Multi-Contrast MRI Registration of Carotid Arteries Based On Cross-sectional Images and Lumen Boundaries

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ABSTRACT

Ischemic stroke has great correlation with carotid atherosclerosis and is mostly caused by vulnerable plaques. It’s particularly important to analysis the components of plaques for the detection of vulnerable plaques. Recently plaque analysis based on multi-contrast magnetic resonance imaging technique has attracted great attention. Though multi-contrast MR imaging has potentials in enhanced demonstration of carotid wall, its performance is hampered by the misalignment of different imaging sequences. In this study, a coarse-to-fine registration strategy based on cross-sectional images and wall boundaries is proposed to solve the problem. It includes two steps: a rigid step using the iterative closest points to register the centerlines of carotid artery extracted from multi-contrast MR images, and a non-rigid step using the thin plate spline base on the boundaries of carotid artery. In the rigid step, the centerline was extracted by tracking the cross-sectional images along the vessel direction calculated based on Hessian matrix. In the non-rigid step, a shape context descriptor is introduced to find corresponding points of two similar boundaries. In addition, the deterministic annealing technique is used to find a globally optimized solution. The proposed strategy was evaluated by newly developed three-dimensional, fast and high resolution multi-contrast black blood MR imaging. Quantitative validation indicated that after registration, the overlap of two boundaries from different sequences is 95.24%, and their mean surface distance is 0.12 mm. In conclusion, the proposed algorithm has improved the accuracy of registration effectively for further component analysis of carotid plaques.

Key words: carotid atherosclerosis, vulnerable plaque, magnetic resonance imaging, registration

1. INTRODUCTION

The rupture of atherosclerotic plaques in the carotid arteries is the main cause of ischemic strokes [1]. It has been demonstrated that vulnerable plaque compositions identified by multi-contrast MRI can help in assessing the risk of rupture. One challenging step to this application is the misalignment caused by patient motion and tissue deformation. To achieve accurate registration between multi-contrast images, several problems need to be addressed: a) patient movement and deformation caused by long scan time of conventional MRI sequences, as we as low resolution; b) complex topology and branching of carotid arteries, making the registration of bifurcations more difficult. Therefore, effective and accurate registration is in great need.

In this study, based on multi-contrast carotid images acquired by three black blood sequences developed by Tsinghua University, which are all fast 3D scans with high resolution and effective blood suppression [2], an automatic two-step feature-based registration algorithm is proposed for better alignment of carotid arteries. It is based on cross-sectional images of carotid artery calculated from volumetric data. In the first step, an iterative closest points (ICP) method is applied on cross-sectional centerlines for coarse rigid registration. In the second step, a shape context descriptor is first introduced to find corresponding points on two lumen contours. Then a non-rigid thin plate spline (TPS) model is employed for fine registration between two lumen boundaries. Finally, quantitative validation of the proposed method was performed on multi-contrast patient data acquired by three sequences.

2. METHODS

2.1 Image data acquisition

MR images were acquired from the Center for Biomedical Imaging Research of Tsinghua University. Seven patients with different degrees of atherosclerotic plaques were scanned by a Philips 3.0 T Achieva TX system (Philips, Best, the Netherlands) with a custom-designed 36-channel neurovascular coil. Three 3D black blood MR sequences newly developed were used to acquire multi-contrast data, i.e., motion sensitized driven equilibrium prepared rapid gradient echo (MERGE), simultaneous noncontrast angiography and intraplaque hemorrhage (SNAP) and T2-weighted volumetric isotropic turbo spin echo acquisition (VISTA). Considering that the SNAP has the best Signal to Noise Ratio (SNR) of lumen, we set SNAP images as fixed images and the other two as moving images.

2.2 Cross-sectional images calculation and centerline extraction

Extracting centerlines from cross-sectional images perpendicular to the vessel direction is beneficial to characterize the topology and morphology of vascular networks. Before centerline extracting, the lumen boundary was segmented using graph cuts method [3]. In this study, the centerline was extracted by tracking their cross-sections along vessel direction from a user-initialized seed point [4].

The cross-section images were calculated based on the Hessian matrix. For a 3D volume image I (x, y, z), the Hessian matrix is defined as:

$$H(x,y,z;\sigma) = \begin{bmatrix} I*\frac{\partial^2 g_\sigma}{\partial^2 x} & I*\frac{\partial^2 g_\sigma}{\partial x \partial y} & I*\frac{\partial^2 g_\sigma}{\partial x \partial z} \\ I*\frac{\partial^2 g_\sigma}{\partial y \partial x} & I*\frac{\partial^2 g_\sigma}{\partial^2 y} & I*\frac{\partial^2 g_\sigma}{\partial y \partial z} \\ I*\frac{\partial^2 g_\sigma}{\partial z \partial x} & I*\frac{\partial^2 g_\sigma}{\partial z \partial y} & I*\frac{\partial^2 g_\sigma}{\partial^2 z} \end{bmatrix} \tag{1}$$

Where

$$g_\sigma(x,y,z) = \frac{1}{(\sigma\sqrt{2\pi})^3} e^{-(x^2+y^2+z^2)/2\sigma^2} \tag{2}$$

The parameter σ is the scale parameter set according to the radius of the blood vessel. The radius was estimated by taking the maximum Euclidean distance from the centroid to the lumen boundary of cross-section image.

Let the eigenvalues of H be λ_1, λ_2, λ_3 ($\lambda_1 \leq \lambda_2 \leq \lambda_3$) and the corresponding eigenvectors be V_1, V_2 and V_3. The eigenvector V_1 represents the vessel direction and the eigenvectors V_2 and V_3 represent the vessel cross-section vectors, respectively. These vessel cross-section vectors were used to create the vessel cross-section image. Then the centerline of a vessel was extracted using a circle enhancement filter as described in literature [4].

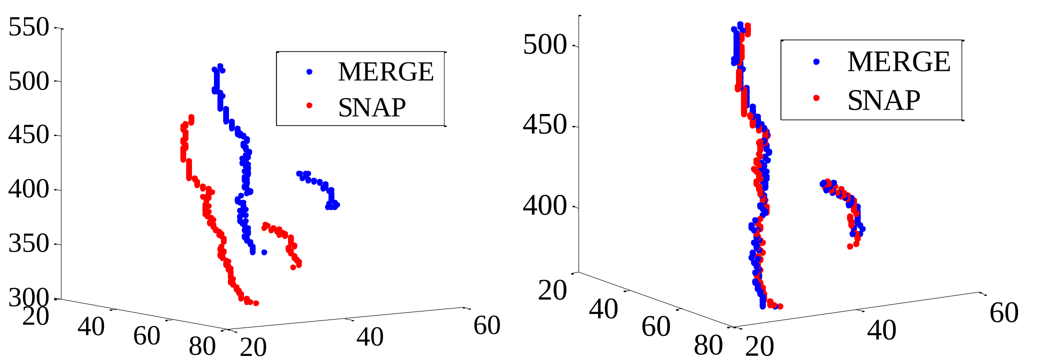
2.3 Two-step registration

The whole registration framework was performed based on the cross-section images. In the initial step, a 3D rigid ICP method was applied based on centerlines extracted from cross-sectional images [5]. After centerline registration, the bifurcation points of different sequence were in alignment.

Considering that the centerline only provides the topology information without the diameter information. In non-rigid step, the registration was performed based on the lumen boundaries of cross-sectional images. The registration accuracy is highly dependent on the point set matching of two boundaries, because the non-rigid deformation of vessels is more flexible. To better handle the mismatching between two lumen boundaries, we introduced the shape context descriptor to find the corresponding points [6]. The shape context at one point captures the distribution over relative positions of other points of the boundary and thus reflects the global shape of the boundary. Moreover, the shape context leads to a robust score for measuring shape similarity, once the boundaries are aligned. Then a non-rigid TPS model was applied based on the corresponding points of the lumen boundaries between two sequences [7]. The deterministic annealing was employed to solve the global optimization problem. [8].

3. RESULTS

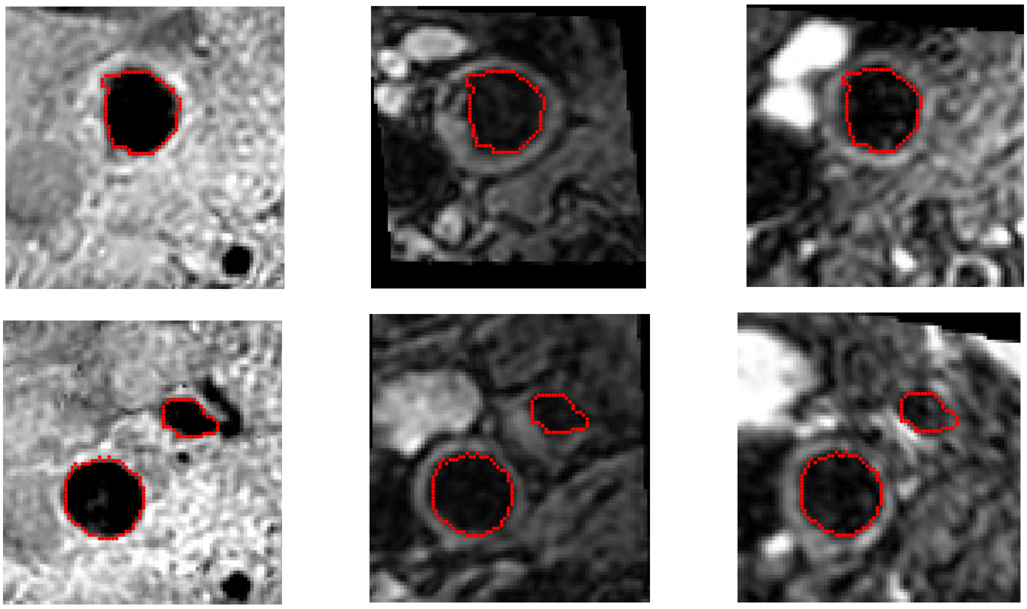
Figure (1) shows the registration result of centerlines of MERGE and SNAP. The positions of two centerlines are in highly coincident after rigid registration.



a) Positions of centerlines before registration (b) Positions of centerlines after registration

Fig.1 the registration result of centerlines

Figure (2) shows the registration result after two-step registration performed on the three sequences. The first row shows the registration results of the trunks of cross-sectional images and the second row shows the bifurcations images. The red lines represent the lumen boundaries of cross-section images of the fixed imaging of SNAP.



a) SNAP b) MERGE c) VISTA

Fig.2 Boundary-based registration results for MERGE and T2W images

Quantitive validation was performed by comparing the three dimensional lumen surfaces of the fixed image and moving image after registration. Both the lumen overlap ratio and distance between the surfaces in different sequences were used to quantify the registration accuracy.

1) The overlap ratio (OR) between two lumens can be calculated as follows:

$$OR = \frac{L_F \cap L_M}{L_F \cup L_M} \tag{3}$$

Where L_F represents the number of voxels in the lumen of the fixed image, and L_M is the number of voxels in the lumen of the moving image.

2) The mean surface distance (MSD) and the max surface distance (MAXD) between the lumen surfaces was defined as:

$$MSD = \frac{1}{n}\sum_{i=1}^{n} \min_{q \in L_M} \sqrt{\left\| p_i - q \right\|^2} \tag{4}$$

$$MAXD = \max_{i=1,2,\cdots n} \min_{q \in L_M} \sqrt{\left\| p_i - q \right\|^2} \tag{5}$$

Where p_i is a point on the fixed lumen surface, n is the total number of points on the fixed lumen surface, and q is a point on the moving lumen surface.

Figure (3) indicated that after the initial rigid step, the mean overlap ratio was 62.51%. Together with non-rigid registration, the overlap ratio was increased to 95.24%.

The MSD and MAXD measurement after the registration using the proposed method is shown in Table 1.

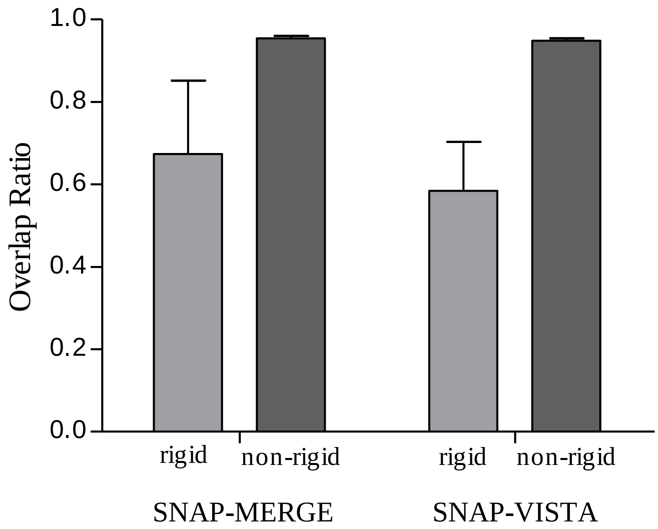


Fig.3 overlap ratio after rigid step and added non-rigid step

Tab.1 MSD and MAXD after the registration using the proposed method

sequences	MSD(mm)	MAXD(mm)
SNAP-MERGE	0.1182 ±0.002	1.1812 ±0.018
SNAP-VISTA	0.1276 ±0.001	1.2114 ±0.1066

Comparing our algorithm with previously reported studies on the registration methods for multi-contrast carotid MR imaging, our method shows better performance. The method of van't Klooster et al [9] was reported to yield an average overlap ratio less than 90% and mean MSD 0.288 ±0.128 mm. The method of Guo et al [10] resulted in mean MSD of 0.21 ±0.02mm and MAXD of 0.9568mm for SNAP and MERGE.

4. CONCLUSION

In this study, an automated coarse-to-fine registration strategy based on cross-sectional images and lumen boundaries of carotid arteries was proposed. Rigid ICP model based on centerline and non-rigid TPS model based on boundaries were employed in the two steps respectively. The centerline was extracted based on the cross-sectional images, which reflect the topology and branches of vessels. With the centerline registration, the bifurcations of different sequences were in alignment. To better utilize the diameter information of vessels, in the non-rigid step, the registration was performed based on lumen boundaries in cross-sectional images. The shape context descriptor was introduced to find corresponding points between two boundaries. Then the non-rigid TPS model was applied in the corresponding points to find the transform relations. With the quantitative evaluation, the proposed method provided an average overlap ratio of 95.24%, mean MSD of 0.12 mm and MAXD of 1.2mm, outperforming widely used intensity-based method. The results demonstrated the efficiency of the two-step algorithm for multi-contrast carotid registration. In addition, newly developed black blood sequences with high resolution and fast scan time were used in this study. With the improved registration of carotid artery, multi-contrast MRI imaging has great potential in assessing rupture risk by plaque composition analysis.

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