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4D Vascular Tree Reconstruction using Moving Grid Deformation

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Abstract— **Perforator flaps have been widely used in plastic surgery for greater survivability and decreased morbidity. However, quantitative analysis of three dimensional (3D) blood flow direction and location has not been examined yet. In this paper, we reconstruct the 3D vascular tree with the incorporation of temporal information (4D) from contrast-agent propagation. A novel computational framework by adopting a moving grid deformation method is presented. To take advantage of temporal information of the bolus propagating, a sequential segmentation procedure is proposed. Moreover, the evolving of the vascular tree (4D vascular tree) is reconstructed through this procedure. Experimental results for anterolateral thigh perforator (ALTP) flap demonstrate the effectiveness of this method.**

I. INTRODUCTION

Perforator flaps have been increasingly used over the past decade ([1],[10]) in plastic surgery. The anterolateral thigh perforator (ALTP) flap is one of the most used perforator flaps. The majority of anatomical vascular studies of ALTP flap in the past have utilized lead oxide injections followed by 2-dimension radiography to determine vascular territories. Although lead oxide treated specimens provide excellent images, limitations of this methodology are well known. In contrast, three dimension radiography can provide not only qualitative data on vascular anatomy, but also information on the direction and location of blood flow within each layer of a perforator flap. Three dimensional anatomy was defined as the appraisal of the perforator vasculature in the sagittal, coronal and transverse views with an evaluation of the direction of blood flow through the perforator vascular tree, as seen in CT-angiography. Indeed to date, no studies have examined three or four dimensional vascular anatomies of the ALTP flap.

To better understand the 3D vascular tree structure, many vessel extraction techniques have been developed. Six main categories of vessel extraction techniques were summarized by [4] as: (1) pattern recognition techniques, (2) model-based approaches, (3) tracking-based approaches, (4) artificial intelligence-based approaches, (5) neural network-based approaches, and (6) miscellaneous tube-like object detection approaches. Unfortunately, no single segmentation method is powerful for every segmentation application. Among model-based approaches, geometric deformable models (GDMs) have become one of the most widely used tools in image segmentation. One problem for GDMs is that the computational cost is usually high. To improve the accuracy and efficiency for GDMs, adaptive grid techniques have been adopted [2],[3]. In the past, adaptive grid methods play as an assistant role in helping improving the accuracy of solution to partial differential equations (PDEs) involved by GDMs, such as level set PDEs. Further applications of adaptive grid methods in image segmentation have not been studied yet.

To adopt adaptive grid methods into image segmentation problem, this paper proposes a novel computational framework for vessel tree segmentation. This study is motivated by concepts from the moving grid method. The moving grid method is one of the adaptive grid methods typically used to improve accuracy and efficiency for solving differential equations [11],[12]. It can capture the salient features of the solution, and re-distribute grid points to those regions where salient features occur. In image segmentation applications, if we well define adaptivity criteria based on some information in image, such as intensity or gradient of intensity, we can apply moving grid method to segmentation problem by moving grid points to the target objects in an image. The fully study about this has not been reported before.

One difficult task in applying moving grid method to image segmentation problem is to define a good adaptivity criterion directly from the raw image. This difficulty is caused by the noise and inconsistency of intensities along the target objects in an image. To avoid this difficulty, we use moving grid method as a platform to develop a new edge linking method. Firstly, an initial segmentation is conducted. Based on this initial segmentation, an adaptivity criterion which sets small value of monitor function in the vessel region and big value of monitor function in non-vessel region is defined. Then, moving grid method is applied according to this adaptivity criterion to generate a grid plot. Up to now, another difficulty of using moving grid method in segmentation problem appears. There is no explicit contour provided by the grid plot. This problem is solved by defining an artificial image on the grid plot, and then performing a simple thresholding segmentation method on the artificial image to obtain the final segmentation. Through this procedure, the vessel tree repairing is automatically done because of the special feature of moving grid method that it moves the spatial grid points continuously and automatically in the space-time domain. This leads to smooth grid contours. Thus, our proposed method doesn't need interpolation, and avoids any search procedures, which is commonly used by many edge linker algorithms.

Besides using the moving grid method, we take advantage of the time information in bolus propagation. A new sequential segmentation procedure is proposed for the initial segmentation. Finally, the evolving of the vascular tree (4D vascular tree) is reconstructed through this sequential segmentation procedure.

II. METHODOLOGY

A. Numerical Grid Generation Techniques

In real world, many science and engineering applications result from solving numerically differential equations. A well-defined grid (mesh) over the computational domain is very important to obtain the valid numerical solution. Higher accuracy of solution typically requires a highly refined grid, however it causes a high computational cost. To solve this problem, adaptive grid techniques are widely used. Adaptive grids are generated according to the salient features of the problem so that the distribution of the grid points reflects the true nature of the solution.

In general, adaptive grid generation methods can be classified into two categories: local refinement and moving grid generation. Local refinement methods insert additional grid points to the desired regions, therefore they require a very complex data structure. On the other hand, moving grid generation methods maintain a fixed number of grid points, and move grid points to new locations to match the adaptive criterion. So moving grid methods are also denoted by the term r-refinement (re-distribute or re-locate). Comparing to local refinement, moving grid methods do not require complicated data structures. Moreover, they maintain fewer grid points than local refinement. As a result, the overall efficiency of moving grid method is significantly improved, in particular for complex geometries in three dimension domain.

In computer vision community, moving grid methods have been applied in certain applications. For example, moving grid method was used for adaptive image reconstruction [8],[9]. Another example is that a 2D grid geometric deformable model was proposed to solve image segmentation problems, and moving grid method was integrated into this model to improve the accuracy and efficiency of solving the level set PDEs associate with the model [3].

However, moving grid methods have not been fully studied in image segmentation. In this paper, we will introduce Liao's moving grid with deformation method [5] in solving our problem, and integrate the deformation method in a novel computational framework for vessel tree segmentation.

B. Moving Grid with the Deformation Method

The original deformation method came from J. Moser's study of volume element of Riemannian manifold [6]. Later, the deformation method was reformulated and applied to moving grid generation by Liao [5]. Especially, deformation method was recently utilized in computer vision and image processing community [3].

The principle of the deformation method is as follows. Let Ω be a rectangle domain, in our case, Ω is the 2D image domain. Initially, domain Ω is covered by a uniform grid (x,y) at time $t=0$. We seek a time dependent grid mapping: $\phi(\cdot,t) : \Omega(0) \rightarrow \Omega(t)$ such that the Jacobian determinant $J(\phi(x,y,t))$ of the grid mapping $\phi(x,y,t)$ be equal to a positive monitor function $m(\phi(x,y,t),t)$ at each time t.

The monitor function $m(\phi(x,y,t),t)$ is designed to control the movement of grid points. In tradition, the monitor function is defined according to the salient feature of solutions in differential equations. In our segmentation problem, it is defined depending on the intensity values in an initially segmented binary image.

The grid mapping ϕ can be computed in two steps. Firstly, we calculate vector field $\overrightarrow{v}(x,y,t)$ from the following first order divergence-curl (div-curl) system:

$$div\,\overrightarrow{v}(x,y,t) = -\frac{\partial}{\partial t}\left(\frac{1}{m(x,y,t)}\right), \tag{1}$$

$$curl\,\overrightarrow{v}(x,y,t) = 0, \tag{2}$$

$$\overrightarrow{v}(x,y,t)\cdot\overrightarrow{n} = 0\ , \quad for\ (x,y) \in \partial\Omega(t), \tag{3}$$

where $\partial\Omega(t)$ denotes the boundary of domain $\Omega(t)$. And we have $t \in [0,T]$ for all the above equations. Alternative notations for *div* and *curl* are:

$$div\,\overrightarrow{v}(x,y,t) = \nabla\cdot\overrightarrow{v}(x,y,t), \tag{4}$$

$$curl\,\overrightarrow{v}(x,y,t) = \nabla\times\overrightarrow{v}(x,y,t), \tag{5}$$

Secondly, we solve the following Ordinary Differential Equation (ODE)to obtain the grid mapping ϕ:

$$\frac{\partial}{\partial t}\phi(x,y,t) = m(\phi(x,y,t),t)\,\overrightarrow{v}(\phi(x,y,t),t), \tag{6}$$

where $t \in [0,T]$.

For correct implementation of the deformation method, the monitor function $m(\phi(x,y,t),t)$ should be normalized. Otherwise, valid solutions can not be obtained. The normalization of the monitor function is done under the following condition:

$$\int_{\Omega(t)} \frac{1}{m(x,y,t)}dxdy = |\Omega(0)|, \tag{7}$$

where $|\Omega(0)|$ means the area over the domain Ω at time $t=0$. The mathematical proof of the theory of the deformation method can be found in [7].

To calculate the vector field $\overrightarrow{v}$ in the first step, an alternative method is to solve a scalar Poisson equation, and then take gradient on the solution of the Poisson equation to get $\overrightarrow{v}$. However, the implementation of (1)-(3) can include new features by setting the right hand side of (2) not be 0. More discussion about this will not be included in this paper.

Least square finite element method (LSFEM) is applied to solve the div-curl system in the first step. For the implementation of LSFEM, we use the framework provided by [11].

Compared with other moving grid generation methods, the advantages of the deformation method are that it directly controls the Jacobian determinant of the grid mapping. That means the size of the grid cell (or volume) is kept to be proportional to the pre-defined monitor function during the grid adaptation process. In particular, the grid mapping has a positive Jacobian determinant, and the grid will not fold into itself. Therefore, it ensures in theory that no grid tangling or overlapping can happen.

C. Initial Segmentation

In this study, the deformation method is not carried out directly on raw images. The segmentation procedure begins with an initial segmentation. A novel sequential segmentation procedure is proposed by utilizing the time information provided by the 4D images. Firstly, every two slices which are scanned at adjacent time are subtracted from each other to get successive image differences. By applying a simple region growing method to do segmentation task on each image difference, a series of segmented image of image difference are obtained. Then we integrate them into a single one to form the complete segmentation, just like constructing a building by adding brick one by one. Through this way, an additional benefit is that the noises are significantly removed.

Furthermore, the evolving of the vascular tree (4D vascular tree) can be obtained through this procedure. Given a certain time t, the vascular tree at time t can be reconstructed by integrating all the segmented image differences which are computed before time t.

D. Defining Artificial Image and Final Segmentation

After the initial segmentation of vessel tree being applied, small breaks along the vessel tree structure exist. Thus, a repairing procedure is required. In this study, a novel vessel tree repairing procedure by using deformation method is proposed.

Based on the initial segmentation, we apply deformation method introduced in section II(B) to obtain a grid plot (x_T, y_T) in which grid points are densely distributed along the initial vessel tree. The key question is that how we utilize the grid plot in the edge linking and tree repairing procedure. A difficult part is that there is no explicit contour provided by the grid plot. To solve this problem, we define a physical meaningful artificial image on the grid plot. This artificial image should have good quality in terms of segmentation. Then a simple thresholding method on the artificial image is applied to obtain the final segmentation.

Firstly, defining the vector field for the grid mapping $\phi(x,y,T)$.

$$\overrightarrow{v_T} = < x_T - x,\ y_T - y >^T, \tag{8}$$

where (x,y) is initial uniform grid. (x_T, y_T) is the grid plot we obtained.

Then, the intensity $I(x_T, y_T)$ of the artificial image at position (x_T, y_T) is defined by computing the divergence of the vector field $\overrightarrow{v_T}$.

$$I(x_T, y_T) = \nabla \cdot \overrightarrow{v_T}. \tag{9}$$

The value of the intensity $I(x_T, y_T)$ is assigned on each grid point of grid plot (x_T, y_T) to form the artificial image. As an understanding, this intensity function is the "force" to drive the movement of grid points.

At last, we apply a simple thresholding method on the artificial image to obtain the final segmentation result.

III. Experimental Results

A. Experimental Methods and Materials

In this study, ALTP flap is used as a baseline research perforator flap. The experiment procedure is addressed below:

The ALTP flaps was dissected suprafascially, based on the largest perforator originating from descending branch of the lateral femoral cutaneous artery. We then performed dynamic CT scans of the flaps using a GE Light Speed 16 slice scanner. For a dynamic scan, a slow injection using a Harvard pump was used to introduce 15 ml of iodinated contrast agent (Omnipaque, Amersham Health) at a 0.2ml rate. During the injection, helical scans were repeated at 4s intervals to volume image the time evolution of flap vascularity. To minimize the volume scan time, the gantry was tilted to 30 degrees, and flaps were placed on a jig with a table angled to the gantry plane. Using a 0.5s rotation time, 10 mm collimation (for 0.625 mm slices), and a 0.938 pitch setting, a 4 mm thick flap can be helically scanned in about 3s. Scans were performed at 80 kVp when using iodinated contrast agent to optimize contrast (typically, scans were performed at 200 mA). To allow optimal resolution reconstructions, raw scan data was saved to permit retrospective reconstruction in regions of interest.

The whole image data set has 27 volumes which were taken at 27 different time. Each volume includes 33 slices. For the resolution, the slice includes 512x512 pixels with 300 mm field of view (FOV) (i.e., 0.56 mm per pixel). Slice thickness is 0.625 mm and the slice interval is 0.625 mm.

B. Vessel Tree Reconstruction

1) Initial Vascular Tree Segmentation: The initial segmentation is performed by following the sequential segmentation procedure presented previously. To better visualizing our method, results are shown on a 50X50 pixels domain. The initial segmentation on this domain is in Fig 1(a).

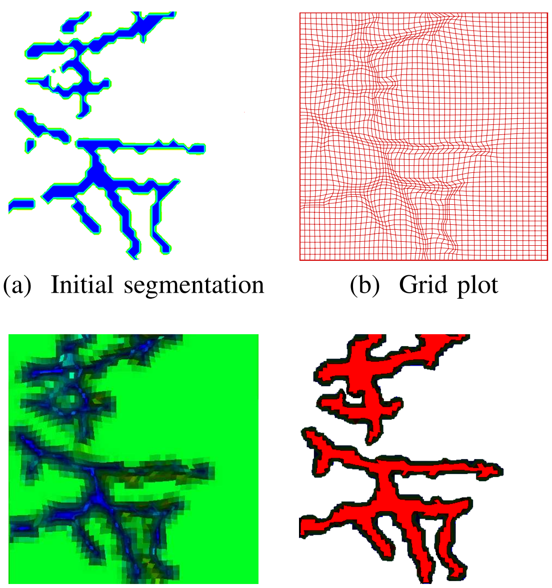
2) Moving grids generation with deformation method: Based on the initial segmentation, deformation method is applied to obtain a grid plot $((x_T, y_T))$ in which grid points are re-distributed toward the position of initial vascular tree. In the implementation of deformation method, a monitor function $\bar{m}(\phi(x,y,t),t)$ according to the position of the initial vascular tree is defined. For a given time t, if $\phi(x,y,t)$ is located on the initial vascular tree, we define $\bar{m}(\phi(x,y,t),t) =$ 0.3, otherwise, $\bar{m}(\phi(x,y,t),t) = 1.0$. $\bar{m}(\phi(x,y,t),t)$ is normalized by equation (7), then system (1)-(3) and (6) are solved. This procedure is repeated until $t = T$. The grid plot is obtained in 10 time steps. Grid plot is in Fig 1(b).

3) Artificial Image Generation: Now we calculate $\overrightarrow{v_T}$ from (8), and $I(x_T, y_T)$ from (9), and assign the value of $I(x_T, y_T)$ to each grid point on grid plot (x_T, y_T). The artificial image is obtained in Fig 1(c).

4) Final Vascular Tree and 4D Vascular Tree: Applying a simple thresholding method on the artificial image to get the final segmentation for each slice (Fig 1(d)). Small breaks in initial segmentation are linked together. The final vascular tree then can be obtained by stacking all the slice segmentation together (Fig 3). The evolving of the vascular tree (4D vascular tree) is demonstrated in Fig 2 and Fig 3.

IV. CONCLUSIONS

In this paper we proposed a novel computational framework for 4D vascular tree reconstruction of ALT flap, which adopts moving grid generation technique with deformation method. Also, a new sequential segmentation procedure is proposed for initial segmentation and the 4D vascular tree reconstruction. The experimental results demonstrated the effectiveness of this computational framework. For the future work, we will study how to utilize the deformation method directly on segmentation by defining a robust monitor function based on information from noisy raw images in order to avoid the initial segmentation procedure.



(a) Initial segmentation (b) Grid plot

(c) Artificial image (d) Final segmentation

Fig. 1. Demonstration of segmentation procedure on a 50X50 slice.

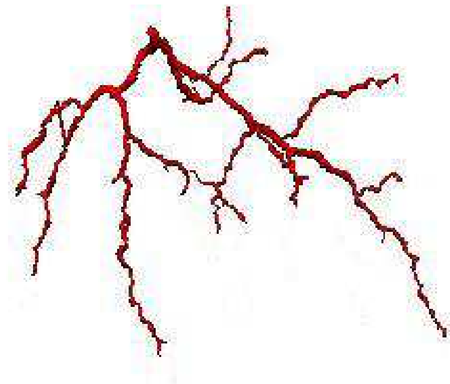


Fig. 2. Evolved vascular tree at certain injection time.

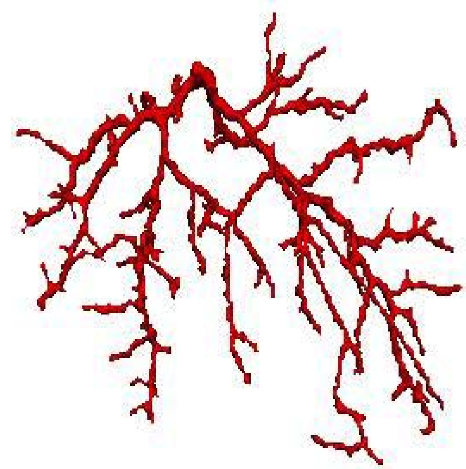


Fig. 3. Full vascular tree.

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