MLESAC Based Localization of Needle Insertion Using 2D Ultrasound Images

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Abstract. In the 2D ultrasound image of ultrasound-guided percutaneous needle insertions, it is difficult to determine the positions of needle axis and tip because of the existence of artifacts and other noises. In this work the speckle is regarded as the noise of an ultrasound image, and a novel algorithm is presented to detect the needle in a 2D ultrasound image. Firstly, the wavelet soft thresholding technique based on BayesShrink rule is used to denoise the speckle of ultrasound image. Secondly, we add Otsu’s thresholding method and morphologic operations to pre-process the ultrasound image. Finally, the localization of the needle is identified and positioned in the 2D ultrasound image based on the maximum likelihood estimation sample consensus (MLESAC) algorithm. The experimental results show that it is valid for estimating the position of needle axis and tip in the ultrasound images with the proposed algorithm. The research work is hopeful to be used in the path planning and robot-assisted needle insertion procedures.

1. Introduction
Percutaneous needle insertions have been widely used in a variety of clinical contexts in recent years, including biopsy [1], brachytherapy [2], anesthesiology [3], ablation [4] and fetal surgery [5]. As image-guided robotic assisted medical technology, ultrasound navigation technology have been widely used in the percutaneous surgery because of its noninvasive, low cost and real-time transmission compared with CT, MRI and nuclear medicine imaging. In practice, because of the existence of sensitive tissues or organs near the target, the detection and segmentation of the needle and the tracking of its trajectory are particularly prominent. However it is difficult to accurately detect and segment the needle from ultrasound image due to the speckle gives ultrasound image characteristic granular appearance and it inherently exists in coherent imaging [6], which affects the resolution and quality of image and increases the difficulty of diagnosis and treatment of doctors. At the same time, due to attenuation, diffraction, diffusion and artifact of ultrasound imaging [7], localization and tracking of 2D ultrasound image in the process of ultrasound-guided percutaneous needle insertion is a crucial factor in image degradation.

Needle detection and segmentation algorithms are based on the line feature detection methods. There existed lots of literatures about the line detection, and a summary of the Hough Transform (HT) was given by Leavers [8], image processing with HT have been widely used for line detection in different areas. Ding et al. used the Hough transformation technique to implement the segmentation of a biopsy needle in real time. Compared to conventional manual segmentation techniques, their approach reduced the computational time by an order of magnitude [9]. Okazawa et al. applied the HT to the medical image, extracted 3 parameters of the slope, intercept and curvature of the line through
the coordinate transformation of the ultrasound image, and used the polynomial least squares regression method to fit the line of ultrasound image [10]. Vrooijink et al. used the HT to locate the centroid of the needle from the radial cross-sectional view of the needle, which is affected by the comet tail artifact (CTA) known as reverberation in 2D ultrasound image [11, 12]. In 3D environment, Aboofazeli et al. used anisotropic diffusion filter deal with speckle reduction in 3D ultrasound image, then used HT copy with the needle detection and segmentation in projected 2D image obtained using a ray casting process, and used the polynomial of the midpoint and endpoint coordinates of the segment to fit the needle trajectory with curvature [13].

Neubach et al. proposed tissue stiffness classification to distinguish soft and stiff tissue in the virtual spring model [14]. Their proposed method used the block-matching algorithm in the elastography to calculate the displacement of region of interest (ROI) pixels, and they estimated the displacement of the local motion of tissue, and detected and tracked the position of the needle tip. The speckle tracking algorithm was used to validate the block-matching algorithm using ultrasound image in the “field I” [15]. Kaya et al. created new needle coordinate system in 2D ultrasound image, and used Gabor filter to denoise the image, in order to strengthen the outline of the needle while inhibiting the other tissue structure. In the frame difference image, the principal component analysis algorithm was used to estimate the needle insertion angle, and then the position and trajectory of the needle were estimated with the RANSAC line estimator [16, 17].

Waine et al. proposed image contrast stretching in ultrasound image to improve the pixel between the needle and soft tissue, and after morphological processing and thresholding, a set of needle point candidates were obtained in the image. At the same time, the position of needle and the shape estimation of needle in 3D space ultrasonic image were obtained by using the M-Estimator Sample Consensus (i.e. MSAC) in 2D ultrasonic image, and the shape modeling of 2D needle was established on the basis of the Euler-Bernoulli beam after Kalman filtering. They realized the needle localization, needle deformation detection and the manipulation of the needle tip, hence the semi-automatic needle steering system is implemented [18, 19]. Uhercik et al. developed a thin surgical tool in 3D ultrasound imaging, such as a biopsy needle or microelectrode, and used the random sample consensus (RANSAC) to fit the model to determine the position of the needle shaft. The position of the needle tip was determined by an intensity drop along the axis [20]. As an extension of [20, 21], Zhao et al. added Kalman filter, RANSAC algorithm and speckle tracking method to simulate 2D ultrasound image in the “field II”, and it improved the stability of RANSAC algorithm in dynamic situation [22, 23]. Neshat et al. and Novotny et al. employed Radon transform to realize real-time detection needle in 3D ultrasound image on the GPU [24, 25].

These methods rarely consider the effect of noise which is caused by image acquisition or transmission on needle detection and segmentation. In this paper, we propose new method to detect biopsy needle and locate the position of biopsy needle axis and tip. This is helpful for ultrasound-guided medical assisted robot to detect the position of needle axis and tip. The rest of the paper is organized as follows. In Section 2, the wavelet soft thresholding processing based on BayesShrink rule for the 2D transverse ultrasound image of needle insertion is used to despeckling, and then the image binarization is executed. In Section 3, the maximum likelihood estimation sample and consensus (MLESAC) algorithm is applied to estimate the needle axis and tip position in 2D ultrasonic image. In Section 4, experiments and results are described. Discussion and conclusion are summarized in Section 5.

2. Image preprocessing

In this section, image preprocessing is comprised of the wavelet transform and image binarization. The wavelet transform is used to decompose the original image, then the soft thresholding and BayesShrink rule technique is dealt with the subband in order to despeckling, image binarization is employed Otsu’s thresholding method and morphologic operations to deal with ultrasound image.
2.1. Wavelet transform

The speckle, which is multiplicative noise, is caused by the limitation of imaging environment and coherent superposition during ultrasonic imaging [26], the speckle decrease the resolution of the ultrasound imaging system, which seriously affected the image quality. The effect of additive noise of ultrasound imaging is small, which is generally negligible. Previous researchers have identified that the despeckling of the wavelet transform outperforms the other standard speckle filters, such as Wiener filter, Lee filter, Kuan filter, enhanced frost filter, Gamma filter and SRAD filter [27], hence we apply the wavelet transform in order to remove the speckle in ultrasound image. In order to separate speckle from the original ultrasound image, the speckle multiplicative noise is transformed into speckle additive noise by logarithmic transform [28], and the ultrasound image with speckle is decomposed by wavelet transform, the steps involved in the wavelet transform are given in the Algorithm 1.

| **Algorithm 1:** Despeckling of ultrasound image using the wavelet transform |
|---|
| **Input:** Original ultrasound image. |
| **Output:** Despecked ultrasound image. |
| **Procedure:** |
| (1) Apply logarithmic transform of input image; |
| (2) Perform wavelet transform in multi-level of subband decomposition on the logarithmic transformed image; |
| (3) Execute thresholding of transformed image of the step (2); |
| (4) Implement inverse transform on the thresholded image of the step (3); |
| (5) Despeckled ultrasound image can be obtained by exponential transform on the inverse transformed image of the step (4). |

2.1.1. Soft thresholding. After the discrete wavelet transform, the detail coefficients of the wavelet function corresponding to the high frequency components and the approximate coefficients of the scaling function corresponding to the low frequency components are obtained from the ultrasound image. The magnitude and number of the signal’s wavelet function coefficients are large and less, the magnitude and number of the speckle’s wavelet function coefficients are small and more. Hence the denoising method of wavelet domain can select threshold on a different levels, and deal with the wavelet function coefficients directly by using threshold or weight. The function of wavelet thresholding is aimed at removing the small wavelet function coefficients and keeping the large wavelet function coefficients. In this paper, the soft thresholding function is chosen to deal with speckle in ultrasound image [29]. The soft thresholding scheme shown in Eq. (1).

\[
W_w = \begin{cases} 
\text{sign}\{X_w\}\{|X_w| - T\}, & \text{Where } |X_w| \geq T \\
0, & \text{Where } |X_w| < T 
\end{cases}
\]  

(1)

Where \(X_w\) denotes input wavelet transform coefficients, \(W_w\) denotes output wavelet transform coefficients after thresholding, \(T\) denotes the threshold limit.

2.1.2. BayesShrink rule. Another crux for the desnoising method of wavelet domain is the selection threshold. In wavelet domain denoising, Generalized Gaussian Distribution (GDD) is empirical used as the distribution model of wavelet coefficients in a subband of a natural image [30], Chang et al. [31] proposed the BayesShrink rule based on the assumption. Compared with the VisuShrink rule and SureShrink rule, the BayesShrink rule performed the best for ultrasound image with speckle [32]. In BayesShrink rule, the formulation for the threshold \(T\) on a given subband is given by

\[ T = \frac{\hat{\sigma}_n^2}{\hat{\sigma}_x}, \]

(2)

Where
\[ \hat{\sigma}_n = \frac{\text{median}\left(\{W_k \mid \text{HH}_i\}\right)}{0.6745} \] (3)

\[ \hat{\sigma}_i = \sqrt{\max(\hat{\sigma}_y^2 - \hat{\sigma}_x^2, 0)} \] (4)

Where \( \hat{\sigma}_n^2 \) denotes the estimated noise variance, \( \hat{\sigma}_i \) denotes the estimated standard deviation for the subband coefficients and \( \text{HH}_i \) denotes the diagonal subband after multiscale wavelet decomposition.

\[ \hat{\sigma}_y^2 = \frac{1}{N_y} \sum_{k=1}^{N_y} W_k^2 \] (5)

Where \( N_y \) denotes the number of transform coefficients \( W_i \) in the subband, \( \hat{\sigma}_y^2 \) denotes the estimated variance of the original image observation.

In [33, 34], the experimental results have shown that wavelet filter bior 6.8 with level 3 yields better performance than other speckle filters in reconstructed image. Hence, the wavelet filter bior 6.8 with level 3 is used in this study to reduce the speckle. An example of the 18 gauge needle insertion with the soft thresholding and BayesShrink rule technique for ultrasound frame sequences is shown in Fig 1.

![Figure 1. Wavelet thresholding](image)

2.2. Image binarization

After the soft thresholding of wavelet domain, the ultrasound image binarization is achieved in three steps, including smoothing, Otsu’s thresholding method and morphologic operations.

It is found in the trials that the image is smoothen and reduce noise by using the disk type structuring element which its radius is 5 pixels, and it is helpful to filter out the structure with no relation with the needle. Then the optimum global thresholding using Otsu’s thresholding method is disposed of the ultrasound image in order to separate needle from the background. Finally, we apply the disk type structuring element which its radius is 5 to morphologic erosion and dilation operations, which is conducive to removal of residual speckle, and clear the spur pixel and the isolate foreground point in the binary image. An example of the 18 gauge needle insertion with the Otsu’s thresholding method for ultrasound frame sequences is shown in Fig 2.

![Figure 2. Otsu’s thresholding method](image)
3. Localization of needle axis and tip

3.1. Location estimation of needle axis

The location of the needle is estimated by the maximum likelihood estimation sample consensus (MLESAC) [35] and the MLESAC originates from the RANSAC [36] which is a robust line estimator. Instead of using as numerous data as possible to estimate the model, RANSAC uses as few data as possible to estimate the model. Now that RANSAC has developed into a RANSAC family, it can be seen from their cost function that it is better than the traditional RANSAC and m-estimator sample consensus (MSAC) [37]. Compared with the latter two methods, MLESAC has considered the quality of inlier more, we apply the MLESAC.

There are a host of outliers near the needle shape of the ultrasound image. The shape and location of the needle axis cannot be discerned from the naked eye. Often times the error distributions for the inliers of the image is modeled with the Gaussian distribution, the error statistics for the outliers is described by the uniform distribution, through the selected distribution, then the estimation model of the inlier of the needle under ultrasound guidance is:

\[
p(e|M) = \gamma \left( \frac{1}{\sqrt{2\pi\sigma}} \right)^d \exp\left( -\frac{e^2}{2\sigma^2} \right) + (1-\gamma) \frac{1}{v}
\]

(6)

Where \( \gamma \) is mixing coefficient and \( v \) is a constant diameter of the search window of mixture model.

The two pixels by random selecting in ultrasound binary image are used as the cardinality \( d \) of the needle model \( M \), that is \( d = 2 \), the parameter is estimated with the selected two pixels as the minimal sample sets (MMS), and the negative log likelihood of the cost function is obtained. We select minimum of sum of the cost function \( \text{Loss}(e|M) \) as the largest consensus set (CS), CS is maximum estimation \( \hat{M} \) of the needle model \( M \):

\[
\text{Loss}(e) = -\log p(e|M) \\
\hat{M} = \arg\min_M \left\{ \sum_{i=1}^n \text{Loss}(e|M) \right\}.
\]

(7)

(8)

Initial estimate of \( \gamma \) is 0.5, \( \eta_i \) is the index for the \( i \)th sampling, where the \( \eta_i = 1 \) denotes the inlier of corresponding data, \( \eta_i = 0 \) denotes the outlier of corresponding data. In [34], it offered the method to tune \( \gamma \) through Expectation Maximization (EM) approach:

\[
\gamma = \frac{1}{n} \sum_{i=1}^n p(\eta_i = 1 | \gamma) = \frac{1}{n} \sum_{i=1}^n \frac{p_i}{p_i + p_o}
\]

(9)

Where \( n \) is the total number of samples, \( p_i \) is the likelihood of a datum given that is the inlier:

\[
p_i = \gamma \left( \frac{1}{\sqrt{2\pi\sigma}} \right)^d \exp\left( -\frac{e^2}{2\sigma^2} \right)
\]

(10)

And \( p_o \) is the likelihood of a datum given that is the outlier:

\[
p_o = (1-\gamma) \frac{1}{v}.
\]

(11)

The position of the needle axis can be estimated by the iteration of the algorithm, as shown in Algorithm 2:

| Algorithm 2: Needle location based on MLESAC algorithm |
|---------------------------------------------------------|
| **Input:** Binary despeckled ultrasound image.         |
| **Output:** Needle axis of the input image.             |
| **Parameters:**                                        |
| \( d \): Cardinality of MMS;                           |

\[\text{Algorithm 2:}\] Needle location based on MLESAC algorithm

| Input: Binary despeckled ultrasound image. |
|-------------------------------------------|
| Output: Needle axis of the input image.   |
| Parameters:                              |
| \( d \): Cardinality of MMS;             |
\( \sigma \): Standard deviation of Gaussian noise, default is 1;

\( n \): Number of iteration.

Procedure:
1. Randomly selecting two pixels as MMS from data of binary image;
2. Use existing RANSAC methods and selecting two pixels to estimate needle model \( M \);
3. Calculate error \( e \);
4. Estimate mixing coefficient \( \gamma \) using EM approach;
5. Compute the cost function \( \text{Loss}(e| M) \) and select minimum of sum of \( \text{Loss}(e| M) \) as the largest CS, i.e. maximum estimation \( \hat{M} \) of the needle model \( M \);
6. Repeat from step (1) to step (5) \( n \) times.

3.2. Location estimation of needle tip

As a consequence of the needle tip pixels is similar to the background in the original image, after the image binarization, the position coordinate of the needle tip is obtained by the background difference method and morphologic operations. Then the coordinate is substituted in the needle model \( \hat{M} \) in order to obtain the position of the needle tip, and the position of the actual tip is estimated. MLESAC algorithm for estimating the axis and tip of a 18-gauge needle frame sequences image is shown in Fig 3.

![Frame images](image)

(a) Frame number = 17  (b) Frame number = 22  (c) Frame number = 30  (d) Frame number = 35  (e) Frame number = 42  (f) Frame number = 48

Figure 3. Location needle axis and tip

4. Experiments and results

4.1. Experimental Setup
1. The ultrasound image are collected using a SPC-2000CIII B-mode ultrasound imaging system (Shengpu Medical Instrument Technical and Equipment Co. Ltd., China) and a 7.5 MHz linear array 2D ultrasound transducer with 128 elements, the lateral resolution and axial resolution of probe is approximately 1mm. The acquired image sizes are 768×576 pixels.
2. The transparent tissue-mimicking phantom is constructed of a 50mm thick polyvinyl alcohol (PVA) [38] sheet 100mm wide and 150mm long, the composition ratio of PVA mass (g), distilled water volume (ml) and dimethyl sulfoxide volume (ml) is 8:40:60, 18 gauge, 20 gauge, 21gauge needles are used in the trials.
3. All algorithms are implemented in MATLAB on a standard PC and run on a 64-bit Window 7 workstation, which has an Inter (R) Core (TM) i5-3470 CPU running at 3.2GHz and 4GB of RAM.

4.2. Experimental Results

In order to prove the effectiveness of the wavelet filter, the signal noise ratio (SNR) is computed using the following equation,

\[
\text{SNR} = 10 \log_{10} \left( \frac{\text{mean}(x,y)}{\text{std}(x,y)} \right)
\]  (12)
Where $I(x,y)$ is the input image. The result of the SNR value is described in Fig 4. It is found that SNR value of the original image is smaller than the after processing the image, which improves quality of the image and indicates that the wavelet soft thresholding technique based on BayesShrink rule is effective in suppressing speckle.

![Figure 4. SNR values for different type needles](image)

Nevertheless, there are still artifacts in the ultrasound image, including reverberations, side lobes, and comet tail artifacts, while the presence of air bubbles in the phantom due to the absence of sufficient cooling of the phantom during the preparation, all of which affect the estimation of the needle axis and tip of the MLESAC algorithm.

Through the 18 gauge, 20 gauge and 21gauge needle experiment, 300 single ultrasound images and 6 frame sequences are obtained, and the feasibility and validity of the MLESAC algorithm for needle detection under the 2D ultrasound image are validated. It is found that the pixel of the needle is less in the first ten frames ultrasound image, the estimation error is larger. As the needle insertion movement, the pixel of the needle outline in the 2D ultrasound image is increased and the phantom is deformed, the robustness of MLESAC can effectively overcome these changes. Six iterations of the EM approach can ensure the convergence of the mixing coefficient $\gamma$ and reduce the time complexity of the algorithm experimentally. When the algorithm iterates 200 times, the execution time of proposed MLESAC line filter method for the single group including 50 frame sequences is $5.5178 \pm 0.1581$ seconds (mean and variance). The result of proposed method which is dealt with the frame number = 35 is demonstrated in Fig 5 by using 18 gauge, 20 gauge, 21gauge, respectively.

![Figure 5. Results of the proposed method in 35 frames](image)
5. Discussion and Conclusion
In this paper, a novel MLESAC-based algorithm is proposed to localize the needle axis and tip in a 2D ultrasound guided. Although the speckle is reduced by the wavelet soft thresholding method based on the BayesShrink rule, the profile of the needle structure may still be intermittent because of the influence of the artifacts in the ultrasound image. After denoising the ultrasound image getting by the probe, the position of needle axis is identified and segmented with the MLESAC algorithm iteration, and the position of needle tip can be tracked through the processing of background difference sequence. Through the percutaneous needle procedures experiments of 18 gauge, 20 gauge and 21 gauge, it shows that MLESAC is effective and robust in the 2D ultrasound image, which solves the localization of needle under ultrasound-guided medical assisted robot in medical diagnostics and therapeutics.

In the future work, we will use the camera to take the needle insertion experiment, compute needle displacement error in the estimation of proposed method and the reality, evaluate the accuracy of the MLESAC algorithm, analysis the validity and robustness of this method to color ultrasound image such as Doppler ultrasound image. Further extensions include localizing position of 3D ultrasound needle and combining these techniques with the cantilever beam model in order to path planning, facilitate target hitting and obstacle avoidance.

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