Needle segmentation using 3D Hough transform in 3D TRUS guided prostate transperineal therapy

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Purpose: Prostate adenocarcinoma is the most common noncutaneous malignancy in American men with over 200 000 new cases diagnosed each year. Prostate interventional therapy, such as cryotherapy and brachytherapy, is an effective treatment for prostate cancer. Its success relies on the correct needle implant position. This paper proposes a robust and efficient needle segmentation method, which acts as an aid to localize the needle in three-dimensional (3D) transrectal ultrasound (TRUS) guided prostate therapy.

Methods: The procedure of locating the needle in a 3D TRUS image is a three-step process. First, the original 3D ultrasound image containing a needle is cropped; the cropped image is then converted to a binary format based on its histogram. Second, a 3D Hough transform based needle segmentation method is applied to the 3D binary image in order to locate the needle axis. The position of the needle endpoint is finally determined by an optimal threshold based analysis of the intensity probability distribution. The overall efficiency is improved through implementing a coarse-fine searching strategy.

The proposed method was validated in tissue-mimicking agar phantoms, chicken breast phantoms, and 3D TRUS patient images from prostate brachytherapy and cryotherapy procedures by comparison to the manual segmentation. The robustness of the proposed approach was tested by means of varying parameters such as needle insertion angle, needle insertion length, binarization threshold level, and cropping size.

Results: The validation results indicate that the proposed Hough transform based method is accurate and robust, with an achieved endpoint localization accuracy of 0.5 mm for agar phantom images, 0.7 mm for chicken breast phantom images, and 1 mm for in vivo patient cryotherapy and brachytherapy images. The mean execution time of needle segmentation algorithm was 2 s for a 3D TRUS image with size of 264 × 376 × 630 voxels.

Conclusions: The proposed needle segmentation algorithm is accurate, robust, and suitable for 3D TRUS guided prostate transperineal therapy. © 2013 American Association of Physicists in Medicine. [http://dx.doi.org/10.1118/1.4795337]

Key words: 3D TRUS, needle segmentation, prostate brachytherapy, prostate cryotherapy, 3D Hough transform

I. INTRODUCTION

Prostate adenocarcinoma (PCa) is the most common noncutaneous malignancy in American men with over 200 000 new cases diagnosed each year.1 Prostate transperineal therapy, such as brachytherapy and cryotherapy, has been a treatment option for clinically localized prostate cancer.2–5 Currently, localizations of inserted needles are subject to the skill level and experience of the physicians due to the difficulties of visualization of the needle in a 2D transrectal ultrasound (TRUS) image. 3D TRUS guided prostate therapy has been increasingly investigated since it can provide the spatial information which is not available in a 2D image.6–13 With information readily available in the third dimension, physicians can more easily view the gland from different angles and more accurately insert the needles in the correct positions. However, US speckle, along with shadows and other artifacts obscure the appearance of the needle, which poses a challenge for physicians while navigating in vivo.14,15 An image-based needle segmentation method has the potential to be an efficient and economical way to augment needle localization in complicated circumstances compared with hardware-based methods. A variety of percutaneous interventions, such as prostate biopsy,16 breast biopsy,17 and liver radio-frequency ablation
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II. METHODS

II.A. 3D Hough transform

The 2D HT has been widely used for line detection in 2D images in different kinds of applications due to its robustness and insensitivity to the noise.\cite{33,34,35,36} The Hough transform is essentially the angular projection of the 2D space onto 1D axis. It is motivated by the line-point duality between image space \((x, y)\) and parameter space \((a, b)\), where \(a\) and \(b\) are the slope and intercept of the line \(y = ax + b\) in the image.\cite{36} To extend 2DHT to 3DHT, it is a critical step to find a good representation for a line in 3D space. There are several different representations for a line in 3D space, such as point-and-vector representation.\cite{37} Denavit and Hartenberg
A desirable representation for the Hough transform should satisfy the following conditions: the set of lines and the set of representations can be placed into a 1-1 correspondence; the line representation should be continuous or differentiable; and the number of parameters should be small (four-parameter representation will be appropriate because a line in 3D space has four degrees-of-freedom). Considering the criterion, Roberts representation is appropriately used with the 3D Hough transform for applications outlined in this paper. A line in 3D space has four independent degrees-of-freedom, but for computational convenience, it is often represented with six parameters. These components are defined in terms of a point and an orientation (represented as a three-tuple over real numbers), e.g., the point \( p = (p_x, p_y, p_z) \) as the position of the point in Cartesian coordinates, and the orientation \( \vec{b} = (b_x, b_y, b_z) \). Then the line \( L \) may be parameterized with a real variable \( t \), expressed as a set of points in 3D space

\[
L = \{ r | r = p + t\vec{b} \}, \quad -\infty < t < \infty, \tag{1}
\]

its corresponding analytic formula is

\[
\frac{x - p_x}{b_x} = \frac{y - p_y}{b_y} = \frac{z - p_z}{b_z}. \tag{2}
\]

Equation (2) is the basic point-and-vector representation of a line in 3D space. In the Roberts representation, some constraints are imposed on this basic representation. The orientation of the line is expressed with a unit vector, given by two angles, azimuth \( \phi \) and elevation \( \theta \) [See Fig. 1(a)]. The orientation \( \vec{b} = (b_x, b_y, b_z) \) is defined as the direction cosines with respect to the coordinate axes \( x, y, \) and \( z \); then

\[
(b_x, b_y, b_z) = (\cos \phi \cos \theta, \sin \phi \cos \theta, \sin \theta), \tag{3}
\]

where \( \vec{b} \cdot \vec{b} = b_x^2 + b_y^2 + b_z^2 = 1 \).

The orientation of the line is determined by two parameters \((\phi, \theta)\), which is similar to the basic point-and-vector representation. A 2D coordinate frame on the \( B \)-plane [see Fig. 1(b)] using cartesian coordinates \((x, y)\) is defined in a way, in which it is perpendicular to the line and passes through the origin. The remaining two parameters are the coordinate values \((x', y')\) in that local frame, which is the intersection of the line with plane. Therefore, the straight line \( L \) can be represented by a four-tuple \((b_x, b_y, x', y')\), where \( b_x \) and \( b_y \) are components of the unit vector \( \vec{b} \) (with the requirement that \( b_x^2 + b_y^2 \leq 1 \)), which lies in the half-space \( z \geq 0(\vec{b}_z \geq 0) \). Actually, \( x' \) and \( y' \) are coordinates of the intersection of line \( L \) with the \( B \)-plane. Roberts representation naturally chooses a rotation transformation sending \( \hat{z} \) into \( \vec{b} \), which determines a coordinate frame on the \( B \)-frame. This coordinate frame is in all cases unique and well-defined, and does not require any special case handling. Then, the basis vectors \( \hat{x} \) and \( \hat{y} \) must be mapped onto the \( B \)-plane, where they can then be used to define the \( x' \)- and \( y' \)-axes. The rotation is specified uniquely and with no singularities in the plane of \( \hat{z} \) and \( \vec{b} \) by an angle of \( \arccos \hat{z} \cdot \vec{b} \) (It must be that \( \hat{z} \cdot \vec{b} \geq 0 \) because \( \vec{b} \) is required to lie in the half-space \( \hat{z} \geq 0 \)). This transformation is analogous to rotating about the axis \( \hat{z} \times \vec{b} \), and at first appears to fail when \( \hat{b} = \hat{z} \); however, the rotation can be defined without reference to a cross-product, and the standard formulas produce the correct result (no rotation) when the rotation angle is zero. The resulting rotation matrix \( A \) is denoted as

\[
A = \begin{pmatrix}
1 - \frac{b_x^2}{1 + b_z^2} & -\frac{b_x b_y}{1 + b_z^2} & b_x \\
-\frac{b_x b_y}{1 + b_z^2} & 1 - \frac{b_y^2}{1 + b_z^2} & b_y \\
-b_z & -b_y & b_z
\end{pmatrix}. \tag{4}
\]

Both mappings from representation to line, and from line into representation are “clean” in this case. Moreover, there is no special case, which requires conditional handling or interpretation. Given a line \( L \) in the standard point-and-orientation representation \((p, \vec{b})\), the \( b_x \) and \( b_y \) parameters in the four-parameter representation can be simply calculated from the
vector $\vec{b}$. The parameters $x'$ and $y'$ can be computed from the rotation matrix $A$,
\[
\begin{align*}
x' &= p \cdot A \hat{x} = \left( 1 - \frac{b_x^2}{l+b_x} \right) p_x - \frac{b_x b_y}{l+b_x} p_y - b_x p_z \\
y' &= p \cdot A \hat{y} = \left( 1 - \frac{b_y^2}{l+b_y} \right) p_y - \frac{b_y b_x}{l+b_y} p_x - b_y p_z.
\end{align*}
\]
(5)

Given a four-tuple $(b_x, b_y, x', y')$ representation, the line $L$ in point-and-orientation form can be derived as follows:
\[
\begin{align*}
x &= x' \left( 1 - \frac{b_x^2}{l+b_x} \right) - y' \frac{b_x b_y}{l+b_x} + t b_x \\
y &= -x' \left( \frac{b_x b_y}{l+b_x} \right) + y' \left( 1 - \frac{b_y^2}{l+b_y} \right) + t b_y \\
z &= -x' b_y - y' b_x + t b_z.
\end{align*}
\]
(6)

Equation (6) cannot be applied directly in the Hough transformation since $x'$ and $y'$ are infinitely bound. Similar to the traditional 2D Hough transform, polar coordinates $(\rho, \alpha)$ are used to take the place of Cartesian coordinates $(x', y')$. Thus, $(b_x, b_y, x', y')$ can be replaced by $(\phi, \theta, \rho, \alpha)$, where $\rho \in (0, \sqrt{N})$ (N is the width of a 3D image) and $\alpha \in (0, 2\pi)$. Finally, a line in 3D space can now be represented by the four-tuple $(b_x, b_y, \rho, \alpha)$, and given by
\[
\begin{align*}
\rho \cos \alpha &= \left( 1 - \frac{b_x^2}{l+b_x} \right) p_x - \frac{b_x b_y}{l+b_x} p_y - b_x p_z \\
\rho \sin \alpha &= \left( 1 - \frac{b_y^2}{l+b_y} \right) p_y - \frac{b_y b_x}{l+b_y} p_x - b_y p_z.
\end{align*}
\]
(7)

where vector $\vec{b}(b_x, b_y, b_z)$ can be represented by $(\phi, \theta)$. Therefore, the Hough parameter space for the 3DHT is a four-dimensional space, represented by a four-tuple $(\phi, \theta, \rho, \alpha)$. $\phi$ varies from $0^\circ$ to $360^\circ$, $\theta$ varies from $0^\circ$ to $180^\circ$, and $\alpha$ varies from $0^\circ$ to $360^\circ$ (usually step $d = 1^\circ$). Only the parameter $\rho$ needs to be computed in the Hough transformation.

II.B. Needle segmentation method

The proposed 3D needle segmentation method is based on the following assumptions: (1) In the 3D TRUS image, the needle appears as a long straight object with its axis length much greater than its diameter; (2) The image intensities of needle voxels are higher than the intensities of the background voxels; (3) The needle always passes into the 3D US image from one known plane ($y-z$ plane in Fig. 2) of the 3D US image without bending. With these hypotheses, our method can be separated into two parts: detecting the needle axis using the proposed 3DHT, and then identifying the needle endpoint.

II.B.1. Locating the needle axis with 3DHT

The 3DHT requires a large amount of memory since allocation of a four-dimensional parameter space [the accumulator $A(\phi, \theta, \rho, \alpha)$] is required. From the definition of the Roberts representation, it is known that the plane $B$ is perpendicular to the line passing through the 3D image data with size $N \times N \times N$. Furthermore, the intersection of plane $B$ with line $L$ must be located at the region that the 3D image is projected onto the plane $B$. The maximum projection area of the 3D image in all directions is $\sqrt{3}N \times \sqrt{3}N$. For the case of converting the coordinate of the intersection point to a polar coordinate, the following condition applies $\rho \in (0, \sqrt{6}N)$. With the angle step and distance interval defined by $d$ degrees and $l$ pixels, respectively, the memory requirement is given by
\[
M_{3DHT} = \frac{360}{d} \times \frac{180}{d} \times \frac{360}{d} \times \frac{\sqrt{6}N}{l} \approx 8 \times 10^7 \times \frac{N}{d^3 l}.
\]
(8)

For the case when $d = 2$, $l = 1$, $N = 300$, the memory requirement for 3DHT is approximately 6GB. However, the memory requirement and searching range will be reduced greatly under the condition that the needle insertion angle $(\phi, \theta)$ is approximately known and the 3D image can be cropped. The
needle axis location method consists of a preprocessing procedure before searching the needle axis.

II.B.1.a. Preprocessing the original 3D US image. In 3D US images, needle voxels generally have a high gray-level value [linear object with high brightness as Fig. 3(a)]. Similarly, some specular reflections from background structures may also appear as high gray-level values, which increases the difficulty of automatic needle segmentation. The orientation and insertion point of the needle are usually approximately known when the needle is inserted manually, or with a motorized mechanical device under computer control.\(^\text{40}\) For example, if the angle between the approximate needle direction and actual needle direction is \(\psi\) [shown in Fig. 2(a), \(\psi \leq [0, 50^\circ]\) in our experiments], then the Hough parameter \(\phi\) can be restricted to \([0, 40^\circ]\). This prior information can be used to discard portions of the 3D US image that do not contain the needle. The needle entry plane [see Fig. 2(b)] is first determined in the axial direction. The ROIs containing needles [rectangles in Fig. 2(b)] are manually chosen, assuming that each ROI includes only one needle. The cropped image is obtained by means of sweeping the ROI through the image cube along the negative direction of the \(x\) axis. The search for the needle can be limited in each uncropped image volume, as illustrated in Fig. 3(b), resulting in a decreased searching range of \(\phi\) in 3DHT. Within the scope of this approach the computational time and memory requirements are greatly decreased, and the robustness of the algorithm is increased. Moreover, the cropping can convert a 3D TRUS image to a number of subvolumes, reducing an original multiple-needle segmentation problem to a sequence of simple single-needle segmentation subproblems.

Since the Hough transform requires a binary image as the input, the binarization threshold needs to be determined after the cropping. We use the histogram of the cropped 3D gray-level image to identify the binarization threshold due to the high intensities of needle voxels in the US images. The histogram \(h(g)\), \(g = 0, 1, \ldots, 255\) of the 3D US image was calculated, where \(g\) represents the gray level. Using the histogram \(h(g)\), the image was then segmented by a threshold of

\[
TH = \operatorname{Max}\left\{ t \left( \sum_{g=0}^{255} h(g) \right) / N \geq p, t = 0, 1, \ldots, 255 \right\},
\]

(9)

where \(N\) is the sum of all the voxel points in the 3D US image, and \(p\) is the percentage of the feature points in the image. The value of \(p\) relates to the gain setting of US machine, needle insertion length and image size, and it must be large enough to ensure that the intensities of 80% needle voxels are greater than \(TH\). After the thresholding operation, all voxels with a gray-level larger than \(TH\) are needle candidate voxels (feature points), and are assigned a value of 1, while the other points with a lower gray level are the background points and are assigned a value of 0.

II.B.1.b. Finding the needle axis. With the traditional searching strategy of the Hough transform, all feature points in the 3D US binary image will be exhaustively examined. The main drawback of exhaustive searching is its large...
Step (1). Searching the candidate needle axis using 3DHT at the coarse stage
This step begins by obtaining a 3D US binary image with low resolution from the original binary image. Suppose that the original 3D US image is \( I(x, y, z) \) with size \( M \times N \times K \). At the coarse stage, we define its lower resolution image, \( g(x, y, z) \), as
\[
g(x, y, z) = I(\lambda x, \lambda y, \lambda z) \quad \text{with} \quad 0 \leq x \leq \frac{M}{\lambda}, \quad 0 \leq y \leq \frac{N}{\lambda}, \quad 0 \leq z \leq \frac{K}{\lambda},
\]
where \( \lambda \) is a magnifying factor (\( \lambda = 2 \) in our experiment). After obtaining the 3D lower resolution image \( g(x, y, z) \), the 3DHT algorithm is used to obtain the needle axis in image \( g(x, y, z) \). Since the 3D low resolution image is smaller than the original one, the speed of the segmentation algorithm is theoretically faster and the memory requirements is potentially smaller. Therefore, the approximate orientation and position of the needle axis can be found at the coarse stage, denoted by \((\phi^*, \theta^*, \rho^*, \alpha^*)\).

Step (2). Searching the needle axis at the fine stage
At the fine stage, the original image \( I(x, y, z) \) is used to obtain a high spatial accuracy. The approximate orientation and position of the needle axis \((\phi^*, \theta^*, \rho^*, \alpha^*)\) is known from the coarse stage. The least squares fitting (LSF) method is used to find more accurate parameters of the needle axis in the vicinity of \((\phi^*, \theta^*, \rho^*, \alpha^*)\) to \((\phi^* + \Delta\phi, \theta^* - \Delta\theta, \rho^* - \Delta\rho, \alpha^* + \Delta\alpha)\) to \((\phi^* + \Delta\phi, \theta^* - \Delta\theta, \rho^* + \Delta\rho, \alpha^* - \Delta\alpha)\). The four-tuple \((\phi^*, \theta^*, \rho^*, \alpha^*)\) can be rewritten as \((x_0, y_0, z_0, l, m, n)\) according to Eq. (3). The 3D line equation is defined as
\[
\frac{x-x_0}{l} = \frac{y-y_0}{m} = \frac{z-z_0}{n}.
\]
Its corresponding projective equation is given by
\[
\begin{align*}
x &= \frac{l}{m}(z-z_0) + x_0 = a_1z + a_2 \\
y &= \frac{m}{n}(z-z_0) + y_0 = b_1z + b_2,
\end{align*}
\]
where \(a_1 = \frac{l}{m}, a_2 = x_0 - \frac{l}{m}z_0, b_1 = \frac{m}{n}, b_2 = y_0 - \frac{m}{n}z_0\).

Based on the LSF, the equations of the two projective planes can be calculated and used to determine their intersection line, which is the desired extraction line. The errors between the practical and theoretical values are defined as
\[
\begin{align*}
D_x &= \sum_{i=1}^{N}(x_i - (a_1z_i + a_2))^2 \\
D_y &= \sum_{i=1}^{N}(y_i - (b_1z_i + b_2))^2,
\end{align*}
\]
where \(a_1, a_2, b_1, \) and \(b_2\) can be obtained by minimizing \(D_x\) and \(D_y\), which determines the desired needle axis. The minimization of \(D_x\) and \(D_y\) is conducted by solving the following derivative equations:
\[
\begin{align*}
a_2\sum_{i=1}^{N}z_i + a_1\sum_{i=1}^{N}z_i^2 &= \sum_{i=1}^{N}z_ix_i \\
b_1\sum_{i=1}^{N}z_i + b_2\sum_{i=1}^{N}z_i^2 &= \sum_{i=1}^{N}z_iy_i,
\end{align*}
\]

II.B.2. Needle tip determination

Typically, the needle is not entirely accessible in the field-of-view as only a portion of the tissue is scanned by the 3D TRUS probe [see hypothesis (3)]. Therefore, only one endpoint (referred to as needle endpoint) needs to be localized. We use Barva’s method to determine the needle endpoint in this paper. The mathematical morphology closing operation with a disk-shaped structuring element is first used to skip small breaks caused by noise in the image. The next step applies a predefined threshold value \(T\) to distinguish needle voxels from background voxels. Given the voxel intensity \(I\), the probabilities of the needle voxel and background voxel are \(P(T_1|I)\) and \(P(T_2|I)\), respectively, which are acquired from training datasets with known needle positions. The parameter \(T\) is estimated by the relationship: \(P(T_1|T) = P(T_2|T)\).

II.C. Experimental methods

II.C.1. 3D US image acquisition

To produce 3D images, video frames from a Philips HDI 5000 (Philips Medical Systems, Bothell, WA) were digitized with a Matrox Meteor II MC video frame grabber (Matrox, Montreal, Canada) at 30 Hz and saved to a personal computer. A Philips biplanar transrectal probe (Philips Medical Systems, Bothell, WA) with a central frequency of 7.5 MHz was rotated around its long axis over 120° so that 2D images were acquired in a fan geometry at a predetermined angular interval (0.5° in our experiments). These acquired 2D planes were reconstructed into a 3D image as the 2D images were acquired. The size of the 3D image was 264 × 376 × 630 voxels, with voxel size of 0.2 × 0.2 × 0.2 mm.40

The segmentation and tracking performance was first evaluated using agar and chicken breast phantoms. A skinless boneless chicken breast, which closely mimic the mechanical properties of tissue for needle insertion and US imaging, was placed into a plexiglass box and filled with agar to stabilize it.26 The needle segmentation algorithm was tested with the use of a rigid rod with a 1.2 mm diameter. The rod was used to avoid the effect of needle deflection, allowing for testing the accuracy of the algorithm under ideal conditions. A total of 20 agar and 20 chicken breast phantom images were used to evaluate our method, and each of them contains only one needle. The proposed approach was also validated with 25 3D TRUS guided cryotherapy images from six patients (five images for each subject). Each cryotherapy image contains one needle. In addition, ten 3D TRUS guided brachytherapy images for five patients (two images for each subject) were used.
II.C.2. Algorithm performance criteria

The algorithm performance was evaluated in each cropped 3D image containing only one needle. One expert chose two needle endpoints manually (starting point \( p_1 \) and ending point \( p_2 \)) by mouse selection using the software developed in our lab. The coordinates of these two points were used to calculate a Roberts line representation \((\phi, \theta, \rho, \alpha)\) in terms of Eqs. (3) and (7). This Roberts line representation and the needle endpoint manually (starting point \( p_1 \)) in Robarts and the needle parameters. A needle tip \( p'_1 \) and a Roberts line representation \((\phi', \theta', \rho', \alpha')\) generated by our algorithm were compared quantitatively to ground truth using the following two metrics:

1. The angular deviation \( \beta \) denotes the angle between the algorithm segmented needle and standard needle in Robarts space

\[
\beta = \arccos \left( \frac{b'_x b_x + b'_y b_y + b'_z b_z}{\sqrt{b'_x^2 + b'_y^2 + b'_z^2} \sqrt{b_x^2 + b_y^2 + b_z^2}} \right),
\]

where \( (b'_x, b'_y, b'_z) = (\cos \phi' \cos \theta', \sin \phi' \cos \theta', \sin \theta') \) and \( (b_x, b_y, b_z) = (\cos \phi \cos \theta, \sin \phi \cos \theta, \sin \theta) \).

2. The position deviation \( \xi \) was defined as the Euclidean distance between the true needle tip \( p_2 \) and segmented tip \( p'_2 \).

3. The proposed algorithm was implemented in C++. The experiments were conducted on a Windows desktop with a Intel Core i3 CPU (3.06 GHz) and 4 GB memory. The mean needle algorithm segmentation time \( t \) is used to describe the efficiency of our segmentation algorithm, where \( t = \frac{1}{n} \sum_{i=1}^{n} T_i \). Each 3D US image was iteratively processed \( n \) times \( (n = 10 \) in our experiments), and \( T_i \) was the computational time required for each iteration.

II.C.3. Parameter selection sensitivity test

II.C.3.a. Default parameter value. The effects of the following parameters were evaluated for agar and chicken breast phantoms: cropped volume dimensions \( a \) and \( b \), insertion angulation \( \psi \), insertion length \( L \), binarization threshold \( p \), and step size \( \lambda \) in coarse-fine searching. Initially, the angular deviation \( \beta \) and position deviation \( \xi \) were evaluated for a selected set of parameter values for each phantom, as listed in Table I. Those tabulated parameters are henceforth designated as the default parameter values. Subsequently, the effect of each parameter on the algorithm performance was investigated by varying each value independently, while the remaining parameters were fixed at their standard values. The corresponding variations in \( \beta \) and \( \xi \) were then recorded. In regard to the cropped volume dimensions, the default value \( a \) was chosen as the median of the five values \((61, 81, 101, 121, 141)\) voxels), and similarly \( b \) was chosen as the median of the five investigated values \((250, 280, 300, 320, 350)\) voxels).

II.C.3.b. Cropped volume dimension. A cropped volume of dimensions \((a \times a \times b)\) described above was used in each of the above cases. For both phantom types, we used \( a = 61, 81, 101, 121, \) and \( 141 \) voxels with the default value \( b = 300 \) voxels, and values of \( b = 250, 280, 300, 320, \) and \( 350 \) voxels with the default value \( a = 81 \) voxels. The computational time \( t \) is solely a function of the cropped volume dimensions \( a \) and \( b \), which varies along with the size \( V = ab^2 \). Similarly, \( t \) was measured with the default value of \( b \), while \( a \) was varied.

II.C.3.c. Binarization threshold \( p \). Binarization is an important preprocessing procedure of 3DHT. The determination of binarization threshold \( p \) with a high level of precision is crucial as it affects the accuracy of the algorithm. The experiments were done for both agar and chicken breast phantoms, by varying different step size from 0.1 to 0.5 in 0.1 increments, while holding all other parameters at their default values.

II.C.3.d. Needle insertion length and orientation. Even though the cropped volume dimensions \( a \) and \( b \) generally depend on \( \psi \), they were kept at their default values, while \( \psi \) was varied from \( 2^\circ \) to \( 50^\circ \) in \( 5^\circ \) steps. For agar and chicken breast phantoms, this was done for 3D images obtained at \( L = 10, 25, \) and \( 45 \) mm, with \( 25 \) mm being the default value in each case.

<table>
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<th>Table I. The default parameter values for the agar and chicken breast phantoms.</th>
<th>( a ) (voxel)</th>
<th>( b ) (voxel)</th>
<th>( \psi ) (°)</th>
<th>( L ) (mm)</th>
<th>( p )</th>
<th>( \lambda )</th>
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<td>101</td>
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</table>

III. RESULTS

III.A. Performance for the default parameter values

Figure 3(a) is an original 3D US image of a needle in an agar phantom. Its cropped image shown in Fig. 3(b), was generated by volume rendering using ray casting. Figure 3(c)
shows the binarization result of the cropped 3D US image, which provides information regarding hyperintense voxels. The segmentation result is shown in Figs. 3(d)–3(f), in which the highlighted solid line is the detected needle axis using our algorithm. The result of one chicken breast phantom image is shown in Fig. 4. Quantitative validation results for the default parameter values listed in Table I are summarized in Table II.

For the agar phantom, we found that $\beta = 0.4^{\circ} \pm 0.16^{\circ}$ and $\xi = 0.5 \pm 0.15$ mm, and for the chicken breast phantom we found $\beta = 0.6^{\circ} \pm 0.21^{\circ}$ and $\xi = 0.7 \pm 0.34$ mm.

### III.B. Effect of varying the cropped volume dimension

The variations of $\beta$ and $\xi$ with the cropped volume dimensions $a$ (varied from 61 to 141) and $b$ (varied from 300 to 350) were small for both agar and chicken breast phantom images, and fell within $\pm 0.2^{\circ}$ and $\pm 0.2$ mm, respectively. These experimental results demonstrate the robustness of the proposed algorithm, provided that the cropped volume includes the entire image of the needle. However, the 3D needle segmentation algorithm will fail when a portion of the needle is mistakenly cropped. Therefore, maintaining the volume during cropping without cutting into the section of the image that contains the needle, is necessary to guarantee segmentation accuracy. The results for the computation time $t$ are plotted in Fig. 5, where $t$ varies in an almost linear fashion with the size of the cropped volume for both phantom types, where $V = a^2 b$. Moreover, $t$ has been found to be slightly higher in chicken breast phantoms than it is for agar phantoms. The difference in the $t$ value is due to the increased number of background (non-needle) objects presented in the chicken breast phantom images after binarization. Therefore, it is best to crop the volume as much as feasible in order to decrease the computational time.

### III.C. Effect of varying the needle insertion length and orientation

The observed $\beta$ and $\xi$ with $\psi$ varying from $0^{\circ}$ to $50^{\circ}$ are plotted in Fig. 6 for each needle insertion length investigated in both agar and chicken breast phantoms. It can be seen that $\beta$ and $\xi$ are both insensitive to $\psi$, whereas both vary slightly with needle insertion length for the case of long insertion lengths (needle length more than 10 mm). At the longest needle insertion length investigated (45 mm in agar and chicken breast phantoms), the mean value of $\beta$ was $0.52^{\circ}$ and $0.62^{\circ}$ for agar and chicken breast phantoms, respectively. The mean value of endpoint position deviation $\xi$ at the longest needle length investigated (45 mm in agar and chicken breast phantoms) were 0.65 and 0.78 mm for agar and chicken breast phantoms, respectively. At the shortest needle insertion length investigated (10 mm in agar phantom), the mean value of $\beta$ increased to about $0.76^{\circ}$, and the mean value of $\xi$ increased to 1.1 mm. For the shortest needle insertion length (10 mm in chicken breast phantom), the mean values of $\beta = 0.82^{\circ}$ and $\xi = 1.2$ mm were found, respectively. There is an increased

### Table II. Segmentation algorithm performance in phantom images for the default parameter values of Table I.

<table>
<thead>
<tr>
<th></th>
<th>$\beta$ (°)</th>
<th>$\xi$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agar</td>
<td>0.4 ± 0.16</td>
<td>0.5 ± 0.15</td>
</tr>
<tr>
<td>Chicken breast</td>
<td>0.6 ± 0.21</td>
<td>0.7 ± 0.32</td>
</tr>
</tbody>
</table>

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**Fig. 4.** Results of needle segmentation during insertion of a needle into a chicken breast phantom with a graphical 3D display of the needle targeting superposed on the view. (a) coronal view, (b) sagittal view, and (c) transverse view.

**Fig. 5.** Computational time result with different volume size.
FIG. 6. Accuracy of the 3D needle segmentation algorithm, as measured by the angular deviation $\beta$ in (a) and (c), and the deviation $\xi$ in length or endpoint position in (b) and (d), between the algorithm and manually segmented 3D needle vectors, plotted as a function of the angular deviation $\psi$ of the a priori approximate needle direction from the manually segmented needle direction.

uncertainty in the needle orientation when inserted to shallow depths, resulting in a corresponding slight offset of the endpoints of the straight line detected by the proposed method.

III.D. Effect of varying binarization threshold $p$

The variation of $\beta$ and $\xi$ with binarization threshold $p$ are plotted in Fig. 7. For agar phantoms, it was found that $\beta < 1^\circ$ and $\xi < 0.85$ mm for $0.25 < p < 0.35$. Also, it was found that $\beta < 1^\circ$ and $\xi < 1$ mm for $0.25 < p < 0.35$. For both agar and chicken breast phantoms, it was found that $\beta$ and $\xi$ generally increased rapidly for $p < 0.2$ and $p > 0.4$. Due to their uniform background, agar phantom images are generally less sensitive to variations in the parameter $p$ than chicken breast phantom images. It is noted that the binarization threshold $p$ acts as a matched filter for the needle voxels. The number of voxels within the binarization that contains echoes is critical, otherwise the estimated direction and endpoint positions of the needle in the 3D US images may be inaccurate. Similarly, the default binarization threshold $p = 0.3$ is not ideal for the different US machine settings, such as gain setting. In order to include more needle voxels into the needle target, a different binarization threshold is used for the different US machine gain settings. The following values for $p = 0.25, 0.3, 0.35$ were found to produce the optimum results in our experiments corresponding to US machine gain settings of 35dB, 40dB, and 50dB, respectively. Optimizing these parameters allows for more needle voxels to be included in the needle candidate cluster, while excluding more background noise.

III.E. Effect of varying step $\lambda$

The results for the computational time $t$ are plotted versus step size $\lambda$ over a range $1 \leq \lambda \leq 5$ as shown in Fig. 8(a), and the values of $\beta$ and $\xi$ with step size $\lambda$ are shown in Figs. 8(b) and 8(c). The parameter $t$ was found to decrease almost linearly with an increasing step size $\lambda$ for both phantom types. Moreover, $t$ is consistently higher for the chicken breast phantom. When $\lambda = 5$, the computational time is 1.5 s for the chicken breast phantom, and 0.8 s for the agar phantom. However, the values of $\beta$ and $\xi$ increase for increasing values of $\lambda$. For the case when $1 \leq \lambda \leq 4$, the values of $\beta$ and $\xi$ slightly increased for both phantom types. When $\lambda \geq 4$, the values increased greatly. Larger values of $\lambda$ can cause
failure of the segmentation. Therefore, \( \lambda = 2 \) is a strategic choice considering the trade off between segmentation efficiency and accuracy.

**III.F. In vivo experimental results**

Figure 9 shows the result of the needle segmentation algorithm in two patient images, obtained during a prostate cryotherapy procedure and a prostate brachytherapy procedure, respectively. The needle orientation and position in relation to the 3D TRUS image are displayed in the reconstructed volume using ray casting rendering. As seen in Fig. 9, the needle has been well segmented from the 3D US images, which is represented by the highlighted solid line. The results in Table III show that the angular errors for patient cryotherapy and brachytherapy datasets are \( 0.8^\circ \pm 0.25^\circ \) and \( 0.8^\circ \pm 0.21^\circ \), respectively, and the tip localization errors for these two types of patient images are \( 1 \pm 0.34 \) and \( 0.9 \pm 0.32 \) mm, respectively. ANOVA analysis with a single factor showed that there is no statistically significant difference between segmentations for two kinds of patient images in terms of angular error and tip localization (\( p = 0.51, F = 0.72 \) and \( p = 0.6, F = 0.82 \), respectively). The mean computational time for each cropped subimage was \( 0.2 \pm 0.05 \) s, leading to a total segmentation time of less than 2 s for each 3D TRUS guided brachytherapy image.

**IV. DISCUSSION AND CONCLUSION**

Needle segmentation plays an important role in 3D TRUS guided prostate transperineal therapy. The main purpose of this study was to develop an image-based needle segmentation method in 3D TRUS images, which can automatically extract the needle from the 3D TRUS images. Thus, segmented needles would be visualized and augmented in the 3D TRUS images, aiding physicians to locate the needle accurately in prostate transperineal therapy. The proposed needle segmentation method is based on 3D HT, which can automatically determine the needle axis with 3D HT and identify the needle endpoint by an optimal threshold of statistical probability distribution of voxel intensity and geometrical information.

**FIG. 8.** Experimental results varying \( \lambda \). (a) computational time, (b) \( \beta \), and (c) \( \xi \) varying \( \lambda \) from 1 to 5. The remaining parameters were kept at their default values, given in Table I.
Finally, a coarse-fine searching strategy is applied to refine the searching result and accelerate this task. The experimental results demonstrate that our approach is capable of accurately determining the needle direction and its endpoint in agar and chicken breast phantoms. The achieved endpoint localization accuracy is 0.5 mm for agar phantom images, and 0.7 mm for chicken breast phantom images. Provided that the volume size is cropped conservatively, the average computational time is close to 2 s for each 3D TRUS image with a size of 264 × 376 × 630 voxels with our dual core 3.4 GHz PC.

Validation on patient 3D TRUS images obtained in prostate cryotherapy and brachytherapy procedures shows that the angular error is 0.8° and tip localization error is 1 mm. The proposed method was also compared to some previous studies. The closest previous studies to our work were by Wei26, 27 and Ding.8, 25 Wei’s method relied on the difference image by subtracting the prescan no-needle image from the postscan needle image. Our proposed method makes use of only the postscan needle image, decreasing the complexity of image acquisition. Furthermore, our method reduced the segmentation errors caused by the motion of the prostate, which is difficult to avoid in Wei’s method. In addition, the orthogonal projection based method proposed in Refs. 8 and 25 was also tested on our cropped images, since it cannot directly segment the images with multiple needles. His method used orthogonal two-dimensional image projections to reduce a 3D segmentation to a 2D segmentation problem, achieving a good computational efficiency (about 10 fps). However, it suffers from interference caused by artifacts. A direct comparison with our method showed that a similar result was obtained in simulated images (agar images) by Ding8, 25 with a root-mean-square mean accuracy in needle endpoint localization of 0.5 mm, which is comparable to our method in agar phantom images. However, it failed to segment the needles in 30% of our patient images. Thus, our proposed approach exhibited the advantages on both accuracy and robustness.

It should be noted that the proposed multiple-needle segmentation technique is not a generalized 3D line detection algorithm, as was especially developed for 3D TRUS guided prostate transperineal therapy,6–9 where needles are typically spaced in an approximately parallel manner. In this application, we made use of this prior information by cropping an input 3D image to several needle subimages by choosing the ROIs manually. The cropping procedure reduces the size of the processed image, improving the computational efficiency. Furthermore, it excluded interference of artifacts appearing as similar structures as needles in patient images [Figs. 3 and 9(b)], which could reduce segmentation accuracy. If several lines such as those shown in Fig. 3(c) or artifacts do exist, our proposed approach will typically segment the longest one. Thus, a careful initialization is required in our application to guarantee a robust segmentation.
Additionally, binarization plays a critical role in our proposed 3D needle segmentation approach. A manual thresholding technique based on histogram was applied to binarize the input needle image in our application. In addition, we also tested automatic thresholding methods, such as OTSU, Niblack and Bernsen.\textsuperscript{41} Qualitative experiments show that these methods can successfully binarize some images, but failed in other cases, since these methods are derived from maximization of log-likelihoods that are based on mixtures of Gaussian distributions. However, the Gaussian model cannot correctly describe intensity distributions for different classes in ultrasound images. A more accurate and robust automatic thresholding method is still highly desired in our application.

The proposed 3DHT based needle segmentation is both a time and memory-consuming approach. It requires a large memory for allocating a four-dimension array, and uses an exhaustive searching strategy when mapping each feature point to the Hough space. The coarse-fine searching strategy used in this study can improve this issue, but a more efficient algorithm is still needed. To speed up the algorithm, such as parallelizing the algorithm and optimizing the searching strategy, remains to be one of our future tasks. In addition, the proposed method can only segment one needle in a 3D TRUS image at a time. We reduced a multiple-needle segmentation problem to a sequence of single-needle segmentation subproblems by means of the cropping when facing the task segmenting multiple needles. The cropping procedure is capable of facilitating the multiple-needle segmentation problem, but adding to the user interactions and increasing the processing complexity. Another future task includes reducing user interaction when dealing with the multiple-needle segmentation. Furthermore, the proposed approach currently would not be able to handle the situation that needles are reflecting and bending since our method is based on the representation of a straight line, which does not allow for the extension to a curved geometry. Curved needle segmentation remains to be another important topic.

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