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An efficient Point Based Registration of Intra-operative Ultrasound images with MR images for computation of brain shift; a Phantom Study

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***Abstract*—Intra-operative brain deformation (brain shift) limits the accuracy of image-guided neuro-surgery systems. Ultrasound imaging as a simple, fast and being real time has become an alternative to MR imaging which is an expensive system for brain shift calculation. The main challenges due to speckle noise and artifacts in US images, is to perform an accurate and fast registration of Us images with pre-operative MR images. In this paper an efficient point based registration method based on the alignment of probability density functions called Coherent Point Drift (CPD) is implemented and compared to the conventional ICP method. To perform this, a brain phantom that allows simulating the brain deformation is made. As the results of our phantom study confirm the CPD method clearly outperforms the ICP algorithm for brain shift calculation. Also the result proves that using intra-operative US has led to recover almost 80% of displacement in the region of interest.**

A. Introduction

Brain surgery operations, such as tumor resections, are quite challenging procedures that require a rigorous planning and image guided techniques during the operation in order to accurately find the position of structures inside the brain [1]. Modern image guided neuro-surgery systems enable the surgeon to navigate within the patient's brain using pre-operative anatomical images (MRI, CT) as a guide by using a computer-tracked probe or other instruments during the procedure in the operating room. The surgeon can localize any point in the patient's brain on the pre-operative images [2], [7]. A major source of error in these systems is brain tissue movement and deformation, so called brain shift. This deformation is a consequence of various combined factors: gravity, leakage of cerebro-spinal fluid (CSF), resection of tissue, edema, swelling of brain structures, and administration of drugs [1], [4].

This problem may be approached in two ways: The shape of the exposed brain can be tracked by sampling its surface with a physical pointer or by using a range sensor, or alternatively, by acquiring tomographic information using an intra-operative imaging device, either MRI or CT or ultrasound [7]. Intra-operative MRI scanners can provide the surgeon with updated anatomical images several times during a procedure, and can therefore be a valuable tool for characterization and correction of brain shift, but a dedicated intra-operative MRI system requires a substantial investment for the scanner itself as well as equipping the operating room with MR-compatible instruments [2], [6], [7].

There are two different ways of using ultrasound imaging in order to obtain a map that corresponds to the anatomy at all times: (1) indirectly: use of ultrasound to track the anatomical changes that occur, use these changes to elastically modify the preoperative image data and navigate according to the manipulated MRI/CT scans; or (2) directly: use of intra-operative ultrasound scans simply by navigating according to these high quality images [5].

The ultimate goal is to correlate the pre-operative data with real time US images that can be used directly to measure for brain shift. The registration of US with pre-operative MR images will allow the surgeon to accurately localize the course of instruments in the operative field, resulting in minimally invasive procedures [8].

Registration of Ultrasound images poses a significant challenge due to the following shortcomings: (i) Low SNR of ultrasound images; (ii) motion ambiguities; (iii) Speckle de-correlation [9].

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Mutual Information (MI) has been used in multimodal registration extensively. But due to US images characteristics specially speckle noises and scale differentiation, this algorithm is not suitable for this purpose. Brain shift is a non-rigid problem and many algorithms exist for non-rigid point set registration which is iteratively alternating between the correspondence and the transformation Estimation.

In this paper for the first time we have used Coherent Point Drift (CPD) algorithm for brain shift calculation applied on phantom data and the results are compared with those obtained by applying traditional ICP method.

The paper is organized as follows. In Section B.1, B.2, B.3 we present our phantom study and its data acquisition. Section B.4 and B.5 describes CPD and ICP methods. Section C is dedicated to experimental results and conclusions are written in Section D.

B. Method and Material

1. Phantom Preparation

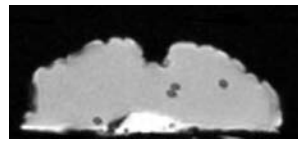
To evaluate and validate the registration techniques in a situation close to a real clinical setting, we performed a phantom study. The phantom was made of PVA-C. This material is presented as a tissue-mimicking material, suitable for application in MR imaging and ultrasound imaging. A 10% by weight PVA in water solution was used to form PVA-C, which is solidified through a freeze–thaw process. The number of freeze–thaw cycles affects the properties of the material. The ultrasound and MR imaging characteristics were investigated using cylindrical Samples of PVA-C. T1 and T2 relaxation values were found to be 718–1034 ms and 108–175 ms, respectively.

In our phantom for simulation of the brain tissue PVA-C 10% and for the ventricle PVA-C 20% has been used. An inflatable catheter was placed in the phantom to simulate a brain lesion, and plastic tubes with inside diameters of 3 mm were inserted to simulate blood vessels [2], [7], [10].

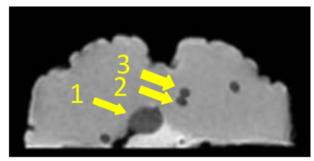
2. MR Imaging

The phantom was scanned using a Siemens 3 T scanner using a standard T1 and T2 weighted protocol with TR=19 ms, TE=4.92 ms, with full brain coverage and 1 mm isotropic resolution.

Before MR imaging the plastic tubes in phantom were filled with water. During MRI, phantom remained in the plastic container and was scanned 2 times: once for plastic tubes without inflating catheter and once for inflating catheter with 5 ml water. By inflating the catheter balloon, the phantom would deform in an elastic non-linear manner as we show in fig. 1. As illustrated in fig. 2, due to the contrast between the PVA 10% (light gray), PVA 20 % (dark gray), the tubes (black) and the water inside the tubes (bright); it is possible to apply the segment tubes as a marker.



(a)



(b)

Fig.1. (a) Sagital MR images of the phantom before inflating catheter (b) and after inflating catheter. (Yellow signs show the main landmarks)

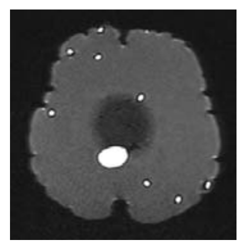


Fig.2. Axial T2 weighted MR images

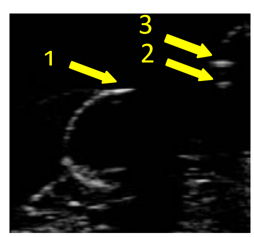


Fig.3. A sample US slice acquired which corresponds to the 58th slice of MRI. (Yellow signs show the main landmarks)

3. US Imaging

Ultrasound images were acquired using HS-2000, Honda Medical Systems ultrasound machine with a multi-frequency linear probe (3.5 MHZ).

We performed some pre-processing such as homomorphic Wiener filtering, edge detection and masking to reduce speckle noise in US images. An example of a pre-processed US image is shown in fig. 3. Some plastic tubes and a catheter full of water were used to create landmarks to be used to calculate total displacements.

4. Iterative Closest Point Method

The ICP algorithm, introduced by Besl and McKay [14], is the most popular method for point set registration due to its simplicity and low computational complexity. ICP iteratively assigns correspondences based on the closest Euclidean distance criterion and finds the least-squares rigid transformation relating the two point sets. If the exact correspondences of the two data sets could be known, then the exact translation and rotation can be found. However the performance of this method suffers from noise and outliers and is it highly dependent on the selection of the initial points.

5. Coherent Point Drift Method

CPD is a robust probabilistic multidimensional method for both rigid and non-rigid point set registration. It considers the alignment of two point sets as a probability density estimation, where 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 it finds the posterior probabilities of centroids, providing the correspondence probability. Given two n-dimensional point sets and fit a GMM to the first point set, whose Gaussian centroids are initialized from the points in the second set. The second point set expressed as $Y = (y_1, \dots, y_M)^T$ should be aligned with the reference point set $X = (x_1, \dots, x_N)^T$. Points in Y are considered the centroids of the GMM, and they fit to the data points X by maximizing the likelihood function. Y_0 is the initial centroid position and it defines a continuous velocity function υ for the template point set such that the current position of centroids is defined as

$$Y = \upsilon(Y_0) + Y_0.$$

Bayes theorem is used to find the parameters Y by maximizing the posteriori probability, or minimizing the energy function:

$$E_{CPD}(Y) = -\sum_{n=1}^{N} log \sum_{m=1}^{M} e^{-\frac{1}{2}\left\|\frac{x_n - y_m}{\sigma}\right\|^2} + \frac{\lambda}{2}\,\phi(Y) \qquad (1)$$

$\phi(Y)$ is a function that is related to the smoothness of the motion. CPD simultaneously finds both the transformation and the correspondence between two point sets without making any prior assumption on the non-rigid transformation model except that of motion coherence. Finally, we used the fast CPD implementation using Fast Gauss Transform (FGT) and low-rank matrix approximation to reduce the computational complexity of the method as low as linear [11],[12].

C .Result

We used the Root Mean Squared Error (RMSE) between the corresponding points after the registration as an error measure in both algorithms.

For using CPD we normalize data to zero mean and unit variance before registration and set the width of Gaussian kernel into 2 and regularization weight into 3. In using ICP all points of two data sets were used and K-Nearest Neighborhood (KNN) was utilized for point matching. Conducting 15 runs of CPD and ICP algorithms, the computational time of them were appeared to be 20 and 10 seconds, respectively and average of iteration were obtained relatively equal for two algorithms.

For comparison of registration error the non-rigid registrations was repeated using only MR data as a gold standard. In this case, we had full volume coverage for both source and target datasets and the overlap of the points were almost complete. CPD results of the intra-operative MRI to pre-operative MRI registration are shown in fig.4.Similar results were obtained for US-MRI registration as shown in fig.5. RMS error using CPD and ICP algorithm for MRI-MRI and US-MRI registrations were calculated as shown in Table 1 and Table 2. The true displacement vector between the landmarks in two set of MR images are illustrated in Table 3. As the result show using intra-operative US recovered 80% displacement in region of interest.

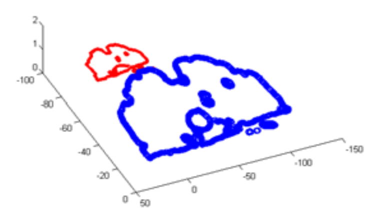


Fig.4. (a) before registration: Points of MRI slice No.58 before deformation (red) , points of MRI slice no.58 which was acquired after deformation(blue)

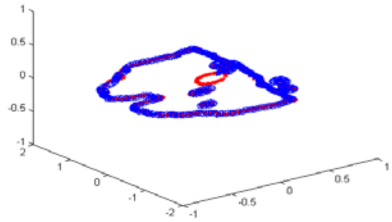


Fig.4. (b) after registration: points of 58th slice MRI before deformation (blue), points of 58th MRI slice after deformation (red).

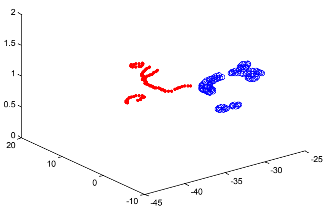


Fig.5: (a) before registration: points of MRI slice no.58 before deformation (red) , points of US slice was acquired to correspond to the 58th slice MRI after deformation (blue)

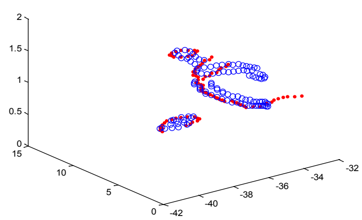


Fig.5: (b) after registration: : points of MRI slice no.58 before deformation (red) , points of US slice was acquired to correspond to the 58th slice MRI after deformation (blue)

Table (1):RMS Error with using CPD

RMSE	MR-MR	US-MR
ΔX	1.08 mm	2.96 mm
ΔY	2. 8 mm	2.94 mm
Total	3 mm	4.17 mm

Table (2): RMS Error with using ICP

RMSE	MR-MR	US-MR
ΔX	5.15 mm	3.61 mm
ΔY	4.18 mm	4.55 mm
Total	6.63 mm	5.8 mm

Table (3): measuring displacement for 3 main landmarks with CPD

Displacement	MR-MR	US-MR
Landmark 1	2 mm	2.9 mm
Landmark 2	2.5 mm	3.6 mm
Landmark 3	4 mm	4.6 mm

D. Discussion and Conclusion

As our experiment proved the ICP algorithm failed to register two sets of images if the rotation angles of images compared to each other are greater than 3 or 4 degrees. In contrast CPD algorithm was found more robust to angle differentiation as the results of registration showed a good match even in the case of 50 degree misalignment. Since ICP is searching iteratively for the closest points, the relative position of images is important as such ICP requires equal initial points in two images; Whereas CPD is not sensible to this problem. CPD is not sensitive to the translation and scaling. It is also reported that CPD is robust to missing points occur due to imperfect image acquisition and incorrect feature extraction. Empirically despite low computational complexity of ICP, CPD is found more accurate and is preferred especially in registration of US images. The main focus of this paper was based on a phantom study, with similar properties to clinical dataset, to find out the impact of parameters of the registration algorithms on the final results. We are currently testing the performance of these two methods on real dataset.

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