TRACKING MICRO TOOL IN A DYNAMIC 3D ULTRASOUND SITUATION USING KALMAN FILTER AND RANSAC ALGORITHM

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Abstract — **Ultrasound guidance is used for many surgical applications such as biopsy and electrode insertion. This paper presents an improved method for tracking such micro tools inserted in human tissues. The RANSAC algorithm** [1] **has been implemented to detect the exact position of the needle in a stationary situation. In this paper, the Kalman filter is added to estimate the position of the needle in a dynamical situation. In the simulation, the RANSAC algorithm is used to get the position of the tip of the needle, and a speckle tracking method is implemented to estimate the inserting speed of the needle. The Kalman filter uses the results given by the two methods above as the measurement to make the estimation of the position of the needle tip. The simulated results show that both, in stationary and dynamic situations, the proposed method gives a more stable results than the RANSAC only algorithm.**

Keywords: RANSAC, Kalman filter, 3D, ultrasound, tracking, simulation, guidance

I. INTRODUCTION

In surgical practice, the technology of micro-tool has been widely developed. The detection and precise positioning and tracking of the micro tools inserted in human tissue are extremely important. In surgery and therapy of breast cancer or liver cancer, ultrasound is widely used for tracking a metal needle inserted in the tissue. However, in vivo situations, the needle doesn't correspond to an acquisition plane of a 2D ultrasound image, the difficulty is to find the exact needle plane. Most of time, only a part of the needle is visible. What's more, some linear structures of tissue that compose the medium can make the volume quite noisy that it is extremely hard to separate the needle from the background. Since the precise navigation of micro tools is essential for reducing the damage to the tissue caused by multiple insertions in wrong places, micro tools tracking using medical imaging has become an intense field of research.

B. Dong *et al.* have introduced a method which depends on snake model and PDE (partial differential equation) for needle localization in 2D ultrasound image [2]; S. Khosravi et al use 2D cameras to establish a database for the position and orientation of the needle, then the needle position in 3D environment was estimated by finding the best fitted model in the database [3]; Z. Yaniv et al have already developed an image guidance system with the Image-Guided Surgery Toolkit for computed tomographic [4]; J. Stoll and P. Dupont used passive markers for tracking the surgical tools using ultrasound [5]; M. Barva and M. Uhercik have implemented the parallel integral projection transform method and the RANSAC algorithm in detection of metallic needle with 3D ultrasound [6], [7]. The RANSAC algorithm has the capability to detect the position of the needle in real time implementation [8], but it needs improvement in stability in case of a dynamic situation.

In this paper, a method to estimate and detect the position of the needle in a series of Ultrasound (US) 3D volumes is proposed. This work is based on RANSAC algorithm, developed by Uhercik *et al.* [7], which has been used for detecting the position of the needle inserted using a 3D US volume acquisition. The main contribution here is to use the Kalman filter and speckle tracking algorithm to make the whole method suitable for dynamic procedures. Our proposition is to realize the prediction and the trajectory of the needle inserting in human's liver.

This paper is organized like below: section II summarized the methods used: Kalman filter, RANSAC algorithm and speckle tracking method; section III gives the simulation results and the statistical characteristic of the results; the conclusion is given out in section IV.

II. METHODS

A. *KALMAN FILTER*

1. Equations of Kalman filter

Kalman filter is an optimal recursive data processing algorithm. It was first published in 1960 by Kalman [9]. The Kalman filter is a set of mathematical equations that provides an efficient computational method to estimate the state of a process, in a way that minimizes the mean of the squared error [10]. This filter can predict the future state of a system, so it is very useful for the prediction of the position of the needle. The five main equations in Kalman filter can be divided into two parts.

The time update equation:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \quad (1)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (2)$$

The measurement update equations:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (3)$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (4)$$

$$P_k = (I - K_k H)P_k^- \quad (5)$$

Here, $\hat{x}_k^-$ represents the priori state estimate and $\hat{x}_k$ is the posteriori state estimate at step k ; A is the state transition matrix; B and u are the control matrix and control vector respectively; P_k^- is the priori estimate error covariance, and P_k is the posteriori estimate covariance at step k . R and Q are the measurement error covariance and processing error covariance respectively. K_k is the Kalman gain.

What should be paid more attention here is the processing error covariance Q , which indicates whether the mathematical model is adapted to the real situation or not; the measurement error covariance R , which affects the Kalman gain K_k . The Kalman gain K_k can weigh the importance of the innovation $(z_k - H\hat{X}_k^-)$.

2. Mathematical model

The problem is how to set the mathematical model for the Kalman filter. Here, the Kalman filter is used to predict the position of the needle in a 3D US volume. First, for the prediction of the position of the needle, 2 points belonging to the axis of the needle can be obtained, so the unit direction vector of the tool's axis can be calculated, and the position of the needle axis is fixed. Because different mediums have different capacities reflecting the ultrasound wave, the intensity of the metal needle along the axis is larger than that of the background. The tip position of the needle can be fixed where the intensity along the needle axis decreased drastically and does not increase anymore within a tolerence gap. [6] However, the needle is not staying still in the volume, but moving in a changing speed. So the speed of unit direction vector should be included in the measurement vector, and also that of the needle tip. Assumming the needle is actuated by hand, the control input is unknow, so the control matrix B and the control vector u are set to zero. If case of a robotic driven needle insertion, there will be a control vector and control matrix as input. So the time update equations for the Kalman filter are

$$\hat{\mathbf{X}}_k^- = \mathbf{A}\hat{\mathbf{X}}_k \quad (6)$$

$$\mathbf{P}_k^- = \mathbf{A}\mathbf{P}_k\mathbf{A}^T + \mathbf{Q} \quad (7)$$

with $\mathbf{X} = [\mathbf{p}_t, \mathbf{v}_t]^T$, $\mathbf{A} = \begin{bmatrix} \mathbf{I}_{3\times3}, \Delta t \times \mathbf{I}_{3\times3} \\ \mathbf{0}_{3\times3}, \mathbf{I}_{3\times3} \end{bmatrix}$, the processing noise is a normal distribution which is the classic processing noise used in Kalman filters [9]. Here notice that the position $\mathbf{p}_t$ and $\mathbf{v}_t$ are 3×1 vector, $\mathbf{p}_t = [x_t, y_t, z_t]$, $\mathbf{v}_t = [v_{tx}, v_{ty}, v_{tz}]$ .The measurement matrix $\mathbf{H} = \mathbf{I}_{6\times6}$, so the measurement vector $\mathbf{Z} = \mathbf{X}$, and the measurement noise is also a normal distribution.

In the next two parts, the RANSAC algorithm used for measuring the position of the needle is first introduced, and then the speckle tracking method which is used for measuring the speed of the needle.

B. RANSAC ALGORITHM

The first objective is to get the position of the needle in a 3D ultrasound volume. Here the RANSAC algorithm is used to estimate the optimal axis for the position of the needle. Below are the four steps for RANSAC algorithm [7].

Step1: Thresholding — Reducing the number of voxels using the assumption that the intensity of the tool voxels is higher than the background.

Step2: Axis localization — Using RANSAC algorithm to estimate an approximate position of the needle axis. Here, we assume that the needle is a thin but straight line.

Step3: Local optimization — Finding a more accurate solution by using local optimization.

Step4: Tip localization — Identifying the endpoint of the tool along the tool axis.

C. SPECKLE TRACKING METHOD

Speckle tracking method can directly track the backscattered echoes generated by ultrasonic scatters in tissue [11]. This method was first published by Robinson *et al*. [12], and then Trahey *et al*. [13]. It was first used to detect the blood velocity with ultrasound. Here speckle tracking method is used to measure the speed of the needle. This method can estimate velocities by estimating the displacement of a speckle pattern in the axial, lateral and elevation directions. First a small 3D region is chosen in the first volume as the kernel region. Then a larger region as searching region is chosen in the second volume. The sum-absolute-difference (SAD) [14] algorithm was chosen to compare the difference between the kernel region and the searching region, because the SAD method gives the same quality results as the normalized correlation method, and it's easier to the further implementation of our method. Also the SAD algorithm is far simpler to implement in digital hardware than normalized correlation. [11] The absolute difference operation in 3D is:

$$\boldsymbol{\varepsilon}(\alpha,\beta,\gamma) = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p}\left|\mathbf{X}_0(i,j,k) - \mathbf{X}_1(i+\alpha, j+\beta, k+\gamma)\right| \quad (8)$$

Here, $\boldsymbol{\varepsilon}$ is the SAD coefficient, $\mathbf{X}_0$ is the kernel region, whose size is $m\times n\times p$, and $\mathbf{X}_1$ is the searching region. The size of $\boldsymbol{\varepsilon}$ is related with the sizes of $\mathbf{X}_0$ and $\mathbf{X}_1$. Suppose $\mathbf{X}_1$ is size $M\times N\times P$, the size of $\boldsymbol{\varepsilon}$ is $(M-m+1)\times(N-n+1)\times(P-p+1)$. The difference of coordinate between the kernel region and the best matching

region indicates the displacement of the needle, dividing the displacement by time, the speed of the needle is obtained. It is used as the second measurement of Kalman filter.

In the experiment, the size of kernel region is set to 7*21*51 (plane * beam * sample), and size of the searching region is 11*37*61.

III. SIMULATIONS

Several simulations with Field II [15], [16] have been done. The parameters used in Field II were given in Table 1.

Name of parameter	Value
Transducer center frequency [MHz]	7.5
Sampling frequency [MHz]	27
Speed of sound [m/s]	1540
Elements of the probe	128
Width of element [mm]	0.1
Height of element [mm]	10
Kerf [mm]	0.017
Focal depth [mm]	50
Range of scan lines [degree]	[-20 20]
Range of scan planes [degree]	[-20 20]

Table 1 Parameters used in the Field II simulation

The simulations are done on a homogeneous phantom with a metal needle whose radius is 0.5 mm. The size of the phantom is $50\times50\times30$ mm^3. For the homogeneous background, the spatial distribution of scatters is uniform distribution, and the spatial density of scatters is 10/mm^3. The reflection coefficient is K distribution, with $\nu=10$, $\lambda=\sqrt{\nu}$. For the metal needle, the spatial distribution of the scatters is uniform distribution with the spatial density of scatters 125/mm^3. The reflection coefficient is set to 7.5 as constant amplitude. In the 3D simulation US volume, there are 53 planes, 71 lines / plane and 2608 samples / line.

The first simulation is to contrast the root mean square error (RMSE) of the RANSAC and RANSAC and Kalman filter in a static situation. Suppose the ground truth of the position of the electrode end point (electrode tip) is known. RANSAC algorithm and RANSAC and Kalman filter were used to estimate the tip position of the electrode of the same length. 50 simulations were done in order to calculate the RMSE. The length of the electrode tested is from 5 mm to 20 mm.

Figure 1 shows the RMSE of the estimation result of the needle tip with different length. It is obvious that the method RANSAC and Kalman reduces the RMSE. In the static case, compared to the use of RANSAC only, the RANSAC and Kalman has decreased the RMSE by 47% in x direction, 38% in y direction, 46% in z direction and 45% of the tip position. That is to say that for a constant position, the proposed method can give a more robust estimation of the position than RANSAC algorithm only. What's more, Figure 1a shows that the precision of the estimation in x direction is the most critical for tip localization. When the length of the

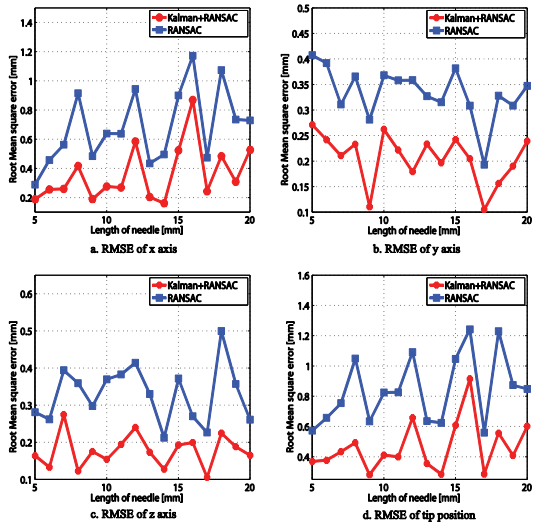


Figure 1 The RMSE of x, y and z coordinate and the RMSE of tip position in a static situation. (Blue square line: RANSAC; Red point line: RANSAC + Kalman)

needle is 16 mm, the RMSE of the tip position reached almost 1.25 mm with RANSAC algorithm, this result also lead to the RMSE of 0.9 mm (length 16 mm) with RANSAC and Kalman. This point also indicates that if the precision would be increased further, the RMES of x direction must be reduced.

The second simulation is to use RANSAC and Kalman to track a moving needle in a series of 16 simulated ultrasound volumes and estimate the position of electrode tip. The inserting speed is 1mm/s and the unit direction vector of the electrode is [0.94, 0, 0.34]. The initial length of the insertion of the electrode is 5 mm. The aim of this experiment is to simulate a dynamical situation of the moving needle. Comparison between real position of the electrode tip the estimate result of RANSAC algorithm and the result of RANSAC and Kalman are given in Figure 2. For each simulation the estimation is performed 50 times.

Figure 2 gives the RMSE of x, y and z coordinate and RMSE of tip position respectively. Because the Kalman filter needs initialization, for the first two volumes, the output result of RANSAC and Kalman is the same as that of RANSAC. The Kalman filter begins to work from the 3rd volume. From figure 2, it is obvious that the RMSE of RANSAC and Kalman is smaller than that of RANSAC only. In the dynamic case, the RMSE of RANSAC and Kalman is decreased by 39% in x direction, 24% in y direction, 34% in z direction and 26% of the tip position So in the constant speed needle inserted situation, the proposed method also gives a more robust performance than RANSAC algorithm only.

IV. CONCLUSION

RANSAC algorithm depends on randomly selected models, and sometimes there is a large error in the returned result. In order to avoid the large error which appears

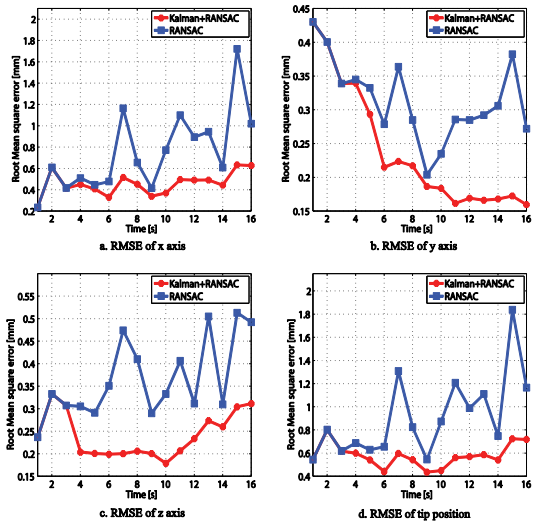


Figure 2 The RMSE of x, y and z coordinate and the RMSE of tip position in a dynamic tracking situation. (Blue square line: RANSAC; Red point line: RANSAC + Kalman)

randomly, the Kalman filter is added. The simulations show that in either the constant situation or the dynamical situation, RANSAC and Kalman performs better than using RANSAC algorithm only. With Kalman filter, the tracking results are more stable, and the estimate error can also be reduced.

Because the axis position of the needle is as important as the tip position, future work will try to include in the Kalman model, both tip and axis of the needle.

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