Live-Wire-Based Segmentation of 3D Anatomical Structures for Image-Guided Lung Interventions

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ABSTRACT
Computed Tomography (CT) has been widely used for assisting in lung cancer detection/diagnosis and treatment. In lung cancer diagnosis, suspect lesions or regions of interest (ROIs) are usually analyzed in screening CT scans. Then, CT-based image-guided minimally invasive procedures are performed for further diagnosis through bronchoscopic or percutaneous approaches. Thus, ROI segmentation is a preliminary but vital step for abnormality detection, procedural planning, and intra-procedural guidance. In lung cancer diagnosis, such ROIs can be tumors, lymph nodes, nodules, etc., which may vary in size, shape, and other complication phenomena. Manual segmentation approaches are time consuming, user-biased, and cannot guarantee reproducible results. Automatic methods do not require user input, but they are usually highly application-dependent. To counterbalance among efficiency, accuracy, and robustness, considerable efforts have been contributed to semi-automatic strategies, which enable full user control, while minimizing human interactions. Among available semi-automatic approaches, the live-wire algorithm has been recognized as a valuable tool for segmentation of a wide range of ROIs from chest CT images. In this paper, a new 3D extension of the traditional 2D live-wire method is proposed for 3D ROI segmentation. In the experiments, the proposed approach is applied to a set of anatomical ROIs from 3D chest CT images, and the results are compared with the segmentation derived from a previous evaluated live-wire-based approach.

Keywords: segmentation, image-guided diagnosis, lung cancer, 3D CT imaging, live wire

1. INTRODUCTION
Segmentation of suspect lesions or regions of interest (ROIs) in CT images is a preliminary but vital step for abnormality detection, procedural planning, and intra-procedural guidance in lung cancer diagnosis and minimally invasive image-guided intervention.1 Diagnosis of lung cancer may involve various type of soft-tissue ROIs, which are presented with complicated phenomena. As a result, segmentation of such ROIs remains as a challenging task. Manual approaches are time consuming and user-biased and cannot guarantee reproducible results. Though automatic methods are attractive because they do not require user input, such methods are usually highly application dependent.2 To counterbalance among efficiency, accuracy, and robustness, semi-automatic strategies have been extensively studied to enable full user control while minimizing human interactions.

Among existent approaches, active contour, or adaptive shape models, and live wire are two popular type of methods, which are easy to be used.3–7 After initial boundary information is given by a user, the active-contour-based method iteratively minimizes a corresponding cost function so as to define a desired contour upon converge of the algorithm. The performance not only relies on the design of the iterative optimization algorithm, but also depends on the initial boundary data, which is usually defined by a user or from a priori knowledge.3,4,8,9 Since the user interaction is not allowed once the iterative process starts, the outcome might not be predictable. And the whole process will be repeated from the beginning when inadequate segmentation is obtained. There is no guarantee that this type of methods will always provide meaningful result to a wide range of objects, and hence limits their usage in medical imaging applications.

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Live wire, also known as intelligent scissors was proposed to provide full user control during the segmentation process to ensure robust and proper outcome while minimizing human interaction to reduce processing time.\textsuperscript{5–7} It has been well recognized as an efficient tool that arguably provides the best combination of manual intervention and automated analysis for general medical image segmentation. Though the live wire method is able to deal with almost all kinds of 2D anatomical structures, its extension to 3D segmentation still requires considerable efforts. In the pass, several 3D methods have been conducted and were formulated by reducing a 3D task to 2D space, including general 3D live wire (GLW), iterative or single-slice live wire (SSLW), and single-click live wire (SCLW).\textsuperscript{7,10–13} GLW is able to deal with a wide range of ROIs and provide robust results. It, however, requires considerable user interactions. SSLW and SCLW depend on a well defined 2D object boundary and propagate this boundary onto adjacent 2D sectional images as an initial contour. Then, the boundary is iteratively adjusted following the redesigned 2D live-wire process, assuming that object boundaries vary slightly from one 2D sectional image to its contiguous images. Though SSLW and SCLW have been validated and proved to be efficient and reliable for dealing with typical ROIs in lung interventions, it is quite difficult to terminate the automatic process, and the iteration may be propagated to other objects.

In this work, the propagation of the SSLW is refined so as to terminate the process properly and prevent incorrect segmentation result when dealing with ROIs sharing ambiguous boundary regions with others. The method is presented in detail in Section 2. Section 3 shows the results and compares them with those derived from SLW. A conclusion is given in Section 4.

2. METHODS

In this work, the major effort focus is to conduct a 3D segmentation scenario by employing the 2D live-wire-based algorithm, whose basic idea is to reduce the boundary-definition problem as a optimal graph search through local active contour analysis.\textsuperscript{6,7} In the SSLW, the termination criteria of this approach rely on: 1) number of voxels of the boundary candidate in the previous processed sectional image; 2) variation of the voxel intensity feature of enclosed object areas between two adjacent slices; 3) boundary conditions, such as shape; 4) difference of incremental total costs, calculated based on live wire paradigm, of a defined boundary candidate compared with that derived from the previous sectional image. Due to the complicated phenomena that might be involved in the processed ROI, the stopping criteria might not be able to terminate the process properly.\textsuperscript{11,14} Implementation of such 3D live-wire approach may end up with re-definition of bounding limits in starting and ending sectional images.

The proposed image steering live wire (SILW) approach still uses mouse cursor to steer the segmentation and only requires several clicks determined by the user to segment a 2D object. As demonstrated in Figure 1, when extended to 3D, a reference 2D cross-section image $S_r$ is selected from the 3D CT image $I$, which is usually a transverse, coronal, or sagittal plane, and the 2D live-wire algorithm is performed to provide an reference boundary $B_r$ whose centroid is defined as $C_r$, with coordinates: $X_c, Y_c, Z_c$, where $X$-axis increases laterally from right to left, $Y$-axis increases from anterior (front) to posterior (back), and $Z$-axis increases from superior (head) to inferior (foot). Then, a baseline $L_b$ passing the centroid $C_r$ is defined on $S_r$, and a new 2D cross-section image $S_0$ is obtained by steering/rotating slightly based on $L_b$. The object boundary $B_r$ is then projected onto $S_0$, and a 2D live-wire algorithm is applied to adjust the boundary to segment the object on image $S_0$, resulting a new boundary $B_0$. In this way, a series of 2D cross-sectional images $S_i, i = 1, 2, \ldots$ can be reconstructed by subsequently steering $S_r$ based on $L_b$ using different angles, and the 2D live-wire algorithm is used to refine the segmentation. Finally, the 3D object is defined after a number of steering covering 180 degree of rotation.

Figure 1 demonstrates how the 2D cross-sectional image is reconstructed by steering $S_r$ based on $L_b$. Assuming that the CT coordinate system is defined in the transverse (X-Y), coronal (X-Z), and sagittal (Y-Z) planes as shown in Figure 1(a), a transverse slice with the region of interest is selected as $S_r$, and the 2D live-wire algorithm is used to segment the object and define the object boundary $B_r$. The baseline $L_b$ is then selected as the intersection between the transverse slice and the sagittal slice passing through the centroid $C_r$. The detailed 3D segmentation algorithm is described as follows:

1. Define the rectangle area based on the object boundary $B_r$ on $S_r$. The width $W_{min}$ (Y direction) and
height $H_{\text{min}}$ (X direction) of this area should cover the ROI on this 2D section.

2. Let $w_i$ and $h_i$ be the width and height of 2D section image $S_i$ ($i = 0, 1, \ldots$). $w_{\text{min},i}$ and $h_{\text{min},i}$ be the width and height of the minimal rectangle of the object boundary $B_i$ on $S_i$.

3. To get the $i$th cross-sectional image, we steer the reference image plane $S_r$ with angle $\theta_i$ centering at the baseline $L_b$. For instance, this scenario is presented here by reconstructing the cross-sectional image starting from a transverse slices. Assume slice $z_i$ was used to reconstruct image $S_i$, then, to determine image $S_{i+1}$, we will use slice $z_{i+1} = z_i + 1$ or $z_{i+1} = z_i - 1$, depending on the rotation direction. In this way, the size and rotation angle of the new image $S_i$ can be defined as below. The length $l$ and rotation angle $\theta$ are calculated by:

$$
\begin{align*}
    l_{i+1} &= \sqrt{(l_i \cdot \cos \theta_i)^2 + z_{i+1}^2} \\
    \theta_{i+1} &= \theta_i + \arcsin \left( \frac{w_{\text{min},i}}{2l_{i+1}} \right)
\end{align*}
$$

(1)

where $l_0 = H_{\text{min}} + L$ and $L$ is an extension length and set to 15 pixels in this application based on our experience; $\Delta x, \Delta y$, and $\Delta z$ are spatial resolution, and $\Delta l$ is calculated by $\Delta x, \Delta y$, and/or $\Delta z$, depending on how the image is steered. The angle, $\theta$, is incremented so that the variation from one reconstruction image to its subsequent image is less than one voxel. The width and height of image $S_i$ are:

$$
w_{i+1} = w_{\text{min},i} + L, \quad h_{i+1} = 2 \cdot l_{i+1} + 1.
$$

4. After determining the size and steering angle of image $S_{i+1}$, the corresponding cross-sectional image is obtained by calculating the 3D coordinates $(x', y', z')$ in the CT space for each point $(n, m)$ on $S_{i+1}$:

$$
\begin{align*}
    x' &= X_c + m \cdot \cos \theta_{i+1} \\
    y' &= Y_c + n \\
    z' &= Z_c + m \cdot \sin \theta_{i+1}
\end{align*}
$$

(2)

5. Then the image intensity is interpolated by:

$$
\begin{align*}
    I'(x', y', z') &= (x' - x)(z' - z)I(x + 1, y, z + 1) + (x - x')(1 + z - z')I(x + 1, y, z) \\
    &\quad + (1 + x - x')(z' - z)I(x, y, z) + (1 + x - x')(1 + z - z')I(x, y, z + 1),
\end{align*}
$$

(3)

where $x$ and $z$ are the largest integers that are smaller than $x'$, and $z'$, respectively, and $y' = y$.

6. Project $B_i$ onto $S_{i+1}$ as initial $B_{i+1}$. For the first cross-sectional image, $B_0 = B_r$. Since sectional image $S_i$ is reconstructed to maximally cover the ROI, $S_i$ might be much larger than area actually covered the ROI. A small working area is defined inside $S_{i+1}$ to reduce processing time and help identify proper boundary. The working area is defined such that it is centered at $C_r$ with width $w_{\text{min},i} + L$ and height $h_{\text{min},i} + L$.

7. Based on initial $B_{i+1}$, boundary seeds are iteratively adjusted so that the total cost to travel through the entire boundary reach minimal, by applying the live-wire segmentation algorithm on $S_{i+1}$ to refine the segmentation result $B_{i+1}$.

8. Repeat the process for $-\pi/2 \leq \theta < \pi/2$.

9. If necessary, steer the 2D local sectional image in another direction and repeat the process above.

Figure 2 gives an example of ROIs that might be defined in image-guided lung intervention. Figures 2(a)-(c) show 2D sectional images that include top, middle, and bottom parts of the ROI (a lower paratracheal lymph node). The top part of this ROI is connected to the bottom part of an adjacent lymph node and the boundary between two lymph nodes is not clear. Figure 2 is the reference slice $S_r$ selected for the segmentation with $B_r$ defined using 2D live wire. Figure 2(c) is the projection of $B_r$ on $S_0$, showing that the object boundary varies slightly when steering $B_r$. $B_{i+1}$ is initialized using $B_i$. So, the variation is even smaller than that demonstrated in this example. Figure 3 shows segmentation of lymph nodes.
Figure 1. This figure shows how a selected reference sectional image $S_r$ is steered to assist in segmenting a 3D object. (a) The 3D coordinate system of the CT volumetric image. It consists of three directions: transverse, coronal, and sagittal directions. A 3D object on a 2D frame, for example a transverse section $S_r$, is a 2D boundary $B_r$. $B_r$ intersects with a sagittal plane on a straight line $L_b$. (b) $S_r$ is steered and $B_r$ is projected onto the new 2D sectional image $S_i$. Since the $S_r$ is steered slightly at a time, the object boundaries on two sequential reconstructed 2D images vary slightly, as shown in Figure 2. The projection of $B_r$ is iteratively adjusted to define $B_i$ on $S_i$. The result $B_i$ is then projected onto $S_{i+1}$ as an initial boundary to define $B_{i+1}$. The process continues until the whole object is defined. (c) This figure shows how a new slice is defined based on a previous 2D image.

Figure 2. Example ROI, a lower paratracheal lymph node, and its appearance on steered 2D sectional images. (a)-(c) Example top, middle, and bottom ROI parts on 2D images. The top part of ROI is merged into the bottom part of another lymph node. (d) is the reference sectional image $S_r$ selected with $B_r$ defined. (e) is the projection of $B_r$ onto images $S_5$, showing the object boundary varies slightly between two sequential images. Notice that $B_i$ is used to initialize $B_{i+1}$, not $B_r$. The difference between $B_i$ and $B_{i+1}$ is even smaller than that in (e).
3. RESULTS

To evaluate the performance of the proposed method, a set of ROIs used for validating the SSLW method were selected. Two high-resolution human chest CT scans were used. Scan 1 contains 702 512×512 2D axial sectional images, with voxel dimensions $\Delta x = \Delta y = 0.64$ mm and $\Delta z = 0.5$ mm. The second scan consists of 578 512×512 2D axial sectional images and has voxel dimensions: $\Delta x = \Delta y = 0.72$ mm and $\Delta z = 0.5$ mm. Both images were acquired without using contrast agent and reconstructed using soft kernels for better presentation of soft-tissue structures, such as lymph nodes and nodules. Scan 2 has lower axial plane resolution and is noisier than Scan 1.

The selected ROIs are lymph nodes that vary in size and shape. They are located in prevascular, retrotracheal, lower paratracheal, subaortic (AP window), and para-aortic lymph node stations. Since the CT images have limited presentation of soft-tissue structures, those ROIs might not be distinguishable from their neighbors because they are usually surrounded by other soft tissues, such as muscle, blood vessels, airway walls, and etc. Among the 20 selected lymph nodes, the SSLW was able to segment 14 of them, seven from each scan. The reference ground truth used for comparison was the segmentation results provided by an expert who used 2D live wire to define each ROI carefully slice by slice, similar to the ground truth adopted in previous live-wire work.

Table 1 gives a summary of the segmentation results derived from two segmentation approaches. Since SSLW may propagate to incorrect areas beyond the top and bottom limits in a processing direction (transverse, coronal, or sagittal), the accuracy was calculated based on main regions of those ROIs. Figure 4 demonstrates segmentation results of the two methods for two lymph nodes from Scan 2.

Though the SSLW demonstrates more accurate segmentation results than SILW, SILW is more flexible and is able to address several limitation arising from the SSLW method: 1) As shown in Figure 5, SSLW might easily propagate beyond the limits of a target, while the SILW is able to distinguish the ROI region from its neighbor; 2) Figure 6 demonstrates that SILW is able to address difficulty ROIs that SSLW might fail to process.

4. CONCLUSION

A semi-automatic approach is developed based on the live-wire algorithm to deal with 3D objects from chest CT image for image-guided lung interventional applications. The approach aims to address issues derived from our previous live-wire-based segmentation methods. The whole idea is to steer a multi-planar reconstruction image to produce a set of cross-sectional images that cover the object. Then, the objection boundary defined using live wire on the reference slice is propagated to the rotated sectional images. The segmentation results, compared with an existent evaluated approach, shows that the proposed approach keeps the efficiency while improving robustness.
<table>
<thead>
<tr>
<th>Lymph Node</th>
<th>Scan 1 (%)</th>
<th>Scan 2 (%)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>( a(M_1, T) )</td>
<td>( a(M_2, T) )</td>
</tr>
<tr>
<td>1</td>
<td>91</td>
<td>87</td>
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<tr>
<td>2</td>
<td>87</td>
<td>83</td>
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<tr>
<td>3</td>
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<td>72</td>
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<td>4</td>
<td>79</td>
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<td>5</td>
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<td>6</td>
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<td>7</td>
<td>75</td>
<td>67</td>
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<td>( \mu )</td>
<td>83</td>
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Table 1. Accuracy of lymph-node segmentation using the SSLW and SILW methods. The segmentation of major body of those ROIs are included here. The bounding areas (top and bottom) were excluded. For main part of SSLW resulted in better segmentation performance than SILW. \( M_1 \): SSLW; \( M_2 \): SILW; \( T \): ground truth.

Figure 4. Example segmentation results derived from the SSLW and SILW methods. (a)-(b) are a lower paratracheal lymph nodes segmented by SSLW and SILW. (c) shows the lymph node in original image. (d)-(e) are a prevascular lymph node segmented by SSLW and SILW. (f) shows the lymph node in original image. SSLW and SILW achieve similar result for the two ROIs.

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REFERENCES
Figure 5. Illustration of several issues using the SSLW method. (a)-(c): A lower paratracheal lymph nodes was segmented, from Scan 2, by SSLW and SILW. As it is shown in (c), the inferior part of the lymph node is very small, pointed by red arrow, and is about to disappear. However, SSLW did not terminate the process and included the superior area of an adjacent lymph node, pointed by green arrow, in (a). As a result, this segmentation may improperly segment two lymph nodes and treat them as one. SILW, however, did not make the same mistake, it distinguished the right area of the ROI from its neighbor, the orange dot as shown in (b). (d)-(f): Another lower paratracheal lymph node was processed from Scan 1. Similar to the previous lymph node, it is about to disappear at the showing location, as pointed by red arrow in (f). SSLW did not stop (d), but SILW did avoid the incorrect region (e).

Figure 6. A difficult ROI was selected in the lower paratracheal region (a). This lymph node was successfully segmented by SILW (b), but SSLW failed due to the complicated neighbor area involved (c).