Performance Evaluation of the Modified Iterative Closest Point Methods for Intra-operative Ultrasound and Pre-operative MR Image Registration of Brain

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A B S T R A C T

Purpose: Intra-operative ultrasound imaging as a non-ionized and being real time has been found very applicable as an intra-operative update of patient data in image guided neurosurgery system. The main point is the accurate registration of intra-operative with pre-operative images. Due to speckle noise in ultrasound images, scale differentiation between MR and ultrasound images and their different resolution, an accurate registration of ultrasound images with pre-operative MR images is a challenging problem.

Methods: In this paper the effect of different steps of the Iterative Closest Point is considered and, then, the best modified version of ICP is introduced for this type of data. To perform this study, a Poly Vinyl Alcohol-Cryogel brain phantom is used which allows simulating brain deformation. The performance of the best version of ICP is compared to a well-known point based algorithm, Coherent Point Drift in terms of accuracy and speed.

Results: The results proved CPD algorithm was more robust than ICP algorithms in the presence of noise, although with a more computational cost. Changing different steps in conventional ICP has led to improve the performance of the ICP. As the results of our phantom study confirm the best version of ICP has not only achieved an accuracy close to CPD method, but also in a much faster approach.

Conclusion: According to a trade off between the speed and accuracy of nine implemented versions of ICP algorithms, using some modified version of ICP is preferred to CPD method.

1. Introduction

In recent years image guided surgery (IGS) system has become a must for conducting surgeries from simple to complex surgical procedures. One of the main areas for using IGS systems is neurosurgery. Image guided neurosurgery systems (IGNS) update 3D patient information using computer-tracked tool and project pre-operative Computer Tomography (CT) or Magnetic Resonance Image (MRI) data into the operative field to an accurate localization of important anatomic structures such as carotid artery or cranial nerves (especially if they are deep in the tumor such as medial peritoneal wing Meningioma or Transsphenoidal pituitary surgery) as well as defining tumor margins for a safe maximal resection of the tumor during the surgery. The key point is the accuracy of intra-operative and pre-operative image registration which has a direct impact on the final target registration error over anatomical point. A major source of error in IGNS system is Brain movement and deformation which invalidates the pre-operative image coordinates. This deformation in the brain is a consequence of various combined factors: gravity, leakage of cerebro-spinal fluid (CSF), retraction and resection of tissue, edema, swelling of brain structures, and administration of drugs [1-5]. A cure to this problem would be to obtain the new deformed coordination of patient

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using an intra-operative imaging system such as MRI, CT and ultrasound. These new data, if correlated to the pre-operative data, can be used directly to measure and correct brain shift. Intra-operative MRI, as a most common modality, can provide the surgeon with updated anatomical images several times during a surgery procedure. It can produce excellent images of the brain's anatomical structures and is being used to study brain deformation but it has its limitations. A dedicated intra-operative MRI system requires a substantial investment for the scanner and equipping the operating room (OR) with MR-compatible instruments, nevertheless intra-operative MRI has been used as gold standard for intra-operative and pre-operative registration accuracy during neurosurgery [6-8].

CT images, as one of the primary modalities which were used intra-operatively, suffer from lower soft tissue contrast compared to MRI; therefore, intra-operative CT images are less functional for brain surgery. Although new approaches for reducing the exposure to the patient and OR staff were proposed, the radiation dose to the patient is one of the most important limitations of the using CT scans in OR. Besides, the physical space occupied by the CT scanner in the OR is another problem [3, 9, 10].

Ultrasound, the alternative imaging system, has a long history of intra-operative using in neurosurgery. Intra-operative ultrasound in neurosurgery for the first time was published by using one-dimensional A-mode images in 1950. [11, 12]. Afterwards, in the early eighties, the first work using 2D real-time B-mode ultrasound imaging was published for brain surgery [13]. They reported that ultrasound may be advantageous for surgical planning and biopsy procedures because of its reliable information of intracranial anatomy. In recent years, intra-operative ultrasound was used for tumor localization and determining the tumor margin in many patients who underwent neurosurgery because of its advantages such as being non-ionized, costless, real time and portable, having little distortion and OR equipment compatibility . It was used for the first time in 1994 by Trobaugh for correlating with preoperative images in Neuro-navigation systems [14-21]. The registration of real time US with pre-operative MR images will allow the surgeon to accurately localize their instruments in the operative field, resulting in MIS procedures. Unfortunately, the limited field of view of ultrasound compared to the pre-operative images (MR or CT) as well as its image quality are two main problems in intra-operative ultrasound image registration. The quality of ultrasound images is highly affected by speckle noises. However, recently special processing modules were added to the image acquisition system in order to suppress the speckles and also to enhance the information content in the ultrasound image but the ultrasound images suffered from the speckles.

On the other hand, brain deformation is a non-rigid problem. Although many algorithms are in place for this non-linear and multimodal registration, finding registration algorithm to cope with the problems in the ultrasound images is a challenge. As an example, intensity based registration algorithms which are using similarity measures such as mutual information, correlation ratio or sum square differences are used extensively in multimodal registration, however, due to speckle noise in US images, scale differentiation between MR and ultrasound images and their different resolution, this type of similarity measures are not suitable for ultrasound-MR image registration. In this study, we have concentrated on feature-based approaches leading to point based registration of multimodal images that are suitable for non-rigid registration [22].

Extraction of features, transforms our gray scale image into dense sets of discrete points. A demanded point set can be extracted from an image based on the locations or the orientation of the corners, boundary points, edge points or salient regions. These points can represent geometric and intensity properties of an image. However, it should be noted that the point based matching almost as well as intensity based registration dealing with speckles. Because of the feature extraction in ultrasound images affected by noise, speckle reduction becomes a must before ultrasound image registration. In our previous works, it was proposed to apply a de-noising filter before feature extraction followed by segmentation which could be useful for reducing outliers, missing points and speckles [23]. At the other end of the problem, point based registration methods iteratively find correspondences between points and, then, estimate the transformation parameters based on these correspondences. Therefore, high dimensionality of point sets is a problem which is also taken into account [24-26].

There are many algorithms in the literature which have been used for point based registration [24, 27]. One of the most common algorithms is the conventional Iterative Closet Point (ICP) algorithm. ICP is the most popular amongst others due to its simplicity and low computational complexity. The ICP algorithm which is used for the alignment of two clouds of points iteratively assigns correspondences based on the closest distance criterion and finds the least-squares transformation relating the two point sets [28]. Despite the high speed convergence of the ICP algorithm, it maybe converged towards local minima instead of the global minimum. Also, The ICP algorithm requires that the initial phase of the two point sets is adequately close to each other and its performance is highly sensitive to the initial relative. To overcome such limitations of conventional ICP, some modified versions of ICP have been introduced based on the first concept of ICP algorithm. These modified versions seek to improve robustness to noises and outliers, speed of convergence and accuracy of conventional ICP [29, 30].

In intra-operative image registration, the algorithm's computational time is of great importance. Therefore, despite the mentioned limitations of ICP, this algorithm cannot be completely discarded due to its time efficiency.

We have undertaken a comprehensive study and comparison of the performance of ICP and its applicable versions to brain shift calculation applied on the brain phantom data. Then, the results of the best modified version of ICP were compared with the well-known and accurate probabilistic registration method called as Coherent Point Drift (CPD) [31] in terms of registration accuracy and computational time. Besides, the effect of pre-filtering on the performance of the best versions of the ICP and CPD is studied.

The paper is organized as follows. Sections B.1, B.2 and B.3 describe a summary of pervious works about the designed phantom and its data acquisition, de-noising method and segmentation of Ultrasound images. Section B.4 describes the modified versions of ICP and CPD methods are studied in part B.5.. Section C is dedicated to experimental results and conclusions are written in Section D.

2. Method and Material

A schematic overview of the proposed method is given in Fig. 1.

2.1. PVA-C Phantom of the Brain

To evaluate and validate the image registration algorithms in a condition close to a real clinical setting, a Brain phantom which was carried out in our previous work is used [23].

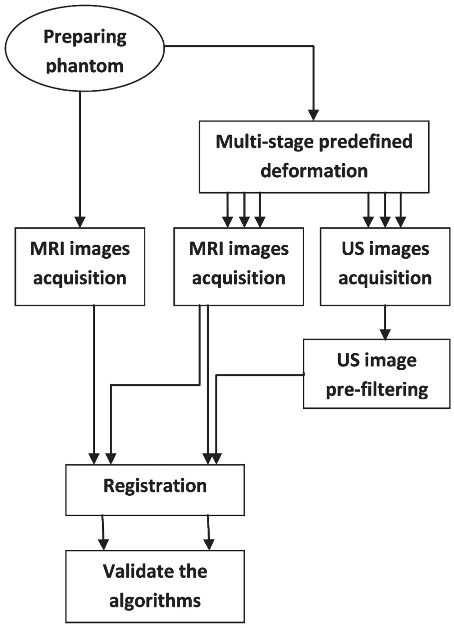


Figure1. A schematic overview of the proposed method

The PVA-C phantom was made of three layers. The first layer, PVA-C 10%, for brain tissue and the second layer, PVA-C 15%, for ventricle simulation were used. The third layer was designed in order to be able to apply the deformation more conveniently. Some tubes with 3mm diameter to mimic vessels and 3 Foley catheters were inserted in different depth and direction. Then, the phantom was deformed by filling balloons of Foley catheters once with 10 ml water and again with 20 ml water. Then, Ultrasound and MR images were acquired before and after deformation respectively (Fig. 2).

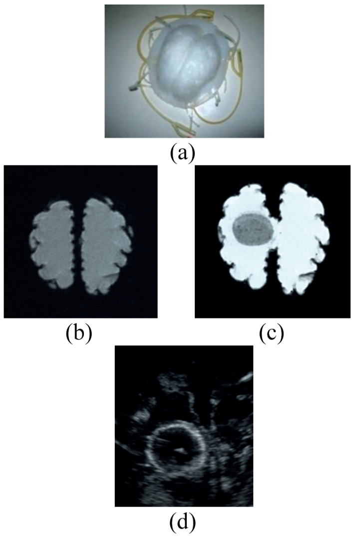
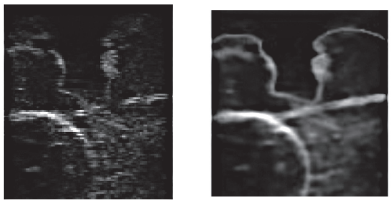


Figure 2. (a) PVA-C phantom of the Brain. **(b)** MRI image before deformation in axial view. **(c), (d)** Corresponding MRI images and Ultrasound images after deformation.

2.2. Ultrasound Image De-Noising

Despite the advantages of diagnosis ultrasound, it suffers from speckle noise which restricts the quality of its images. There have been a variety of techniques to speckle reduction in literature. In our previous work in 2012, we focused on common single scale methods such as Median, wiener and Lee which are mainly based on the intensity of the images and diffusion filters. These are based on the gradients of intensity of the images because single scale methods have a reasonable computational time [23]. As shown previously, SRAD filters had significant differences with median, wiener and Lee filters in terms of the value of signal to noise ratio and with other diffusion filters such as Weickert, PM, Catte-PM in terms of Root Mean Square Error (RMSE), correlation coefficient and edge preserving index. Consequently, it had the best performance to de-noise our phantom ultrasound images (Fig. 3).



(a) (b)

Figure 2. (a) original US image. **(b)** Ultrasound images after applying SRAD filter.

2.3. US Image Segmentation

After selecting a suitable de-noising method to correct extraction of features, an efficient segmentation method is necessary. In our last work, we concentrated on Chan-Vese (CV) method as a non-parametric active contour based on the level set function concept which has been used extensively for image segmentation. Level sets do not require any parameterization of the evolving contour and also do not need initial boundary which includes objects. This model could detect more than one object and boundaries in an image which is very important for this type of data. Previously, we optimized the parameters of CV for ultrasound images of our phantom and, then, a canny edge detector was used to edge detection of ultrasound images [23].

2.4. Modified Versions of ICP

The key concept of the conventional ICP algorithm can be summarized in two steps:

1) Compute correspondences between the two cloud points.

2) Compute a transformation which minimizes distance between corresponding points.

Iteratively repeating these two steps typically results in a convergence to the desired transformation as shown in equation1.

$$(R, T) = \arg\min_{R,T} \sum_{i=1}^{N} w_i \left(R * p_i + \vec{T} - q_i\right)^2 \quad (1)$$

Where p_i, q_i denote data points and model points respectively. Also matrix R and T are rotation and translation matrix respectively which are defined transformation. The w_i is weight correspond to i th pair point.

The ICP algorithm was considered with more detail and its steps could be classified into six steps: Selecting points, matching points, weighting pair points, rejecting points, computing error metric and minimizing the error metric. To overcome such limitations of ICP, some modified versions of it have been proposed by changing various stages of the algorithm, from selecting points to minimization strategy.

We have performed extensive experiments to consider the performance of these modified versions from standpoints speed and the accuracy of the registration algorithm. We continue to describe all of these six steps and introduce our selected phases in each step.

2.4.1. Selecting Points

Considering only selected points instead of all the points before applying the ICP algorithm was proposed to reduce computational complexity and it may also help to reject outliers. This stage speeds up computations of the algorithm for the next step. Uniform sub sampling, random sampling, selecting points with high intensity gradient and many other methods were proposed for this step of ICP algorithm. Random sampling of ultrasound data had not a good effect on the ICP results, perhaps due to the properties of the ultrasound images of phantom. The uniform down sampling with rate ¼ was chosen experimentally for sampling the points of ultrasound image.

2. 4.2. Matching Pair Points

The second stage of ICP that we will describe is finding the corresponding points in two point sets. Many algorithms have been proposed for matching point pairs. Finding the closest points in the other mesh is most common in the matching stage. Instead of using brute force in the conventional ICP which is calculating the simple Euclidean distance to all neighbor candidates and picking the closest point, nearest neighbor searching methods such as KD trees and Delaunay triangulations and Projecting the source point onto the destination mesh could be used to increase the accuracy of the algorithm. Considering the type of our data in this study, Delaunay triangulations, Brute force and KD-Tree matching are compared in terms of speed and accuracy.

It should be noted that in a 2-D point set, Delaunay matching is performed as follows: Three points form a valid triangle if an important point is that the circum circle of the triangle must not contain any other points from the point set. The Delaunay triangulation is not necessarily defined uniquely and might not be defined at all. Also, in the KD-Tree matching a tentative backtracking search to identify nearest neighbors is used.

Table 1. Nine modified versions of the ICP that were proposed

Method	Sampling	Matching	Rejecting	Weighting	Error Metric
ICP	Non	Brute force	Non	Constant Weight	Point to point
ICP-1	Down sampling	Brute force	Non	Constant Weight	Point to point
ICP-2	Down sampling	Brute force	10%	Constant Weight	Point to point
ICP-3	Down sampling	Brute force	10%	Constant Weight	Point to plane
ICP-4	Down sampling	Delaunay	Non	Constant Weight	Point to point
ICP-5	Down sampling	Delaunay	10%	Constant Weight	Point to point
ICP-6	Down sampling	Delaunay	10%	Fuzzy weight	Point to point
ICP-7	Down sampling	Delaunay	10%	Fuzzy weight	Point to plane
ICP-8	Down sampling	KD-Tree	10%	Fuzzy weight	Point to point
ICP-9	Down sampling	KD-Tree	10%	Fuzzy weight	Point to plane

2.4.3. Weighting Pair Points

Allocating different weights to the corresponding pair could be useful to reduce the effect of outliers. These weights can be defined based on distance, color, curvature and tangent normal. In this step, we use the identical weight (equal to one) for all point pairs in the dataset once and another one linear fuzzy weight according to the pair points' distances are assigned to them. It seems that this weighting may be useful to reduce the effect of outliers in RMS errors.

2.4.4. Rejecting Points

Rejecting points are similar to assigning weights to corresponding pair points. The purpose of this concept is to eliminate outliers to reduce the root mean square error. Various strategies can be used for rejecting the pairs Such as:

- Rejection of pairs with greater point-to-point distance compared to predefined threshold.
- Rejection of the worst n% of pairs based on certain metric, usually rejecting based on point-to-point distance.
- Rejection of pairs whose point-to-point distance is larger than some multiple of the standard deviation of the distances. We tested both the conventional ICP algorithm with no point rejection as well as rejecting 10% of the points with maximum distance.

2.4.5. Error Metric

One of the most important parts of the ICP algorithm is the error measurement which is minimized in the each iteration of the algorithm. Point to point and point to plane errors are used as a common error metric. Point to point criteria minimizes the sum square differences between distances of corresponding points in the dataset. Whereas point to the plane minimizes the 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. Besides, the number of points to make plane is an effective parameter on the registration error. These errors can be expressed as 2, 3 equation respectively.

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

$$E = \sum_{i=1}^{N} \left[\left(R_{p_i} + \vec{T} - q_i \right) . \vec{n_i} \right] \tag{3}$$

In the point to plane error metric $\overrightarrow{(n_i)}$ denotes the estimated tangent normals at the i th model point.

2.4.6. Minimizing Error Metric

Many solutions have been proposed for minimizing error metric. Many closed form solutions, such as SVD, are also used for minimization point to point error metric. The SVD is commonly used in linear minimization problems. The point to plane problem must be solved by generic non-linear methods such as Levenberg-Marquardt, or by linearization of the rotation matrix. This problem does not have any closed form solution. SVD and Levenberg-Marquardt methods were used for point to point and point to plane minimization respectively.

Based on all the above mentioned steps we obtained nine useful modified versions of ICP for this application. These versions are named from ICP1 to ICP9 considering their properties in Table.1.

2. 5. Coherent Point Drift Method

The CPD method which was introduced as a robust probabilistic multidimensional method for non-rigid point set registration and considered the alignment of two point sets as probability density estimation, with motion coherence constraint for the first time was used for ultrasound-MR image registration in 2011[32]. In this method one point set represents the Gaussian Mixture Model (GMM) centroids and the other represents the data points. This algorithm iteratively fits the GMM centroids by maximizing the likelihood and finds the posterior probabilities of centroids and has been showing good registration accuracy.

3. Result

For point-based registration, we used the RMSE between the corresponding points after the registration as an error measure in all of the algorithms. The nine modified versions of the ICP and the conventional ICP are compared to each other and with the CPD method.

The algorithms were tested on 20 two dimensional data containing a mean and a maximum deformation of about 17 mm and 21.2 mm respectively. The mean and variance of RMS error, mean and variance of convergence time and number of iterations are shown in Table.2. A comparison between conventional ICP and its modified versions indicates the role of each step in ICP algorithm. As expected, down sampling of the ultrasound image points speed up the algorithm (Fig.4). In spite of the increade in the accuracy of registration algorithm in this case, we cannot comment about the effect of it on the accuracy decisively. Besides, processes of rejecting the points have led to increase the speed and accuracy of the algorithms (Fig.5).

Table 2. Modified versions of ICP and the conventional ICP are compared in RMS error and convergence time with a fixed number of iterations. These results are also compared to CPD method

Method	RMS Error Total (mm)	Time (s)	Iteration
ICP	2.77±0.03	45± 2	10
ICP-1	2.67±0.07	37± 1	10
ICP-2	2.34±0.03	34± 1	10
ICP-3	2.14±0.02	39± 1	10
ICP-4	2.30±0.07	40 ± 2	10
ICP-5	2.16±0.05	37± 1	10
ICP-6	1.93±0.05	37± 2	10
ICP-7	1.71±0.06	41± 2	10
ICP-8	1.69±0.04	43± 1	10
ICP-9	1.63±0.03	44± 2	10
CPD	1.28±0.06	95± 2	75

Modified versions of ICP and the conventional ICP are compared in RMS error and convergence time with a fixed number of iterations. These results are also compared to CPD method

Using linear fuzzy weight according to the distances of points instead of using constant weight lead to an increased registration accuracy and it does not have any impressive effect on the computational time (Fig.6). Delaunay matching has also improved the accuracy of ICP algorithm, but it has a negative effect on the speed of algorithm for this data set. KD-Tree matching have the best result compared to Brute force and Delaunay for point matching in accuracy and it is performing slower than two others (Fig.7).

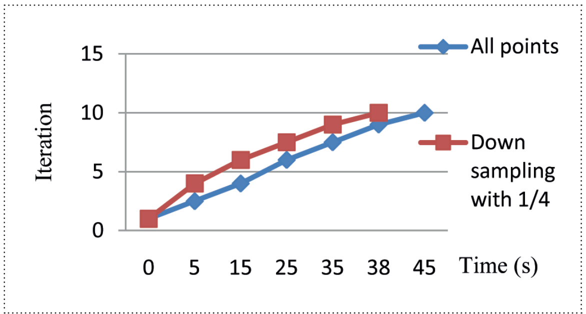


Figure 4. Effect of down sampling on the speed of the algorithm.

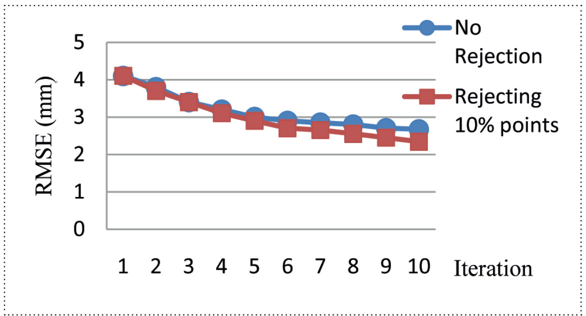


Figure 5. Effect of rejecting on the accuracy of the algorithm.

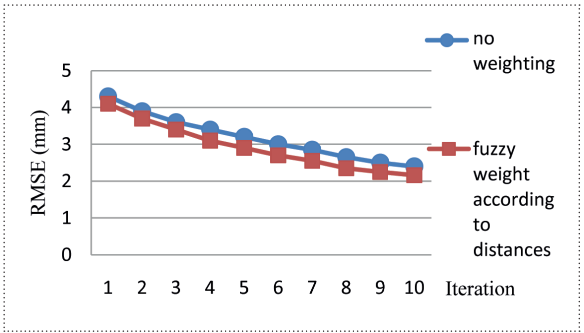


Figure 6. Effect of weighting on the accuracy of the algorithm.

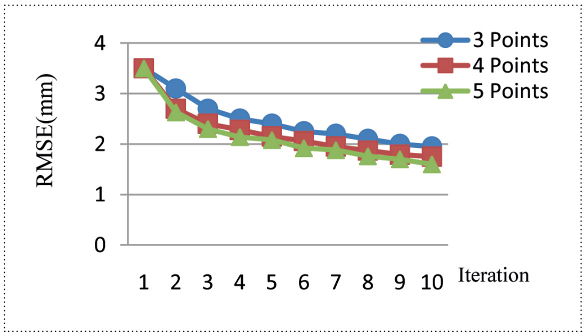


Figure 7.Effect of matching on the accuracy of the algorithm.

Using point to plane error metric strategy instead of point to point error metric, in spite of decreasing computation time of the algorithm, improves the accuracy of registration. In point to plane error metric, the number of points to make plane is one of the important parameters. As shown in Fig.8, when the numbers of points are increased the accuracy of ICP is increased, however, due to high computational time the number of points 4 is selected to make a plane.

Our experiment showed ICP-9 has performed the best results in terms of accuracy. Its speed was acceptable and was about conventional ICP. The selected, as the best configuration among modified versions of the ICP uses down sampling of rate ¼, 10% rejection of points, using linear fuzzy weights , KD-Tree matching and point to plane error metric.

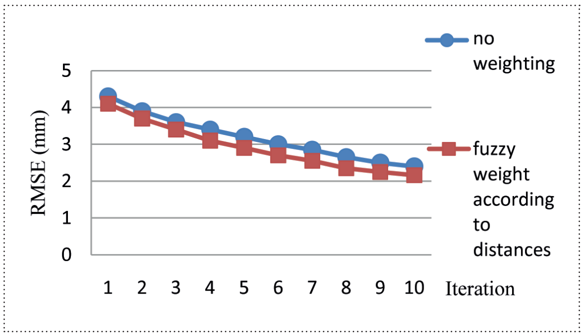


Figure 8. Effect of number of points in point-plane error metric.

For the comparison of registration error, the non-rigid registration procedure was repeated using only MR data set as gold standard. RMS error was calculated in MR-MR and US-MR registration for the best version of the ICP is compared to CPD results. To evaluate the effect of noise reduction on the performance of ICP and CPD, we applied the registration algorithm on noisy images (table. 3). By comparing the results in table 3, it can be found that de-noising filters are more effective on the accuracy of ICP than CPD. After using suitable de-noising and segmentation methods such as SRAD and CV, the result in ICP-9 was found close to CPD result in the accuracy of registration, while the execution time of ICP is about half of the CPD time. It should be noted that 25 runs were conducted for registration algorithms. The algorithms are implemented in Matlab, and tested on a Pentium4 CPU 2.4GHz with 4GB RAM.

Table 3. Result of RMS error for ICP-8 and CPD in MR-MR and US-MR.

RMSE (mm)	With using de-noising filters on US images		Without using de-noising filters on US images	
	ICP-8	CPD	ICP-8	CPD
MR-MR	0.91	0.83	0.91	0.83
Ultrasound-MR	1.63	1.28	2.22	1.39

4. Conclusion

The utilization of intra-operative ultrasound imaging has become very applicable in neurosurgeries for the calculation of brain shift. The SRAD filter was implemented and, then the de-noised image was segmented by Chan-Vese method as a non-parametric active contour. Consequently, images that contain discrete points were achieved. In this paper the effect of pre-filtering on the accuracy of registration algorithms are considered.

Some modified versions of ICP were compared to each other as a well-known method for point based registration in terms of speed and accuracy registration.

In the ICPs KD-Tree matching performed more accurate than a simple Euclidean distance and Delaunay matching. Also point to plane error metric was found effective to increase the accuracy of algorithm. To reduce the effect of noises rejecting, down sampling and weighting of points were used. This version of the ICP clearly outperforms the conventional ICP in terms of precision. At the other end the accurate and well-known CPD method requires that each data point represented by a GMM model. Therefore, it takes more time than ICP methods. The uniform distribution is also used to account noise and outliers which led CPD to be more robust than ICPs in the presence of noise and outliers.

Therefore, de-noising filters on the ultrasound images have more impacts on ICP performance.

According to a trade off between the speed of the best version of ICP algorithm and its accuracy, it is recommended to use the best version of ICP as compared to CPD method for de-noised Ultrasound images.

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