A Shape Based Rotation Invariant Method for Ultrasound-MR Image Registration: A Phantom Study

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Abstract— **In this work, a new shape based method to improve the accuracy of Brain Ultrasound-MRI image registration is proposed. The method is based on modified Shape Context (SC) descriptor in combination with CPD algorithm. An extensive experiment was carried out to evaluate the robustness of this method against different initialization conditions. As the results prove, the overall performance of the proposed algorithm outperforms both SC and CPD methods. In order to have control over the registration procedure, we simulated the deformations, missing points and outliers according to our Phantom MRI images.**

I. INTRODUCTION

Medical imaging has been used widely for clinical purposes to reveal, diagnose and examine diseases. These images are usually taken with different modalities, viewpoints or in different times. As such, there is widespread need and interest in accurately registering information from these images [1].

Image registration or image alignment algorithms can be categorized into intensity-based and feature-based methods [2]. In the case of Ultrasound (US) and Magnetic Resonance (MR) image registration, the completely different nature of the represented information results in the failure of the prevalent intensity-based registration approaches. One such example is registration methods that use mutual information or correlation ratio as a cost function [3]. Therefore, Image registration is typically expressed as a point matching problem since point representations are general and easy to extract [4]. Image registration can also be classified according to the transformation model used to relate the target and the reference image space. The transformations can be either linear transformations (which include the rigid and other affine transforms) or elastic, "non-rigid" ones [1]. Whereas the linear transformations are global in nature, they cannot model local geometric differences between images [2]. The intra-operative brain deformations aren't usually drastic and displacements larger than 20 mm are not expected in most the cases [5, 6], however, in some papers this quantity was reported to be up to 50 mm [7]. Furthermore, these deformations change smoothly and hence it's not unreasonable to consider the deformation roughly rigid. Our method takes advantages of both models.

Now, what is of importance is how to register the given two point sets with each other. The basic idea is to determine the corresponding points between the point sets, and then, to find a transformation which could match them. Usually, this process is accomplished iteratively due to the complexity of the problem [8, 9]. Doppler ultrasound-MRI Registration faces a large amount of outliers extracted from Doppler images incorrectly. Moreover, because of the limited field of view and discontinuity of US images, some points and vessel branches are missed in 3D reconstructions. This largely depends on the ultrasound-probe posture in the imaging process, and large in-plane rotation with respect to MRI images may exist. These deficiencies restrict direct use of many registration algorithms due to their requirement of acceptable initialization. In the following, some well-known point based registration methods will be discussed in order to understand the weaknesses of each method.

II. PREVIOUS WORKS

Iterative Closest Point (ICP), as a well-known rigid registration method which uses the distance criterion to match the points in the two point sets. Some improved methods were developed based on ICP such as Trimmed ICP (TrICP) which is more robust to noise and less sensitive to good initial estimation [10]. Nevertheless, these methods look for closest point as a corresponding point, therefore, they may be trapped in local minimum easily in lack of a good initialization. Robust point matching (RPM) introduced by Gold et al [11], performs registration using deterministic annealing and soft assignment of correspondences between point sets. Whereas in ICP the correspondence generated by the nearest-neighbor heuristic is binary, RPM uses a soft correspondence. The correspondences found in RPM are always one-to-one, which is not always the case in ICP. The thin plate spline robust point matching (TPS-RPM) algorithm by Chui and Rangarajan, augments the RPM method to perform non-rigid registration by parameterizing the transformation as a thin plate spline [8]. Belongie et al [12], present the notion of Shape Context (SC) as a shape descriptor which tags a log- polar histogram to each point. These histograms contain information about the neighbor's distances and relative angles and describe the distribution of the local points in its vicinity [4]. They measure the similarity of histograms to prescribe the proper corresponding pair from the second point set. Coherent Point

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Drift (CPD) is another method that aligns two locally non-linear deformed point sets, introduced by Myronenko et al [13]. They use the motion coherency concept to constrain the maximum likelihood optimization. This method is proved to have an accurate result and a robust functionality in presence of outlier and missing points, however, as [13] mentioned, the performance of CPD may be affected by large in-plane rotations. Farnia et al [14], proposed CPD as an efficient point-based registration method for registering US-MRI brain images with misalignment up to 50 degrees.

Considering the points mentioned above, we should look for a method that reduces our dependence on initial conditions. Only after implementation of such a method, we will be able to make use of CPD and its benefits. Generally, shape based methods and in particular, shape context descriptors (SC), could help us in achieving this goal. However, as explained in the following sections, it should be modified first in the case of our data.

Therefore, our contribution in this work was to propose a two-stage approach to deal with the US-MR image registration problem. First, a modified shape based algorithm with a rational rejection manner was introduced that could prepare an effective initialization and minimize the false correspond detection; Second, the CPD algorithm was employed to minimize the residual error and improve registration precision.

In the following section our brain phantom is described. In the second section, a modified shape-based method (including point selection, finding the corresponding point, and false correspond rejection) will be studied. Finally, we compare the results of the CPD algorithm with our two-stage method in different amounts of missing points, outliers and rotation degrees.

III. Material and Methods

A. Phantom

Based on the proposed method by Surry et al [15], and our previous experiments [14], for preparing a brain phantom, we provided a 10% by weight Polyvinyl Alcohol (PVA) solution which was solidified properly by freeze–thaw process. Brain phantoms typically deform using inflation of an implanted catheter which could model the pushing-outward tumors. Due to the fact that sometimes the brain collapses inwards, we made an effort to consider this type of deformations in our phantom. The recently designed phantom includes a flexible mesh implemented inside. At some points there are several inelastic fibers that create the connections between mesh nodes and controllable screws. In the inflatable phantoms, although the volume of injected fluid can be controlled (normally in the range of 10 ml), the amount of deformation in each point is unknown. This quantity should be calculated by registering MR images before and after the deformation. In the mentioned procedure, magnitude of error varies depending on the methods in which segmentation and registration are done. As an alternative, it is feasible to measure the deformation directly by means of controlling the mesh's deformation and the movement of screws, as shown in Fig. 1. To the best of our knowledge, the proposed phantom is unique in terms of collapsing inward, though we hope to be able to improve it in the future.

Shape Context

As a rich descriptor, shape context depicts the distribution of adjacent points in a log-polar histogram. A Chi-square (χ^2) test is selected for the histogram similarity measurement [12], as formulated in (1).

$$C_{i,j} = \frac{1}{2}\sum_{k=1}^{K} \frac{\left[h_i(k) - h_j(k)\right]^2}{h_i(k) + h_j(k)} \qquad (1)$$

Where, $C_{i,j}$ denotes the cost function of two points i and j and should be zero ideally for the best match. For each point in the reference set, (R_i), we need to find the best match in the target, (T_j). $h_i(k)$ and $h_j(k)$ denote the K-bin normalized histogram at R_i and T_j respectively. More details about the shape histogram formation are available in Belongie's paper [12], though there are some issues that should be addressed.

In [12], finding points with most shape context similarity was considered equivalent to finding corresponding pair points. The validation of this point matching is somehow data dependent. In fact, one point in the first shape may be matched to two or more points far apart in the other shape. Consider the circled point in the red point set (Fig. 3), if we want to find its corresponding point from the blue point set, there are several alternatives based on the neighborhood of the circle's radius. In an ideal situation, by extending the neighborhood's radius, the probability of selecting a wrong corresponding point will be reduced. But in the presence of missing points and outliers, increasing the radius results in incremental differences among the shape contexts, and thus, one has to assent to more errors. Since we cannot increase

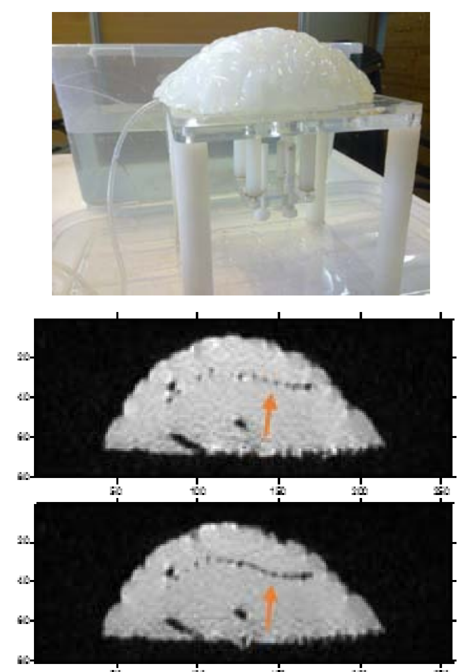

Figure 1. Brain phantom. By moving up and down the screws, the internal mesh deformed to a certain extent. This deformation is well shown in MR images.

the neighborhood radius there must be a way to reject wrongly selected corresponding points.

Another point to be mentioned is that in [12] for the sake of generality and simplicity, they expect no special features for the point selection step (like being landmarks, curvature extremum, etc.) and all of the points were considered in the registration procedure. In point sets with great amount of similar data, many points have almost the same shape context (think of a vessel with little curvature). This redundant data will add no new information and in presence of slight number of missing points or outliers could be simply misleading. So, we added a simple criterion for our point selection which is the maximum inner difference. To resolve these shortcomings, the following strategy was created as the modified shape based method:

a. Point selection: as a first step, we sorted the target points based on their second order derivative of shape context to avoid redundancy. This approach resulted in a selection of well distributed, significant SC features among the redundant ones. We looked for various shape contexts with maximum inner difference criterion and employed a formula as (2, 3):

$$f_j = Sort\left(\sum_{i=1}^{J} Ct_{i,j} - \sum_{i=1}^{J} Ct_{i+1,j}\right), \qquad i,j = 1,\dots,J \qquad (2)$$

$$T_{iter}(k) = \underbrace{Max}_{1\to l}\left(f_j - f_{j+1}\right) \qquad (3)$$

Where $Ct_{i,j}$ indicates shape context dissimilarity of target points with each other. Summation of $Ct_{i,j}$ denotes the total SC difference of the point j with all other points in T.

b. Finding corresponding points: Next, the corresponding point for the selected targets should be found. In this stage, there is not a large difference in comparison to the original method, except that the minimization was done in two-way manner.

$$\begin{array}{cc} & \begin{array}{ccccc} \phantom{SC_{1,1}} & & j'th\ column \downarrow & & \phantom{SC_{1,J}} \end{array} \\ SC = & \begin{bmatrix} SC_{1,1} & \cdots & SC_{1,j} & \cdots & SC_{1,J} \\ \vdots & & \vdots & & \vdots \\ SC_{i,1} & \vdots & SC_{i,j} & \vdots & SC_{i,J} \\ \vdots & & \vdots & & \vdots \\ SC_{I,1} & \cdots & SC_{I,j} & \cdots & SC_{I,J} \end{bmatrix} \leftarrow i'th\ row \end{array}$$

As the reader may recall, the shape context (SC) matrix is in order of $I \times J$, where I and J are related to the reference and target point's number, respectively. For the selected target point, j, the most similar reference point, i, will be determined (minimum of j'th column of SC). On the other hand, the point j must be the most similar point to i among the other points of target set (minimum in i'th row of SC). This double-check helps to reduce the probability of outlier selection. This routine will be continued iteratively until an adequate number of corresponding pairs are extracted.

c. False corresponding rejection: As previously mentioned, "The best match" doesn't always mean the best corresponding point. At this stage we must validate the accuracy of the corresponding points that were matched in the earlier stage. Regarding the fact that the brain displacement is not too much [5, 6], we expect the relative distances between selected points in both reference and target point sets to remain fixed, Fig. 4. So, we calculated the pair wise distances of each point set (*ab, ac, bc* … and *a'b', a'c', b'c'*… in Fig. 4) and compared the corresponding distances. As illustrated in the Fig. 4, the relative distance ratio (which is called RDR hereafter) in the original points are more or less the same, however, this ratio will not remain constant for the outliers.

The correct scale ratio will be revealed according to the majority's RDR, and corresponding points with obvious difference in RDR regarded as possible outliers and will be rejected. Simply by applying the appropriate rigid transformation between extracted corresponding points, an effective initialization will be yielded. Henceforth, it is feasible to apply registration methods which need an acceptable initialization. Due to reasons mentioned earlier in the introduction section, CPD was selected

IV. Results

In order to compare the algorithm's performance with each other, proper error criterion should be determined first. This is based on how much of the algorithm's target goal is achieved. As can be seen in Fig. 5, we assess our results with the deformed data before adding outlier and missing points. In this way, the one-to-one correspondence among the data will be established.

To show the performance of the proposed algorithm, we compared the results with CPD and simple shape based algorithms, in different amounts of missing points, outliers and in-plane rotations. Each test was repeated 100 times and the RMS error was reported. Fig. 6 illustrates the algorithm's sensitivity to different axes and different degrees of rotation. The in-plane rotations were accomplished in the range of 0°-150° and the 3D rotations in the range of 0°-75°. In Fig. 7, the applied missing points were a combination of ensemble (0-20 %) and random (0-10 %) missing; and the outlier points were added in the range of 0-30 % of the total data. As it could be seen, our method has comparable performance in presence of outlier and missing points, in relation to CPD.

V. Conclusion

We proposed a two-stage registration method to improve the accuracy of brain Ultrasound-MR image registration in different initial conditions. As expected, our method removed the dependency on the initial condition, using the modified shape context descriptor. Although our method is

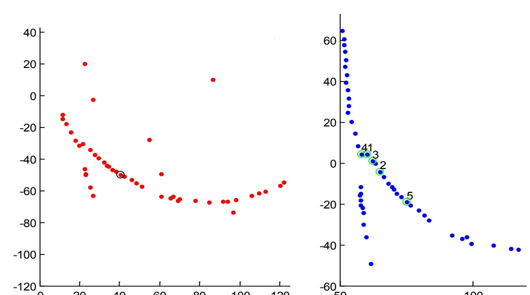

Figure 3. Vessel mimicking centerline extracted from phantom MR image (left) and its deformed, noisy form (right). The black circled point may have more than 1 similar correspond according to local shape similarity.

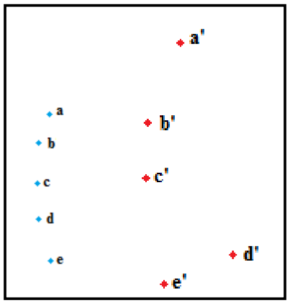

Figure 4. The points in 2 point sets should roughly preserve relative distances. In this example d' can be considered as an outlier and the corresponding point d rejected from selected points, due to:

$$\left[RDR \approx {}^{bc}/_{b'c'} \approx {}^{ce}/_{c'e'} \neq {}^{bd}/_{b'd'}\right].$$

robust against various amounts of missing and outlier points to an acceptable extent, the CPD is the best approach in these cases.

We tried to take the US imaging deficiencies into consideration so that the applied missing and outlier points were not far from reality, however, the study should be examined on real ultrasound data as well.

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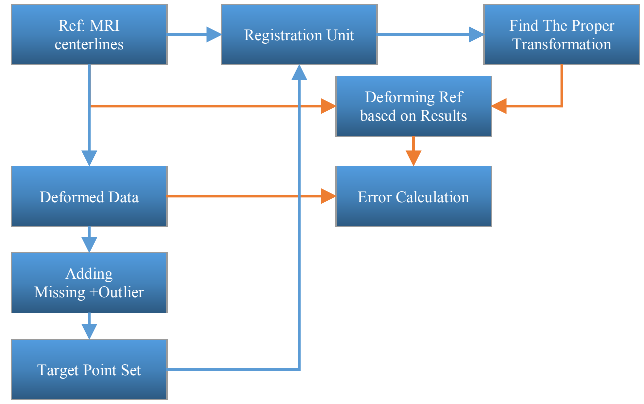

Figure 5. Error calculation block diagram

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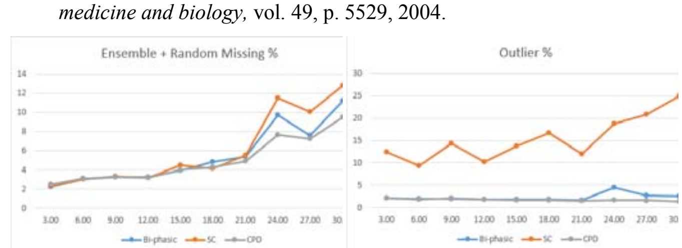

Figure 7. Performance of our method in comparison with CPD, simple SC at different percent of missing and outlier.

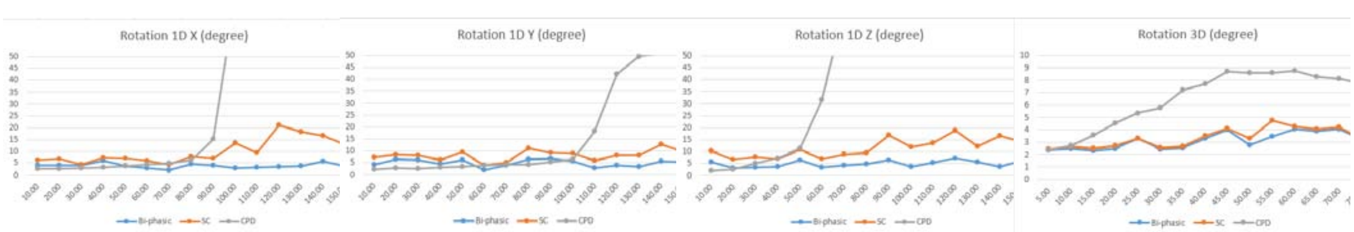

Figure 6. Performance of our method in comparison with CPD, simple SC at different amount of rotation and in a different axis. From left to right, the rotation around x, y, z axis and 3d rotation is illustrated, respectively.