Accurate Quantification of Local Changes for Carotid Arteries in 3D Ultrasound Images Using Convex Optimization-Based Deformable Registration

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ABSTRACT
Registration of longitudinally acquired 3D ultrasound (US) images plays an important role in monitoring and quantifying progression/regression of carotid atherosclerosis. We introduce an image-based non-rigid registration algorithm to align the baseline 3D carotid US with longitudinal images acquired over several follow-up time points. This algorithm minimizes the sum of absolute intensity differences (SAD) under a variational optical-flow perspective within a multi-scale optimization framework to capture local and global deformations. Outer wall and lumen were segmented manually on each image, and the performance of the registration algorithm was quantified by Dice similarity coefficient (DSC) and mean absolute distance (MAD) of the outer wall and lumen surfaces after registration. In this study, images for 5 subjects were registered initially by rigid registration, followed by the proposed algorithm. Mean DSC generated by the proposed algorithm was 79.3 ± 3.8\% for lumen and 85.9 ± 4.0\% for outer wall, compared to 73.9 ± 3.4\% and 84.7 ± 3.2\% generated by rigid registration. Mean MAD of 0.46±0.08mm and 0.52±0.13mm were generated for lumen and outer wall respectively by the proposed algorithm, compared to 0.55±0.08mm and 0.54±0.11mm generated by rigid registration. The mean registration time of our method per image pair was 143 ± 23s.

Keywords: Deformable image registration, Carotid artery, 3D Ultrasound

1. INTRODUCTION
Stroke is among the leading causes of death and disability worldwide. In China, about 1.5 to 2 million new strokes occur each year.\textsuperscript{1} Most strokes associated with carotid atherosclerosis\textsuperscript{2} can be prevented by therapy and lifestyle/dietary changes.\textsuperscript{3} Recent development of 3D US imaging have made direct visualization of carotid atherosclerosis and subsequent quantification of plaque and vessel wall burden possible.\textsuperscript{4,5} However, most clinical studies applied volumetric/areal measures, such as intima-media thickness (IMT), total plaque area (TPA), vessel wall volume (VWV) and total plaque volume (TPV),\textsuperscript{6} to quantify vessel wall and plaque quantification. These global measurements did not provide information for spatial distribution of carotid disease, which is a focal disease with plaque burden primarily located in bends and bifurcations.

In this work, we introduce a new deformable image registration-based method, by registering carotid US images at different time points, to monitor and quantify the local progression/regression of carotid atherosclerotic burdens. Although registration image- and surface-based methods have been previously proposed to register carotid arteries at baseline and follow-up before assessment on local change of vessel wall and plaques, registration methods capable of registering a series of longitudinally acquired images for a patient have been lacking. Chiu et al.\textsuperscript{7} proposed a surface-based method to register the manually segmented carotid surfaces before computing the point-wise vessel-wall-plus-plaque thickness change (VWT-Change). Manual segmentation of carotid wall and lumen is time-consuming and susceptible to observer variability.

The surface-based registration technique was a rigid technique that did not take into account non-rigid deformation caused by the difference of head orientation in the baseline and follow-up scanning session. Gupta et
al.\textsuperscript{8} used feature-based iterative closest point algorithm to compute a coarse registration, then applied intensity-based rigid registration model to correct misalignments between carotid images caused by the relative motion of patient during different image acquisition sessions. In his work rigid transformation model coupled with mutual information (MI) similarity measure and Powell optimizer was adopted. Nanayakkara et al.\textsuperscript{9,10} proposed a twisting and bending model to model movements of the neck during image acquisition process at two time points. This model was evaluated on 3D US images acquired on the same day at two different head positions of patients and was shown to provide more accurate registration than rigid registration. All of the techniques described above were validated for registration between a pair of images. Whether they are capable of registering a series of longitudinal images acquired for a patient accurately was not studied.

2. NEW OR BREAKTHROUGH WORK TO BE PRESENTED

In this study, we propose a new image-based non-rigid registration method to quantify local changes of carotid arteries in 3D US images at different time points. The proposed registration method makes full use of image intensity information with a coarse-to-fine scheme designed to capture large nonlinear deformations, which may occur under heavy medication.\textsuperscript{11} In addition, an efficient dual-optimization based algorithm is then employed to compute an updated incremental deformation field at each resolution scale, which is also implemented using general-purpose programming on graphics processing units (GPGPU) to obtain high computational efficiency. Experimental results (Section 5) demonstrated improvement in accuracy over rigid registration.

3. METHOD

In order to monitor local and temporal plaque changes, we register the baseline US image $I_f(x)$ to the follow-up acquired US image $I_r(x)$: we first compute a rigid transformation to correct the global misalignment in location and orientation of the two arteries; then, an image-based non-rigid registration is employed to capture local deformable changes in details.

3.1 Rigid Alignment

To compute rigid alignment, 4 pairs of corresponding landmarks are manually chosen in the two input images as shown in Fig. 1: the manual landmarks are located at the bifurcation (BF), centroid of common carotid artery (CCA) distal to BF around 1.5 cm and centroids of internal carotid artery (ICA) and external carotid artery (ECA) distal to BF around 1 cm, respectively. In fact, the rigid alignment comprises of two steps: translation to ensure the resulting coincidence of two BF landmarks, and rotation around BF point to minimize the sum of square distances between the pairs of landmarks at CCA, ECA and ICA distal ends. Denote the branch points (CCA, ECA and ICA centroids) on reference image $I_r(x)$ and floating image $I_f(x)$ after translation as $m \times n$ matrices $A$ and $B$ respectively. $m$ is the dimension and $n$ represents the number of points. The optimum rotation matrix $\text{Rot}$ around origin can be efficiently computed using the method proposed by Umeyama et al.,\textsuperscript{12}

$$\text{Rot} = USV^T$$

(1)
where $S$ is chosen as

$$S = \begin{cases} I & \text{if } \det(U)\det(V) = 1 \\ \text{diag}(1, 1, -1) & \text{if } \det(U)\det(V) = -1 \end{cases}$$

and $UDV^T$ is the singular value decomposition of the matrix $AB^T$ ($UU^T = VV^T = I$, $D = \text{diag}(d_i)$, $d_1 \geq d_2 \ldots \geq d_m \geq 0$).

The optimal transformation matrix $Trans$ around BF can be written as:

$$Trans = T_{BF} Rot^* T_{-BF},$$

where $T$ represents a $4 \times 4$ translation matrix and $Rot^*$ is the $4 \times 4$ homogeneous matrix of rotation matrix $Rot$ computed in Eq. 1.

### 3.2 Deformable Registration

After rigid alignment, a multi-scale sequential dual optimization-based method is employed to estimate the non-linear deformation field $u(x) = [u_1(x), u_2(x), u_3(x)]^T$, which efficiently minimizes the following objective function

$$\min_u P(I_f, I_r; u) + R(u)$$

where $P(I_f, I_r; u)$ represents a dissimilarity measure of the two input images $I_f(x)$ and $I_r(x)$ under deformation by $u$, and $R(u)$ is the regularization function to match a deformation field with the required smoothness.

In this study, we utilize the sum of absolute intensity differences (SAD):

$$\min_u P(I_f, I_r; u) := \int_\Omega |I_f(x + u) - I_r(x)| \, dx, \quad (4)$$

as a dissimilarity measurement of the two input US images, and the non-smooth convex total-variation functions as the regularization term, i.e.

$$R(u) := \alpha \sum_{i=1}^3 \int_\Omega |\nabla u_i| \, dx. \quad (5)$$

Due to the high non-linearity and non-convexity of image functions $I_f(x)$ and $I_r(x)$, it is challenging to directly optimize the energy function (3), even if its regularization term $R(u)$ is convex. To address this issue, we explore an incremental linearization and convexification approach to solving the studied optimization problem (3), under a multi-scale coarse-to-fine optimization perspective. Its algorithmic scheme is implemented on GPUs to achieve high efficiency in numerics.

### 4. EXPERIMENTAL SETUP

The proposed method was evaluated for baseline and follow-up 3D US carotid image pairs of five subjects. These subjects used in our experiment are with carotid stenosis over 60% (according to carotid Doppler flow velocities) and all subjects provided written informed consent to the study protocol. For each subject, at baseline and three months later, the left and right carotid arteries were scanned over a distance of 4 cm, with the bifurcation located approximately at the center. All scans were performed using a Philips/ATL HDI 5000 US machine with an L12-5 probe with a central frequency of 8.5 MHz attached to a motorized linear mover 3D US acquisition system. The 3D images were then reconstructed from the set of 2D frames during the scan.

The carotid artery outer wall and lumen boundaries in the reference and registered 3D US images were manually segmented by a clinical expert for evaluation of the proposed registration algorithm. The registration error was estimated by two different types of metrics: volume-based and surface distance-based metrics. Volume-based metric DSC ($DSC = \frac{2\text{volume overlap}}{\text{volume union}}$) represents the overlapping between the two volumes enclosed by reference and registered surfaces. Mean absolute distance (MAD) is used as the surface distance-based metric, which represents the average distance between two surfaces.
5. RESULTS

Fig. 2 shows the registration result for an example subject from axial, sagittal and coronal views. Fig. 3 gives a comparison of lumen and wall surfaces after rigid and deformable registration with the corresponding manual surfaces at follow-up. Compared with rigid registration (Figs. 3 (a) and (c)), the proposed deformable registration (Figs. 3 (b) and (d)) offers higher overlap with manual segmentations (denoted by silver surfaces) for both lumen and wall. As shown in Fig. 3(c), the manual lumen surface of follow-up time point shrinks compared with aligned surface at the position pointed out by the arrow, indicating the possible progression of carotid plaque. The transformed surface after non-linear registration achieved better consistency with the manual surface at the same position in Fig. 3(d).

Tab. 1 gives quantitative results in terms of DSC and MAD. Both the initial rigid alignment and nonlinear registration results were analyzed and compared. For lumen surfaces, our nonlinear registration method yielded a mean of DSC 79.3\% versus rigid alignment mean DSC of 73.9\% and reduced the surface distance error (MAD) from 0.55mm to 0.46mm while the registration accuracy did not improve much compared with rigid method for wall surface. The high overlap of wall surfaces (mean DSC of 84.7) indicates the rigid alignment is able to capture the global change of the vessels and significant improvement in registration accuracy illustrates the big potential of using our non-rigid registration method for assessing and monitoring local and temporal changes in carotid atherosclerotic burden, in an accurate and efficient way.

The registration method was performed on a PC with an Intel Core i7-4770 CPU@ 3.4 GHz with 8 GB of memory. The mean registration time of our method per image pair was 143 ± 23 s in addition to 48 ± 11 s for manual initialization of landmarks.

6. DISCUSSIONS AND CONCLUSIONS

Effective monitoring of carotid plaque changes using noninvasive US imaging technique is vital for quantifying progression and regression of carotid atherosclerosis at risk for stroke and in response to therapy. In this work, we proposed a deformable registration-based method to analyze 3D carotid US images taken at baseline and follow-up and attempted to assess the local change using the deformation of lumen and wall surface. The proposed method is image-based, and therefore, does not require segmentation as in surface-based registration techniques.
Figure 3. Comparison of registered surfaces from baseline image and manually segmented surfaces at follow-up. First column shows the wall and lumen comparison after rigid alignment and second row displays the comparison of surfaces after deformable registration. Manual surfaces are denoted in silver and registered surfaces in opaque blue.

Table 1. Quantitative registration results for five 3D US carotid image pairs regarding Dice Similarity Coefficient (DSC %) and Mean Absolute Distance (MAD mm). The registration accuracy (including rigid alignment and deformable registration) was obtained by comparing the transformed surface with manually segmented surfaces at the second time point.

<table>
<thead>
<tr>
<th>Sub#</th>
<th>Rigid alignment</th>
<th>Deformable registration</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Lumen</td>
<td>MAD</td>
</tr>
<tr>
<td>1</td>
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<td>0.56</td>
</tr>
<tr>
<td>2</td>
<td>72.2</td>
<td>0.58</td>
</tr>
<tr>
<td>3</td>
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</tr>
<tr>
<td>5</td>
<td>79.1</td>
<td>0.47</td>
</tr>
<tr>
<td>All</td>
<td>73.9 ± 3.4</td>
<td>0.55 ± 0.08</td>
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We showed that the proposed image-based deformable registration method is capable of obtaining the spatial distribution of local changes in both wall and lumen surfaces. In addition, the adoption of general-purpose programming on graphics processing units (GPGPU) technique achieved high computational efficiency. Experiment results show that our deformable registration obtained much higher overlap for lumen surfaces comparing with rigid registration, which confirmed the proposed algorithm can be used for assessing local changes in atherosclerotic burden over time.

REFERENCES


