Automatic Needle Segmentation in 3D Ultrasound Images Using 3D Improved Hough Transform

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ABSTRACT

3D ultrasound (US) is a new technology that can be used for a variety of diagnostic applications, such as obstetrical, vascular, and urological imaging, and has been explored greatly potential in the applications of image-guided surgery and therapy. Uterine adenoma and uterine bleeding are the two most prevalent diseases in Chinese woman, and a minimally invasive ablation system using a needle-like RF button electrode is widely used to destroy tumor cells or stop bleeding. To avoid accidents or death of the patient by inaccurate localizations of the electrode and the tumor position during treatment, 3D US guidance system was developed. In this paper, a new automated technique, the 3D Improved Hough Transform (3DIHT) algorithm, which is potentially fast, accurate, and robust to provide needle segmentation in 3D US image for use of 3D US imaging guidance, was presented. Based on the coarse-fine search strategy and a four parameter representation of lines in 3D space, 3DIHT algorithm can segment needles quickly, accurately and robustly. The technique was evaluated using the 3D US images acquired by scanning a water phantom. The segmentation position deviation of the line was less than 2mm and angular deviation was much less than 2°. The average computational time measured on a Pentium IV 2.80GHz PC computer with a 381×381×250 image was less than 2s.

Key words: 3D ultrasound images, needle segmentation, 3D Improved Hough transform

1 INTRODUCTION

3D US is a developing technology that benefits from the advances in computer technology and 3D visualization techniques. It has been widely used in a variety of diagnostic applications such as obstetrical, vascular, and urological imaging [1,2]. In the past few years, use of 3D US has been explored for the applications in image-guided surgery [3] and therapy [4-6]. In this paper, we explored the use of 3D US for the accurate localization of the needles used in these applications.

Uterine adenoma and uterine bleeding are two most prevalent diseases in pregnant women in China. Traditionally, physicians perform an invasive operation to remove the tumor, cut or partially cut the uterus with the help of a celioscope or hysteroscope. Recently, a minimally invasive ablation system using a needle-like RF electrode was developed. The high temperature produced by the electrode destroys tumor cells or stops uterine bleeding.
The current uterine adenoma and uterine bleeding ablation system used in Chinese hospitals is guided by 2D ultrasound (US) imaging. The physician operates the RF electrode and the US probe with both hands simultaneously, or with the help of other physician. The insertion of the electrode guided by 2D US images is highly dependent on the skill of the physician. Because the electrode is needle-like, the physician can only observe the whole electrode when it is completely located on the image plane. Any hand motion may cause the electrode to exit the US plane and lead to errors in locating the tip of the electrode. This not only increases the difficulty in localizing the electrode but also is the main cause of accidents, even the death of patients.

However, stereotactic 3D ultrasound Image-guided RF ablation system [6] developed in our laboratory could overcome many of the limitations of 2D US technique, by providing accurate localization of the 3D needle trajectory and tip position. The 3D US image was reconstructed from a sequence of 2D US images using a rotational scanning approach of an abdominal US probe. However, the segmentation of the needle in a 3D US image is needed.

The segmentation of a needle in a 3D ultrasound image of the uterus is difficult because of speckle noise, low contrast, signal loss due to shadowing, refraction and reverberation artifacts. These effects often make traditional local operators, such as edge detectors, difficult to find the needle. Thus, the challenge of needle segmentation is to develop a fast and robust needle segmentation technique that is not sensitive to missing sections due to the echo shadows or boundary “noise” due to image speckle. To solve the problem, some needle segmentation methods have been proposed [7-8]. But the segmenting time required is highly depending on the widths of the needle parameter ranges, according to the information about the approximate needle position and orientation in priori, or cannot provide accurate segmentation, even produce incorrect segmentation.

In this paper, we described a new automated technique, the 3D Improved Hough Transform (3DIHT) algorithm, which is potentially fast, accurate, and robust to provide needle segmentation in 3D US image for use of 3D US imaging guidance. Based on the coarse-fine search strategy [9] and the representation (Φ, θ, ρ, α) of lines in 3D space [10], we used the 3DIHT algorithm to segment needles quickly, accurately and robustly.

The paper is organized as follows: In Section 2 the new representation (Φ, θ, ρ, α) of straight lines in 3D space and the 3D Hough Transform (3DHT) algorithm is described. In Section 3, the 3D Improved Hough Transform algorithm is discussed in detail. In Section 4 the methods of evaluations are described. The experimental results and discussion are presented in Section 5. We made our conclusion in Section 6.

2 3D HOUGH TRANSFORM ALGORITHM

2.1 Representation (Φ, θ, ρ, α) of straight lines in 3D space

A straight line in 3D Cartesian coordinate can be defined in terms of a point \( p \) and an orientation vector \( b \). We can represent each of these components as a 3-tuple. Therefore, a line can be expressed by 6 parameters. Is it possible to represent a line with less parameter?

In 1988, Roberts [10] proposed a representation of straight lines in 3D space. First, the orientation vector \( b \) of a line \( L \) is specified by two angles azimuth \( \Phi \) and elevation \( \theta \) as \((\cos\Phi\cos\theta, \sin\Phi\cos\theta, \sin\theta)\), which is showed in Fig.1 (a). Then, the position of the line is described as shown in Fig.1 (b): rotate the original Cartesian coordinate frame \( X-Y-Z \) such that the new coordinate \( Z' \) is overlapped with the orientation vector \( b \). Now, the intersection \( P \) of the line with the plane \( X'OY' \) can be described as \((x', y', 0)\) in new Cartesian coordinate frame, i.e., two parameters.
In this way, the straight line $L$ is represented by a 4-tuple $(\Phi, \theta, \rho, \alpha)$, where the intersection of the line with the plane could be given as the polar coordinates $(\rho, \alpha)$. To prevent double representation of the same line, the angles must be constrained the ranges $\Phi \in [0, 2\pi)$ and $\theta \in [0, \pi/2]$. According to the rotation, the line $L$ can be determined by the below two equations with the new 4-tuple $(\Phi, \theta, \rho, \alpha)$:

$$
\begin{align*}
(1 - \frac{b_x^2}{1 + b_x^2})x - \frac{b_x b_y}{1 + b_x^2}y - b_x z &= x' \\
(1 - \frac{b_y^2}{1 + b_y^2})y - \frac{b_y b_y}{1 + b_y^2}x - b_y z &= y'
\end{align*}
$$

(1)

where $(b_x, b_y, b_z) = (\cos \Phi \cos \theta, \sin \Phi \cos \theta, \sin \theta)$, $(x', y') = (\rho \cos \alpha, \rho \sin \alpha)$.

Fig. 1. Representation $(\Phi, \theta, \rho, \alpha)$ of a straight line $L$ in 3D Cartesian coordinate. (a) The orientation vector $b$ of a line $L$ is specified by two angles azimuth $\Phi$ and elevation $\theta$; (b) The point $P$ is determined by $(X', Y')$, where $(X', Y', Z')$ is a rotational coordinate of $(X, Y, Z)$ when $Z'$ is overlapped with $b$.

2.2 3D Hough Transform method with the new line representation

Based on the new line representation of $(\Phi, \theta, \rho, \alpha)$, the 3D Hough transform (3DHT) [7] can be extended from 2D Hough transform to detect the straight needles in 3D US images. For each point $(x, y, z)$ in 3D image, the parameters $(\rho, \alpha)$ of the needle can be solved if the parameters $(\Phi, \theta)$ are specified. We assume that there is only one needle in each 3D US image in our application.

The 3D Hough transformation algorithm with the new line representation is composed of following steps:

Step 1: Create a set $D$ of all edge points of a 3D image. Determine the proper threshold according to the histogram of the 3D image, and convert the original 3D image into a binary 3D edge image.

Step 2: Calculate the Hough parameter accumulator $H(\Phi, \theta, \rho, \alpha)$. The ranges of 3D line parameters can be further decreased if the approximate needle position and orientation are known. Initialize $H(\Phi, \theta, \rho, \alpha)$ with zeros.

Step 3: For each 3D edge point $(x, y, z)$, calculate all possible parameters $(\Phi, \theta, \rho, \alpha)$ using the 3D line’s equations, and accumulate the $H(\Phi, \theta, \rho, \alpha)$.
Step 4: Detect the global maximum cell $H_{\text{max}}$ in the $H(\Phi, \theta, \rho, \alpha)$. $(\Phi_{\text{max}}, \theta_{\text{max}}, \rho_{\text{max}}, \alpha_{\text{max}})$ will be the parameters of the needle in the 3D image.

3 3D IMPROVED HOUGH TRANSFORM ALGORITHM

3.1 Volume cropping

In 3D US image, the voxels of needle echoes generally have a high gray value. However, due to specular reflection, some background structures may also appear a high gray value such as the white surface in the middle and at the top of the original 3D US image, as shown in Fig. 2(a). This increases the difficulty in automatic segmentation of needle in a 3D US image using 3D Hough transform methods. To overcome this problem, it is needed to crop these structures before we employ the 3D Hough transform.

Moreover, volume cropping can considerably reduce the amount of data, which have to be processed for each projection image, and reduce the required image processing time, which is critical in image guided surgery and therapy application. In uterine adenoma surgery and therapy using RF ablation, the orientation and insertion point of the needle are usually approximately known, e.g., when the needle is inserted manually, or with a motorized mechanical device under computer control. This a priori knowledge can be used to discard portions of the 3D US image, which do not contain the needle, so that the search for the needle can be restricted to the remaining cropped image volume, as illustrated in Fig. 2(b). We used the method proposed in Ref. [8] to perform the volume cropping of the 3D US images.

3.2 Coarse-fine search strategy

In a variety of fast implementation algorithms of the Hough Transform, the Multi-resolution Hough Transform (MHT) proposed by Antiquzzaman is the fastest [11]. It was motivated by the hierarchical representations of both image space and parameter space, where different resolutions are used at different stages of the procedures. Unfortunately use of a lower resolution in parameter space will lead to a decrease of needle segmentation accuracy. Furthermore, the selection of parameter values such as the resolution at different stages is rather difficult and often causes a variation of the accuracy and affects the robustness of the method. Ding [9] used a two stage search strategy (coarse–fine search strategy) in image space only to segment needles in 2D US images in real-time. We used the coarse-fine search strategy in 3D image space only in 3DIHT method to segment needle in 3D US images.

3.3 3D Improved Hough Transform method

In 3D Improved Hough transform method, we used the coarse-fine search strategy to segment needles in 3D US images. Suppose that the original 3D US image is $f(x, y, z)$ with a size of $M \times N \times K$. At the coarse stage, we define its lower resolution image, $g(x, y, z)$, as

$$g(x, y, z) = f(\lambda x, \lambda y, \lambda z)$$

$$0 \leq x \leq M, 0 \leq y \leq N, 0 \leq z \leq K$$

(2)

where $\lambda$ is a magnifying factor and $M, N, K$ is the size of $g(x, y, z)$ determined by

$$M = \frac{M}{\lambda}, N = \frac{N}{\lambda}, K = \frac{K}{\lambda}$$

(3)

In the lower resolution 3D US image $g(x, y, z)$, the needle can be segmented more quickly because of the smaller images,
by using 3DHT method without any prior information of the needle. Therefore at the coarse stage, the approximate orientation and position of the needle were found, denoted by \((\Phi', \theta', \rho', \alpha')\).

At the fine stage, the original image \(f(x, y, z)\) was used to obtain high spatial accuracy. The approximate needle orientation and position \((\Phi', \theta', \rho', \alpha')\) were known from the coarse stage. At the fine stage the 3DHT method was used to detect needles accurately while the parameter ranges of \((\Phi, \theta, \rho, \alpha)\) were set to be the vicinity of \((\Phi', \theta', \rho', \alpha')\), i.e., \((\Phi'-\Delta\Phi, \theta'-\Delta\theta, \rho'-\Delta\rho, \alpha'-\Delta\alpha)\) to \((\Phi'+\Delta\Phi, \theta'+\Delta\theta, \rho'+\Delta\rho, \alpha'+\Delta\alpha)\). The deviation \(\Delta\Phi, \Delta\theta, \Delta\rho\) and \(\Delta\alpha\) were set to be proportional to magnifying factor \(\lambda\), i.e., \(\Delta=k\lambda\), for the sake of simplification. In our experiments \(k=0.5\) was used. \((\Phi^*, \theta^*, \rho^*, \alpha^*)\) is the needle detected in 3D US image. We assume that there is only one needle in each 3D US image, and \(D\) is the length of the 3D US image cube’s diagonal.

The steps of the algorithm are described as follows:

1. Create a set \(D\) for all edge points of a 3D image.
   Set the proper threshold according to the histogram of the 3D image, and convert the original 3D image into a binary edge 3D image.

2. At the coarse stage, use 3DHT method described in Sec. 2.2 to get the approximate orientation and position of the needle, denoted by \((\Phi', \theta', \rho', \alpha')\).
   Obtain the lower resolution image \(g(x, y, z)\) from the original image \(f(x, y, z)\). Use the 3DHT method to segment needle in image \(g(x, y, z)\) with the whole parameter ranges, where \(\Phi\in[0,2\pi]\), \(\theta\in[0,\pi/2]\), \(\alpha\in[0,2\pi]\) and \(\rho\in(0,D]\).

3. At the fine stage, use 3DHT method to detect the needle in original 3D US images.
   Use 3DHT method to detect needles accurately while the parameter ranges of \((\Phi, \theta, \rho, \alpha)\) were set to be the vicinity of \((\Phi', \theta', \rho', \alpha')\) such as \((\Phi'-\Delta\Phi, \theta'-\Delta\theta, \rho'-\Delta\rho, \alpha'-\Delta\alpha)\) to \((\Phi'+\Delta\Phi, \theta'+\Delta\theta, \rho'+\Delta\rho, \alpha'+\Delta\alpha)\). The parameter deviations \(\Delta\) were set to be proportional to magnifying factor \(\lambda\).

4. At the fine stage, find the line parameters \((\Phi^*, \theta^*, \rho^*, \alpha^*)\) as the maximum point in \(H(\Phi, \theta, \rho, \alpha)\). \((\Phi^*, \theta^*, \rho^*, \alpha^*)\) is the parameters of the needle in the 3D image.

4 EXPERIMENTAL EVALUATION: METHODS

4.1 3D US image acquisition and manual needle segmentation

A 3D US image guidance system developed in our laboratory [6] was used to obtain our experimental 3D US images of water phantom. To evaluate the performance of 3DIHT algorithm, we compared our automatic segmentation results with manual segmentation. Using the 3D US image guidance software, we can segment the needle in 3D US images manually [7].

4.2 Evaluation of accuracy and speed

We compared the detected needle parameters \((\Phi_d, \theta_d, \rho_d, \alpha_d)\) by using 3DIHT algorithm with the standard parameters \((\Phi_s, \theta_s, \rho_s, \alpha_s)\) with respect to the manual segmentation [7]. The evaluation of accuracy includes angular deviation and position deviation between the segmented needles and the manually segmented needles.
(1) Orientation Deviation

The orientation deviation $\beta$ is described as the angular between the orientations of the segmented needles and the actual needles, and is defined below:

$$
\cos(\beta) = \frac{|b_{dx}b_{ax} + b_{dy}b_{ay} + b_{dz}b_{az}|}{\sqrt{b_{dx}^2 + b_{dy}^2 + b_{dz}^2} \cdot \sqrt{b_{ax}^2 + b_{ay}^2 + b_{az}^2}}
$$

(4)

where $b_d = (b_{dx}, b_{dy}, b_{dz}) = (\cos\Phi_d\cos\theta_d, \sin\Phi_d\cos\theta_d, \sin\theta_d)$ and $b_s = (b_{sx}, b_{sy}, b_{sz}) = (\cos\Phi_s\cos\theta_s, \sin\Phi_s\cos\theta_s, \sin\theta_s)$

(2) Position Deviation

The position deviation $L$ is described as the Euclidean distance between the two intersections of the detected needles and the actual needles with the B-planes, and is defined below:

$$
L = \sqrt{(\rho_d \cos \alpha_d - \rho_s \cos \alpha_s)^2 + (\rho_d \sin \alpha_d - \rho_s \sin \alpha_s)^2}
$$

(5)

(3) Speed

We measured the computational time used during the segmentation for $n$ trials ($n=10$ in our experiments), and averaged the time $t$ required to describe the speed of our segmentation algorithm.

5 EXPERIMENTAL EVALUATION: RESULTS

We used the 3D US image guidance system developed in our laboratory [6] to obtain our experimental 3D US images of water phantom with a straight nylon line mimicking a needle (Fig. 2(a)). The size of the reconstructed 3D US image in our experiments was 381×381×250 with a voxel dimension of 0.234mm×0.234mm×0.312mm. According to the approximate orientation and insertion point of the needle, the original 3D US image is cropped by using the methods in Ref. [8] (Fig. 2(b)). The size of the cropped 3D US image is 228×228×70 with the same voxel dimensions.

![Fig.2](a) ![Fig.2](b)

Fig.2. A 3D US image of water phantom before and after volume cropping. (a) Multi-planar view of the 3D image before volume cropping; (b) Multi-planar view of the 3D image after volume cropping.

We implemented our 3D Improved Hough transforms method by Visual C++6.0 programs to achieve automatic needle segmentation on a Pentium IV 1.0 GHz PC computer running Microsoft Windows XP software system.
Fig. 3. Segmentation of a needle in 3D US image (with the MIP volume rendered visualization). (a) Original 3D image; (b) Segmentation using 3DIHT; (c) Segmentation using 3DHT; (d) Segmentation using 3DRHT; (e) Random incorrect segmentation using 3DRHT.
The experimental results of the needle segmentation using 3DIHT, which compared with results of 3DHT and 3DRHT methods, are show in Fig. 3 and Table 1. We used the method in Ref. [12] to threshold the cropped 3DUS images and performed the above three methods respectively. In the 3DIHT method, we set the magnifying factor $\lambda$ to 5, and the parameter deviation factor $k$ between 0.5 and 0.8, for the sake of simplification. At the coarse stage, the intervals were set to be about 2.0 while at the fine stage the intervals were set to be about 1.0. The parameters in 3DHT and 3DRHT were also be set properly according to Ref. [7]. Because of the randomicity of the 3DRHT, we calculated the average deviation of orientation and position and the computational time for the trials of 100.

From Fig. 3(b)-3(d), we can see that the needle in 3D US images can be segmented accurately by using 3DIHT method, compared with the results of 3DHT and 3DRHT. Figure 3(e) indicated that the segmented result of the 3DRHT would be wrong randomly because of the randomicity of 3DRHT. The experiment results of Table 1 show that the orientation deviation of the segmentation using 3DIHT method was less than 2 ° and the position deviation was less than 2 mm. The average computational time is less than 2 seconds.

Compared with the results using 3DIHT and 3DRHT methods from Table 1, we found that needle segmentations with 3DIHT will be more accurate and correctly. We can also find that the needle segmentation with 3DIHT will be faster than with 3DHT method, while the time cost using 3DHT method is highly depending on the widths of the needle parameter ranges, according to the information about the approximate needle position and orientation in priori.

### 6 CONCLUSIONS

In this paper, we described the 3D Improved Hough Transform algorithm, which based on coarse-fine search strategy and the representation $(\Phi, \theta, \rho, \alpha)$ of lines in 3D space, for needle segmentations in 3D US images. The experiments with water phantom ultrasound images demonstrated that the 3DIHT method could perform accurate needle segmentation from 3D US images quickly, accurately and correctly. The orientation deviation of the segmentation of 3DIHT method was less than 2 ° and position deviation was less than 2 mm, while the computational time was less than 2s. It concluded that the 3DIHT is more accurate and stable than 3DRHT, and is faster and more robust than 3DHT method. Our future work includes dealing with the multi-needle segmentation problems.

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<th>$\beta$</th>
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