34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

On The Performance of Improved ICP Algorithms for Registration of Intra-Ultrasound with Pre-MR Images; A Phantom Study

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***Abstract*—Ultrasound imaging as a simple and being real time has been found very applicable for intra-operative updates of pre-operative MRI data in image guided neurosurgery system. The main challenge here is the presence of speckle noise which influences the accuracy of registration of US-MR images, intra-operatively. In this paper the performance of two improved versions of the well known Iterative Closest Point (ICP) algorithms to deal with noise and outliers are considered and compared with conventional ICP method. To perform this study in a condition close to real clinical setting, a PVA-C brain phantom is made. As the results show improved versions of ICP are found more robust and precise than ICP algorithms in the presence of noise and outliers. Then the effect of various de-noising methods including diffusion filters on the accuracy of point-based registration is evaluated. The role of a proper diffusion filter for de-noising of US images has also improved the performance of the ICP algorithm and its variants about 35% and 20%, respectively.**

I. INTRODUCTION

In recent years image guided surgery (IGS) system has become a must for conducting complex surgical procedures such as brain surgeries. The key point here is the accuracy of intra-operative and pre-operative image registration which has direct impact on the final target registration error over anatomical point. A major source of error in IGS system is tissue movement and deformation such as brain shift which invalidates the pre-operative image coordination [1-3].

A cure to this problem is to obtain the new coordination of patient image dataset using intra-operative ultrasound imaging system. In recent years intra-operative ultrasound imaging has found very applicable in minimally invasive surgeries. It is being as non- ionized, costless, OR equipment compatibility, real time and portable system [4,5]. Unfortunately, the quality of ultrasound images is highly affected by speckle noise. The main goal of this paper is to consider the effect of applying various de-noising methods in particular diffusion based pre-filtering on the accuracy of registration of intra-operative US image with pre-operative MRI dataset.

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Intensity based registration uses similarity measures like Mutual Information which has been extensively used in multimodal registration. But due to speckle noises, scale differentiation between MR and US images and their different resolution, this type of similarity measures is not suitable for US-MRI registration. In this work we have concentrated on feature-based approaches leading to point based registration of multimodal images that are suitable for non-rigid registration [6].

Extraction of features, transforms our gray scale image into dense sets of discrete points. A point set can be extracted from an image based on the locations or orientation of corners, boundary points, edge points or salient regions. These points can represent geometric and intensity properties of an image. Point based registration iteratively find correspondences between points and then estimate the transformation parameters based on these correspondences [7-9]. However, point matching algorithm highly suffers from Existence of noise, outliers, and missing points in point set of image due to image acquisition and specially feature extraction. To deal with this problem it has been proposed to apply an efficient de-noising filter before feature extraction followed by segmentation algorithm for reducing outliers and missing points.

There are many algorithms in the literature that have been used for point based registration [7, 10]. One of the most common algorithms is the Iterative Closest Point (ICP) algorithm. ICP is the most popular among others due to its simplicity and low computational complexity. Despite high speed convergence of ICP algorithm its performance is highly sensitive to the initial relative. To overcome such limitations of ICP some variants of it have been introduced based on the concept of ICP since the introduction of ICP by Besl and McKay [11]. These variants seek to improve robustness to noise, speed of convergence and accuracy of conventional ICP [12,13].

Coherent Point Drift (CPD) algorithm as a probabilistic method has been found very robust to the noise and applicable in non-rigid point based registration [10]. As we already showed in our previous work [14], the CPD algorithm requires considerable computational cost therefore it is not suitable for real time registration.

In this paper we have compared the performance of conventional ICP with two improved versions of ICP for brain shift calculation applied on a brain phantom. The results are compared in terms of the speed and registration accuracy. Then, the effect of de-noising filters on the performance of registration algorithms is studied.

II. METHODS AND MATERIALS

A. *Phantom preparation and imaging*

To evaluate and validate the registration and de-noising techniques in a condition close to a real clinical setting, a phantom study is carried out in this work. The phantom was made of Poly vinyl alcohol Cryogel (PVA-C). This material is presented as a soft tissue-mimicking material and suitable for application in MR and ultrasound imaging [3, 15].

In our phantom we used PVA-C 10% for brain tissue and PVA-C 15% for the ventricle simulation. We placed some tubes with 3mm diameter for mimicking vessels and 3 Foley catheter inserted in different depth and direction. This catheter can be used to deform the phantom in different manner (Fig.1).The phantom was then scanned using a Siemens 3T scanner using a standard T1 weighted protocol with TR=11ms, TE=4.92 ms and 1 mm slice thickness. The plastic tubes in phantom were first filled with water to acquire MR images. The made phantom can be deformed in an elastic non-linear manner by inflating the catheter balloon (Fig2). Each balloon of 3 Foley catheters was filled once with 10 ml water and again with 20 ml water, thereby the phantom was scanned with MRI system in 6 situations and as a result 30 data with large deformation was acquired. Ultrasound images correspond to this 30 image dataset were acquired using HS-2000, Honda Medical Systems ultrasound machine with multi-frequency linear with central frequency 5 MHZ.

B. *US image de-noising*

US image suffers from speckle noise as an intrinsic phenomenon that restricts the quality of ultrasound images. These noises appear due to random constructive and destructive interference between coherent echoes. There have been a variety of techniques for speckle reduction in literature.

In this paper, we focused on common single scale de-noising filters such as Median, wiener and Lee which are mainly based on intensity of images and diffusion filters which work based on gradients of intensity of the images.

Diffusion filters are found as an efficient smoothing algorithm by introducing conductance parameter as a measure of image smoothness which is related to the gradient magnitude of image. The key idea of the diffusion filters is to control the smoothing process when reached into edges. These filters tend to change the conductance parameter adaptively to achieve more diffusion in the interior regions, where the gradient is small and less diffusion occurs at the edges where the gradient becomes larger. This proves the ability of these filters in reducing the noise level while keeping the main features of an image. For the first time Perona and Malik [16] proposed the concept of nonlinear diffusion in noise reduction and applied the PDE equation to smooth the image.

$$\begin{cases} \frac{\partial I}{\partial t} = div(C\|\nabla I\|.\nabla I) \\ I(t=0) = I_0 \end{cases} \tag{1}$$

Where, C is the diffusion function or in the other words the edge preserving function. They introduced two diffusion coefficients as follows:

$$C_1 = \frac{1}{1+\left(\frac{\|\nabla I\|}{k}\right)^2} \quad , \quad C_2 = \exp\left[-\left(\frac{\|\nabla I\|}{k}\right)^2\right] \tag{2}$$

Also another diffusion coefficient was introduced by Weickert [17]:

$$C(x) = 1 - \exp\left[-3.31\left(x/k\right)^2\right] \tag{3}$$

For noisy images with speckles, the gradient of the noise is almost comparable to gradient of the features. So it seems P-M filters amplify the noise of image or increase the stair effect near the smoothed edges. To overcome this effect Catte proposed a new coefficient which is called Catte-PM model [18]. In this model, the smoothness resulted from applying the Gaussian filter with small σ, makes it less sensitive to noise.

$$\begin{cases} \frac{\partial I}{\partial t} = div[C\|G(\sigma) * I\|].\nabla I \\ I(t=0) = I_0 \end{cases} \tag{4}$$

Yu and Acton proposed a method which was sensitive to edge with an instantaneous coefficient of variation [19]. This method is called Speckle Reduction Anisotropic Diffusion (SRAD). This method not only preserves edges but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. Unlike other diffusion techniques that process log-compressed data, this technique analysis the data directly in order to preserve useful information in the image. This filter is modeled with below diffusion coefficients:

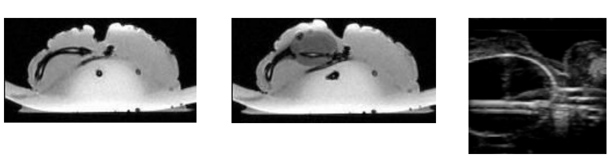
$$C(q) = \frac{1}{1+\frac{q^2-q_0^2}{q_0^2(1+q_0^2)}} \tag{5}$$

$$q_0(t) = q_0 \exp(-\rho t) \tag{6}$$

$$q = \sqrt{\frac{\frac{1}{2}\left(\frac{\nabla I}{I}\right)^2 - \frac{1}{4^2}\left(\frac{\nabla^2 I}{I}\right)^2}{\left(1+\frac{1}{4}\frac{\nabla^2 I}{I}\right)^2}} \tag{7}$$

The performance of these de-noising filters are evaluated using four evaluation parameters named Signal to Noise Ratio (SNR), Root Mean Square Error (RMSE), Correlation Coefficient (COC), and edge preserving index (EPI).

Fig.1 The phantom that was made from PVA-C



(a) (b) (c)

Fig.2 (a) Coronal view of MR image before deformation (b) Corresponding MR image after deformation (c) Corresponding US image after deformation

C. *Iterative Closest Point (ICP) and Improved ICP*

The ICP algorithm is used for the alignment of two clouds of points. The main concept of the original ICP algorithm can be expressed in finding correspondences between the two point set and computing a transformation which minimizes distance between corresponding point pairs. ICP iteratively repeats these two steps until convergences to the desired transformation. The algorithm will converge rapidly in the first iteration but may converge towards local minima instead of the global minimum. ICP requires that the initial pose of the two point sets are adequately close, which is not always possible, especially in non-rigid transformation.

The stages of ICP algorithm can be broken into six steps; Selecting points, matching points, weighting points, rejecting points, error metric and minimizing the error metric. To overcome limitations of ICP some variants of ICP have been proposed by tackling some of these stages of the algorithm. We have performed extensive experiments to consider the performance of these variants to evaluate their speed and accuracy on the registration. We then proposed *two improved versions of ICP algorithm* by modifying some of the above mentioned stages based on our application needs.

We continue to describe six steps of improved ICP algorithms. In the selecting points stage, reducing the number of points by applying down sampling could be useful to reduce computational complexity and rejecting outliers while keeping the accuracy of the algorithm. The down sampling rate was chosen ¼, experimentally. The second stage of ICP is to finding the correspondence between points. Finding closest points in the other mesh is most common in matching stage. Instead of using Euclidean distance in the conventional ICP, nearest neighbor searching and Delaunay triangulations are used to increase the accuracy of the algorithm.

In the process of weighting pairs we propose using identical weights for all point pairs in the dataset.

Next step, rejecting points is similar to assigning weights to corresponding pairs. The purpose of this stage is to eliminate outliers. We propose rejection of 10% of pairs with maximum distant points to points is adequate.

One of the most important parts of the ICP algorithm is the error measurement to be minimized during iteration of the algorithm. Point to point and point to plane errors were used as a common error metrics. Point to point criteria minimizes the sum square differences between distances of corresponding points in the dataset. Point to plane minimizes sum of differences between source points and the tangent Plane which contains corresponding target points. This is done by minimizing the dot products of the vectors $\overrightarrow{p_i q_i}$ and normal $\overrightarrow{n_i}$, where p and q are source and target points. These errors can be expressed as 8, 9 equations respectively.

$$E = \sum_{i=1}^{N} \left\| R_{p_i} + \vec{T} - q_i \right\|^2 \tag{8}$$

$$E = \sum_{i=1}^{N} \left[\left(R_{p_i} + \vec{T} - q_i \right) . \vec{n_i} \right]^2 \tag{9}$$

The point to point and point to plane minimization problem were solved by applying SVD and non-linear method Levenberg-Marquardt respectively.

Based on the above mentioned modifications two improved versions of ICP algorithm, ICP-1 and ICP-2, were built with applying down sampling in target points, Delaunay triangulations method for finding corresponding pair points and rejecting 10% of pair points. In ICP1 and ICP2, point to point and point to plane error metric are used, respectively.

III. RESULTS

An extensive experiment is carried out on the evaluation of the most well known de-noising filters on US images. The results of applying eight filters for de-noising of US images are shown in Fig.3. The mean of evaluation parameters named SNR, RMSE, COC and EPI were obtained for thirty US dataset as illustrated in Table.1. SRAD filters showed significant differences with other de-noising filters in terms of the value of SNR and with other diffusion filters in terms of RMSE, COC and EPI. Consequently, SRAD has performed best results for de-noising, due to its ability to enhance the edges as expected.

For point-based registration, we used the RMSE between the corresponding points after the registration as an error measure in all of the algorithms. As shown in Table.2, two improved ICP algorithms and the conventional ICP are compared to each other for US-MRI registration in our data set in terms of accuracy, speed and number of iterations.

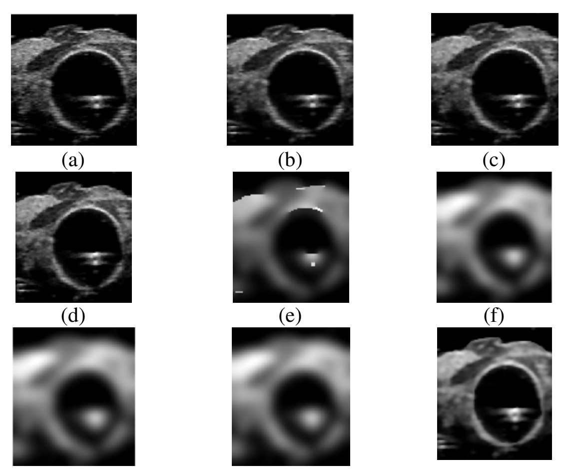


Fig.3 (a) original US image. US images after applying filters (b) Median.(c) Wiener.(d) Lee .(e) PM1.(f) PM2 .(g) Catte. (h) Weickert. (i) SRAD

Table.1
The mean of SNR, RMSE, COC and EPI are applied to compare de-noising filters in 30 data

Parameters / Filter	SNR (db) (mean±std)	RMSE (mm) (mean±std)	COC (<1) (mean±std)	EPI (<1) (mean±std)
Median	12.04±1.26	0.06±0.05	0.90±0.01	0.72±0.05
Wiener	12.75±1.25	0.05±0.04	0.91±0.01	0.73±0.05

Lee	12.91±1.23	0.05±0.3	0.93±0.02	0.74±0.06
PM1	19.19±1.05	0.12±0.09	0.89±0.01	0.63±0.07
PM2	16.08±1.26	0.16±0.11	0.76±0.03	0.14±0.01
Catte	16.31±1.21	0.17±0.11	0.78±0.02	0.12±0.01
Weickert	18.41±1.15	0.14±0.08	0.79±0.02	0.11±0.02
RAMP	20.48±1.01	0.12±0.07	0.88±0.04	0.75±0.02
SRAD	32.96±0.96	0.03±0.002	0.98±0.01	0.95±0.01

Table.2
Comparison between two improved ICPs and conventional ICP

Parameter / Method	RMS Error Total (mm) (mean±std)	Time (s) (mean±std)	Iteration (num)
Conventional ICP	2.77 ± 0.2	47 ± 3	10
Improved-1 ICP	2.03 ± 0.2	25 ± 3	10
Improved-2 ICP	1.66 ± 0.3	34 ± 2	10

In Table.3 results of US-MRI registration are compared with MRI-MRI registration of before/after deformation images as a gold standard. The difference between the result of US-MR and MR-MR image registration with using ICP-1&2 are found 0.6 mm and 0.5 mm, respectively.

To evaluate the effect of noise reduction on the performance of ICPs, original images before de-noising were used for registration. Comparison between the results of noisy and de-noised image are shown in Table 4. It can be seen that among de-noising filters, the SRAD has shown more influence on the accuracy of conventional ICP based registration as compared to improved versions of ICP. The results also show that the two proposed ICP algorithms are more robust than conventional ICP in presence of noise.

IV. CONCLUSION

The utilization of intra-operative ultrasound imaging has become recently very attractive in neurosurgeries for calculation of brain shift. However, presence of speckle noise appeared in US images can have impact on the accuracy registration as the main challenging problem in point to pint registration methods.

In this paper by conducting a phantom based study the effect of pre-filtering methods on the accuracy of registration algorithms are considered. Diffusion filters were implemented and were compared to each other and SRAD filter proved to be the best filters in simultaneous enhancement of edges and reduction of noise due to considering direction of edges.

It was shown that the two improved version of ICP, ICP-1&2 algorithms are able to increase the accuracy of point based registration of US-MR images as compared to conventional ICP by order of 27% and 40%, respectively.

We also showed that using SRAD filter for de-noising of US image has led to improve the performance of conventional ICP, ICP-1 and ICP-2 about 35%, 20% and 17% respectively.

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Table.3
Comparison between US-MR and MR-MR image registration

Method / Modality	RMSE(mm) with Improved-1 ICP	RMSE(mm) with Improved-2 ICP
MRI-MRI	1.43	1.16
US-MRI	2.03	1.66

Table.4
Result of RMS error for two Improved ICPs and conventional ICP before/after using de-noising filters

Error / Method	RMSE Before de-noising (mm)	RMSE After de-noising (mm)
ICP	3.73	2.77
Improved-1 ICP	2.43	2.03
Improved-2 ICP	1.99	1.66