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A Robust Registration Method for Real-time Ultrasound Image Fusion with Pre-acquired 3D Dataset

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***Abstract*—In recent years real-time ultrasound (US) image fusion with pre-acquired 3D dataset has become widely used in both diagnosis and image-guided interventions. The accuracy of a US image fusion system heavily depends on the image registration method. However, the registration procedure of this application is inevitably interfered by possible outliers in the corresponding point pairs. This is either caused by image feature difference between two modalities or by tissue shifting and deformation of patient body between two imaging studies. While traditional methods often ignore the position error of registration points, we present a random sample consensus-based algorithm to reduce the impact of outliers and improve the robustness. To evaluate our algorithm, a simulation study is carried out, and the new method is compared with state-of-the-art, least square (LS) method. It is shown that our new method is comparable with LS method under non-outlier condition, but it performs significantly better when outliers exist.**

I. INTRODUCTION

A. Ultrasound Image Fusion

Ultrasound image fusion is a technique that locates and fuses a corresponding image slice of another 3D medical imaging modality with the real-time ultrasound image [1]. This method is widely used in various clinical ultrasound applications such as ultrasound-guided interventions [2] [3] and intra-operative ultrasound scans [4]. The main objective is to combine the real-time property of ultrasound together with the good image quality of CT and MRI, and to provide more reliable medical images to clinicians.

Ultrasound image fusion makes use of electromagnetic (EM) tracking systems to track US probe as well as the imaging plane extended from it. A registration procedure between the patients, real-time US image and pre-acquired 3D CT/MR images is carried out. Therefore a real-time relationship between US imaging planes and 3D CT/MR image space is built, and the fused image can be displayed to users. The system is shown in Figure 1.

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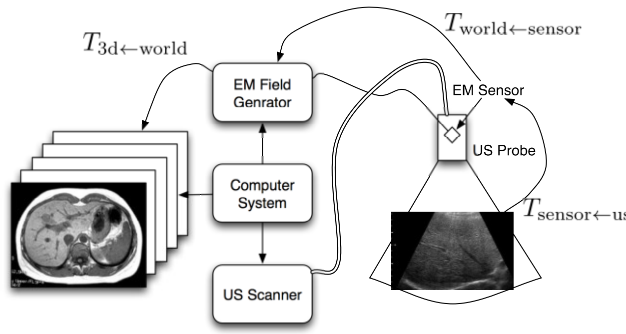


Fig. 1. Ultrasound image fusion system overview

B. Registration in Ultrasound Image Fusion

In order to register US images with pre-scanned 3D CT/MR images, a spatial transform from any point in US image coordinate system $\vec{x}_{us}$ to the corresponding point in 3D image coordinate system $\vec{x}_{3d}$ needs to be determined. In our system shown in Figure 1, this transform is divided into three parts as follows:

$$\vec{x}_{3d} = T_{3d\leftarrow world} \cdot T_{world\leftarrow sensor} \cdot T_{sensor\leftarrow us} \cdot \vec{x}_{us}$$

Among these three transforms, $T_{sensor\leftarrow us}$ is calibrated and fixed once the EM sensor is attached to the US probe, and $T_{world\leftarrow sensor}$ is measured by the EM tracker. The accuracies of both are determined during manufacture. Transform $T_{3d\leftarrow world}$,however, is calculated during registration. Therefore the performance of the registration method becomes an important factor to the overall accuracy of the whole system.

During registration, clinicians usually point out several anatomic landmarks in both ultrasound and CT/MR images. The system meanwhile record the corresponding $T_{world\leftarrow sensor}$. In this way, several pairs of points in world coordinate system and 3D image coordinate system are picked, and the registration problem becomes an absolute orientation (AO) problem.

Although there are many general solutions to the AO problem, the registration of ultrasound image fusion has its own challenges. In the point pair data acquired from the above procedure, the probability of the occurrence of outliers is large, due to the following reasons:

- The same anatomic landmark may produce different image features under different image modality. This may cause large localization error in the landmark picking procedure on both images.
- The tissue shifting and deformation of a patient between

two imaging studies are difficult to avoid, and there can be a significant offset of the same landmark between two image modalities.

Therefore, besides general accuracy, the registration algorithm used in an ultrasound image fusion system should also be able to resist the interference of outliers.

Traditional registration algorithms used in US image fusion systems are usually borrowed from image-guided surgery (IGS). One of the most widely used method is Horn's closed form, least square method [5], [6]. Although producing accurate results in IGS [7], it ignores the problem pointed out above. In this paper, we present a registration algorithm to meet the special needs of an ultrasound image fusion application.

II. METHODS

A. General Description

During the registration procedure, we can get n pairs of $\vec{x}_{us,i}, T_{world \leftarrow sensor,i}, \vec{x}_{3d,i}$. Since transform $T_{sensor \leftarrow us}$ is calibrated beforehand, we are able to get all n coordinate pairs of landmarks under the 'world' ($\vec{w}_i$) and 'model' ($\vec{m}_i$) coordinate systems:

$$\vec{w}_i = T_{world \leftarrow sensor} \cdot T_{sensor \leftarrow us} \cdot \vec{x}_{us,i}$$
$$\vec{m}_i = \vec{x}_{3d,i}$$

Using the above paired points, a registration algorithm will be able to calculate the transform from 'world' coordinates to 'model' coordinates, which in our US image fusion system is $T_{3d \leftarrow world}$.

Our algorithm is inspired by a divide-and-conquer solution to the AO problem, presented by Micheals and Boult in [8]. Their method divides point pairs into subsets of four, solves the subset problem, and uses the weighted average of all solutions of subsets as the final solution. However, since US image fusion registration has relatively few point pairs and only several outliers may exist, we improved their algorithm using Random Sampling Consensus (RANSAC) technique [9] during subset dividing.

B. Subset Registration

In a 4-point pair subset, the registration problem can be solved in a unit quaternion based closed form manner.

First, we use a unit quaternion $\dot{q}$ and a 3D translation vector $\vec{t}$ to represent a rigid 3D spatial transform:

$$\vec{m} = T_{m \leftarrow w}(\vec{w}) = \dot{q}\vec{w}\dot{q}^* + \vec{t}$$

In order to get the rotation part of the transform, it is needed to centralize both world point set and model point set according to their own centroids. We call the centroids $\vec{c}_m, \vec{c}_w$ respectively.

The rotation part can be determined by any 3 point-pairs of the entire subset. We call them $\{\vec{w}_1, \vec{w}_2, \vec{w}_3\}$ and $\{\vec{m}_1, \vec{m}_2, \vec{m}_3\}$ respectively. By developing the transformation equations of these 3 point-pairs directly, we get an equation of Q, which is

$$Q = \left[q_{sx}, q_{sy}, q_{sz}, q_{xy}, q_{yz}, q_{xz}, q_{ss}, q_{xx}, q_{yy}, q_{zz}\right]^t$$

$$W_{i,1} = \begin{bmatrix} 0 & 2w_{i_z} & -2w_{i_y} & 2w_{i_y} & 0 & 2w_{i_z} \\ -2w_{i_z} & 0 & 2w_{i_x} & 2w_{i_x} & 2w_{i_z} & 0 \\ 2w_{i_y} & -2w_{i_x} & 0 & 0 & 2w_{i_y} & 2w_{i_x} \end{bmatrix}$$

$$W_{i,2} = \begin{bmatrix} w_{i_x} & w_{i_x} & -w_{i_x} & -w_{i_x} \\ w_{i_y} & -w_{i_y} & w_{i_y} & -w_{i_y} \\ w_{i_z} & -w_{i_z} & -w_{i_z} & w_{i_z} \end{bmatrix}$$

$$\begin{bmatrix} W_{1,1} & & & & & & W_{1,2} & & & \\ W_{2,1} & & & & & & W_{2,2} & & & \\ W_{3,1} & & & & & & W_{3,2} & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \\ Q \\ \\ \end{bmatrix} = \begin{bmatrix} \vec{m}_1 \\ \vec{m}_2 \\ \vec{m}_3 \\ 1 \end{bmatrix}$$

Here, $q_{\xi\zeta} = q_\xi q_\zeta, \xi, \zeta \in \{x, y, z, s\}$.

If the above equation is treated as a pure linear system, there isa unique solution of Q. Using $q_{ss}, q_{xx}, q_{yy}, q_{zz}$, the absolute of every component of $\dot{q}$ is computed, and their signs are determined by the other components of Q.

Once the optimal rotation $\dot{q}_{opt}$ is calculated, according to Horn [5], the optimal translation vector is

$$\vec{t}_{opt} = \vec{c}_m - \dot{q}_{opt}\vec{c}_w\dot{q}^*_{opt}$$

The above procedure solves the registration problem of a four-point pair subset, and we call it *Extract4*.

C. Weighting Function

To make use of the results from subset calculations and get a more reliable and accurate solution, a weighted averaging method is used. The weighting function is based on the evaluation of a subset registration. The following 2 evaluation factors are used:

Miss-registration Distance

$$d = \sum_i \left|\vec{m}_i - \left(\dot{q}\vec{w}_i\dot{q}^* + \vec{t}\right)\right|$$

Computational Consensus

$$\begin{aligned} p = {} & |q_{ss}q_{xx} - (q_{sx})^2| + |q_{ss}q_{yy} - (q_{sy})^2| \\ & + |q_{ss}q_{zz} - (q_{sz})^2| + |q_{xx}q_{yy} - (q_{xy})^2| \\ & + |q_{yy}q_{zz} - (q_{yz})^2| + |q_{xx}q_{zz} - (q_{xz})^2| \end{aligned}$$

If the whole procedure is noiseless,$d = 0, p = 0$. Under a more practical, noisy situation, the value of d, p represents the reliability of that particular subset result. We use $1/p^2d^2$ as the weighting function.

D. RANSAC-based Framework

Random Sampling Consensus (RANSAC) is a widely used technique for outlier suppression. The basic idea of RANSAC is to randomly sample the whole data set into many subsets, solve the problem on each subset, and merge these solutions into a weighted average as the final solution. Based on this technique and the *Extract4* procedure described above, we

Algorithm 1: Our Registration Algorithm

Input: Point set W, M, iterations m
Output: Rotation $\dot{q}$, translation $\vec{t}$

for $i \leftarrow 1$ **to** m **do**
  Generate 4 random numbers from $1, 2, \ldots, n$
  Save them as s_1, s_2, s_3, s_4
  $W_4 \leftarrow \{\vec{w}_{s_1}, \ldots, \vec{w}_{s_4}\}$
  $M_4 \leftarrow \{\vec{m}_{s_1}, \ldots, \vec{m}_{s_4}\}$
  $(\dot{q}_i, \vec{t}_i, p_i, d_i) \leftarrow$ `Extract4` (W_4, M_4)
  weight [i] $\leftarrow 1/p_i^2 d_i^2$
  sumWeight $\leftarrow$ sumWeight + weight [i]
  $\dot{q} \leftarrow \dot{q}_i \cdot$ weight [i]
  $\vec{t} \leftarrow \vec{t}_i \cdot$ weight [i]

$\dot{q} \leftarrow \dot{q}$ / sumWeight
$\vec{t} \leftarrow \vec{t}$ / sumWeight

develop the algorithm shown in Algorithm 1.

Compared with the method presented by Micheals and Boult, our algorithm uses RANSAC rather than a sequential sampling approach during subset generation. This is based on the following two considerations in ultrasound image fusion applications:

- The number of point pairs is limited due to reliable anatomic landmark number and operating time. Our RANSAC approach makes full use of these data.
- The landmarks are usually picked in some kind of order, rather than randomly. Our RANSAC approach is not affected by this relevance between data points.

III. RESULTS

A. Simulation and Evaluation

To evaluate the performance of our algorithm, we made a simulation test, and compared its results with the results of the least square solution presented by Horn.

The following simulation is carried out to test the accuracy of our algorithm in general situation (Gaussian noise only) and when outliers exist.

1) Generate point data before transform ('world' points)
2) Generate a random rigid transform
3) Calculate data after transform ('model' points)
4) Add Gaussian noise on both ends
5) Generate outliers if needed
6) Carry out both algorithms on the data

The pre-transform data is 10 randomly sampled points on a sphere with radius of 10.00 cm, and the Gaussian noise is with zero average and isotropic, and is controlled by its variance σ^2. Outliers are achieved by a direct random translation on the post-transform points. Two parameters control them: the number of outliers (n_o), and the distance they move (d_o).

The registration error of the algorithms is evaluated using Average Distance Metrics (ADM), which is calculated as follows:

$$\mathrm{ADM}(W, M, \dot{q}, \vec{t}) = \frac{1}{n}\sum_{i=1}^{n}\left\|\vec{m}_i - \vec{t} - \dot{q}\vec{w}_i\dot{q}^*\right\|$$

In occasions with outliers, it is not fair to evaluatethe registration error with all point pairs. Outliers are not supposed to be registered and should be excluded when the overall registration error is evaluated. So we compute the ADM value of all the point pairs that are not outliers. It is called 'Cleaned' ADM (ADM-C).

B. Simulation Results

First, we evaluate the accuracy of our algorithm under pure Gaussian noise situation. No outlier is generated, and the power of noise is tuned up gradually. The result is presented in Figure 2.

Under the condition of pure Gaussian noise, our method gives a similar result as least square method, which is the optimal solution for the case of Gaussian noise.

Second, outliers are added. In Figure 3(a), the outlier distance is fixed to 2.00 cm, and in Figure 3(b), the number of outliers is fixed to 4. In both cases, a small Gaussian noise is used, $\sigma = 0.0387$, for both pre- and post-transform data.

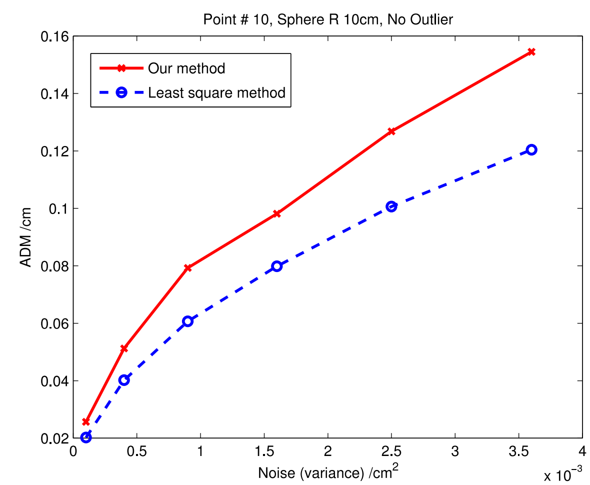
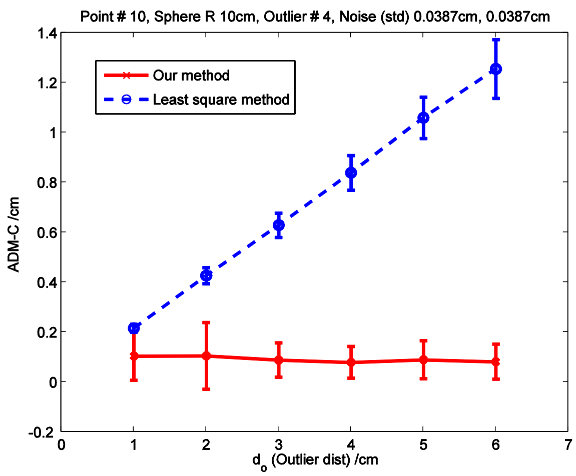


Fig. 2. Accuracy with Gaussian noise only

The power of Gaussian noise in these two cases is chosen based on a previous work on fiducial localization error of image in point-based registration [10], which stated that the average of pointing error on an image is similar to the pixel size of that image. In our case 0.3 ~ 0.4 mm is the common pixel size for US, CT and MR images. The random floating distance of outliers is determined based on an estimation of common organ deformation.

According to these results, it is shown that our algorithm performs significantly better than the widely used LS approach, with the existence of noticeable outliers. Note that in Figure 3(a), when outlier number comes to 6, our method becomes unstable. It is because there are not enough 'good' data points left to get sampled (since total point pair number is only 10).



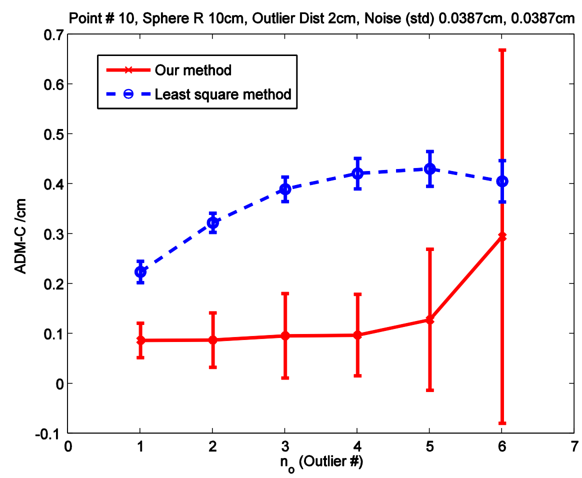


Fig. 3. Accuracy with outlier existence
Left (a): $d_o = 4.00$ cm, n_o changing. Right (b): $n_o = 4$, d_o changing.

IV. DISCUSSION

In this article, we discuss the registration problem in ultrasound image fusion system and its influence upon the accuracy of the whole system. The specific considerations of a registration algorithm used in this kind of system are analyzed. Based on these analyses, a RANSAC-based registration algorithm is presented and evaluated.

The comparison study of our method and the traditional least square method leads us to the following conclusions:

- **LS algorithm is vulnerable to outliers.** Due to its assumption of Gaussian noise, when outliers exist, LS method is significantly interfered and results in large error. However, as we have emphasized in previous analysis, these outliers are inevitable and difficult to isolate in US image fusion applications.
- **Our algorithm is reliable under Gaussian noise condition.** When Gaussian distribution can model noise, LS algorithm is mathematically optimal. Our method gives comparable result in this condition which means it is reliable in general practice.
- **The new algorithm is generally stable.** It is shown in the simulation that: as long as the data set contains some pairs (more than subset size) of 'good' points, our new algorithm is not sensitive to either outlier number or their floating distance, and thus is stable.

Although, due to the randomness nature of RANSAC, our method may produce results with relatively large variance among different trails, there are some tips to get a more reproducible result. For a relatively large data set, increasing sampling number m in RANSAC framework can reduce the variance. When the data set is small, it is acceptable to enumerate all possible subsets, and the randomness of our method is fully eliminated.

Furthermore, our method can be used to isolate outliers in the registration procedure. When the registration error of 'good' point pairs is reduced, the error of outliers is emphasized, and outliers are easier to recognize. These outliers in US image fusion applications contain useful information. Especially whenan outlier is caused by tissue shifting or deformation, itslocation can be used as a starting point for a shifting or deformation detection and correction.

REFERENCES

[1] J. W. Trobaugh, P. Kessman, D. Dietz, and R. Bucholz, "Ultrasound in Image Fusion: A Framework and Applications," in*IEEE Ultrasounics Symposium*, pp. 1393-1396, 1997.

[2] J. Krücker, S. Xu, N. Glossop, P. Guion, P. Choyke, and I. Ocak, "Fusion of realtimetransrectal ultrasound with pre-acquired MRI for multi-modality prostate imaging," in*Proc. of SPIE*, vol. 6509, no. 5, 2007.

[3] I. Kaplan, N. E. Oldenburg, P. Meskell, M. Blake, P. Church, and E. J. Holupka, "Real time MRI-ultrasound image guided stereotactic prostate biopsy." *Magnetic resonance imaging*, vol. 20, no. 3, pp. 295–9, Apr. 2002.

[4] R. M. Comeau, A. F. Sadikot, A. Fenster, and T. M. Peters, "Intraoperative ultrasound for guidance and tissue shift correction in image-guided neurosurgery." *Medical physics*, vol. 27, no. 4, pp. 787–800, Apr. 2000.

[5] B. K. P. Horn, "Closed-form solution of absolute orientation using unit quaternions," *J.Opt. Soc.Am. A*, vol. 4, no. 4, p. 629, Apr. 1987.

[6] B. Horn, H. M. Hilden, and S. Negahdaripour, "Closed-form solution of absolute orientation using orthonormal matrices," *J. Opt. Soc. Am. A*, vol. 5, no. 7, pp. 1127–1135, 1988.

[7] J. Bai, "A Study on the Registration Method and Precision in Image Guided Surgery," *Journal of Biomedical Engineering*, 2008.

[8] R. J. Micheals and T. E. Boult, "On the Robustness of Absolute Orientation," in *Proc. International Conference on Robotics and Applications*, no. 1, 2000.

[9] M. A. Fischler and R. C. Bolles, "Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography," *Communications of the ACM*, vol. 24, no. 6, 1981.

[10] W. Liu, H. Ding, H. Han, Q. Xue, Z. Sun, and G. Wang, "The study of Fiducial Localization Error of image in point-based registration." in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, vol. 2009, no. 2, Jan. 2009, pp. 5088–91.