, the value of \( \omega \) in Eq. (6) can influence the appearance of the bladder surface: a larger \( \omega \) gives higher priority to the points with high confidence level; as such, the surface is required to approach further to the positions defined by them. The changes of the surfaces are illustrated in Fig. 4(a), in which the surfaces built with \( \omega = 0.2, 0.4, 0.6, 0.8 \) were overlapped with the one built with \( \omega = 0 \) to show their differences intuitively. In this example, one can verify that if \( \omega \) is too large, the information carried by the points with low confidence level tends to be discarded in the reconstruction; this situation can be verified in Fig. 4(b): the upper left parts of the bladder disappear when \( \omega = 0.9 \) and 1.0 due to the lack of points with high confidence level at there. Therefore, if the points with high confidence level have an uneven spatial distribution, the weight of the distance to all the sampled boundary points should not be small in order to keep the integrity and correctness of the surface.

To quantitatively measure the differences among these surfaces, four indexes were used:

\[
I_1 = \text{Ave} \left( d \left( \bar{x} \right) \right), \quad I_2 = \text{Ave} \left( d_i \left( \bar{x} \right) \right), \quad I_3 = \text{Ave} \left( d \left( p, \Gamma \right) \right), \quad I_4 = \text{Ave} \left( d \left( p, \Gamma \right) \right), \tag{7}
\]

where \( \Gamma \) is the surface, \( P \) is the point set composed by all the sampled boundary points, \( P_i \) denotes its subset composed by the points with high confidence level, \( \text{Ave} \) stands for the average operator, and the point-to-surface distance is calculated as:

\[
d \left( p, \Gamma \right) = \min_{p \in \Gamma} d \left( p, p' \right), \tag{8}
\]

where \( d \left( p, p' \right) \) is the Euclidean distance between the two points.
$I_1$ and $I_2$ are two measures related to the proposed energy functional that calculate the average distances of the surface segments to the sampled boundary points and to the points with high confidence level; the two values can indicate the overall approaching of the surface segments to the boundaries. $I_3$ is the average distance of the sampled boundary points to the built surface, and $I_4$ is the average distance of the points with high confidence level to the surface; these two measures show how close the boundary points are to the local surface patch. Hence, the four indexes can indicate different aspects of the built surfaces, and their values for the four surfaces in Fig. 4 are indicated in Table 1. From Table 1, one can realize that when $\omega$ increases, the value of $I_1$ increases and $I_2$ decreases, which satisfies the tendency defined in the energy functional. However, the changes of $I_3$ and $I_4$ does not have an explicit trend, because the two measures can be influenced considerably by the local changes of surface; for example, when $\omega$ increases from 0.6 to 0.8 the upper right sides of the bladder extend further, and both measures decreased. Based on the appearances of these surfaces and the four distance measures, the surface built with $\omega = 0.8$ was considered as a proper model; furthermore, Fig. 5 shows its differences to the two surfaces built from the axial and sagittal view planes, respectively. One can confirm that the surface built from the multi-view planes has more geometric changes that cannot be captured on a single view; for example, in Fig. 5(a) the concave region caused by the uterus at the upper side of the bladder can be clearly identified in the surfaces built from the sagittal and multi-view planes, while this region is much tenderly presented in the surface built from the axial view because the changes cannot be captured clearly due to gaps between the axial planes. Based on the similar reason, in Fig. 5(b) the horizontal changes on the surface can be better seen on the surfaces built from the axial and multi-view planes than from the sagittal planes. Table 2 presents the surface area and the volume of the three surfaces built to show their differences and influences to the quantitative analysis of the urinary bladder.

5. Conclusion

The proposed algorithm combines the multi-view information and provides a flexible and accurate method to build the 3D bladder surface model. The cross-sectional
boundaries of the bladder are evaluated based on their reliabilities; and their influences to reconstruction are weighted according to the confidence levels. As such, the confusions caused by the inaccurate segmentation from multi-view imaging planes are naturally handled; the bladder surface is obtained through surface evolution based on its weighted distances to the cross-sectional boundaries under the smoothness constrain. Compared with the ones built from a single view plane, the surface built from multiple views contains more geometric details and changes.

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Conflict of interest

The authors report no conflicts of interest.

References


Table 1 - Comparisons among the surfaces built with different distance weights using the four measures defined in Eq. (7)

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>$I_1$ (mm)</th>
<th>$I_2$ (mm)</th>
<th>$I_3$ (mm)</th>
<th>$I_4$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.87</td>
<td>1.31</td>
<td>0.67</td>
<td>0.76</td>
</tr>
<tr>
<td>0.2</td>
<td>0.89</td>
<td>1.24</td>
<td>0.59</td>
<td>0.63</td>
</tr>
<tr>
<td>0.4</td>
<td>0.95</td>
<td>1.17</td>
<td>0.62</td>
<td>0.54</td>
</tr>
<tr>
<td>0.6</td>
<td>0.97</td>
<td>1.14</td>
<td>0.72</td>
<td>0.57</td>
</tr>
<tr>
<td>0.8</td>
<td>0.98</td>
<td>1.12</td>
<td>0.70</td>
<td>0.48</td>
</tr>
<tr>
<td>1</td>
<td>0.98</td>
<td>1.10</td>
<td>0.70</td>
<td>0.62</td>
</tr>
</tbody>
</table>
Table 2 - Volumes and surface areas of the surfaces built from multiple views and from the axial and sagittal views. (S - Surface built from multi-view planes, S₁ - Surface built from axial planes, S₂ - surface built from sagittal planes.)

<table>
<thead>
<tr>
<th></th>
<th>Volume (cm³)</th>
<th>Area (cm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>225.11</td>
<td>208.94</td>
</tr>
<tr>
<td>S₁</td>
<td>245.60</td>
<td>217.98</td>
</tr>
<tr>
<td>S₂</td>
<td>210.24</td>
<td>201.42</td>
</tr>
</tbody>
</table>
FIGURE CAPTIONS

Figure 1: T2-weighted MR images of the female pelvic cavity in which the boundary of the urinary bladder is unclear: (a) axial view, with the blurred posterior bladder region marked by the rectangle; (b) sagittal view (Labels: 1-bladder; 2-vagina).
Figure 2: The bladder surfaces built by the marching cubes algorithm using the axial boundaries (with transparent yellow color) and sagittal boundaries (with solid white color).
Figure 3: (a) Profiles of the urinary bladder through stacking the sagittal boundaries; (b) Profiles of the bladder by stacking the boundaries from multi-view planes; (c) Sampled boundary points with the initial surface, the ones with high confidence level are highlighted with red color; (d) The bladder surface reconstructed using the proposed algorithm with $\omega = 0.8$.
Figure 4: (a) The bladder surfaces using the proposed algorithm (transparent yellow color) built with $\omega = 0.2, 0.4, 0.6, 0.8$ from left to right overlapped with the surface built with $\omega = 0$ (solid white color, with all the points are treated equally); (b) The bladder surface built with $\omega = 0.8, 0.9, 1$ (only based on the points with high confidence level) overlapped with the surface built with $\omega = 0$, the disappearing region is marked by a red asterisk.
Figure 5: A comparison between the surfaces built from the multiple views (middle one with $\omega = 0.8$) and the ones from the axial (on the right) and sagittal views (on the left): (a) from the upper sides; (b) from the lateral sides.