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Level Set Based Automatic Segmentation of Human Aorta

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ABSTRACT

Segmentation of aorta and other blood vessels from standard 3D CT or MRI scans needs a lot of hand work if to do it by a standard segmentation software like Mimimcs and Amira.

In this paper, we present a new level set based deformable model for the segmentation of human aorta from 3D image dataset. Accurate 3D geometrical models are essential for realistic computational fluid analysis of the blood flow in human aortas, which can improve our understanding of flow-related aortic diseases. Segmentation of the human aorta is however difficult, due to its complex topology and intensity inhomogeneity in the image structures. The proposed method uses a hypothesized interaction force between the geometries of the deformable surface and image objects which can greatly improve the performance of the deformable model in extracting complex geometries, deep boundary concavities, and in handling weak image edges. The results show that the new deformable model can be used to efficiently segment complex structures such as the human aorta from medical images.

Key Words: *level set, deformable model, segmentation, human aorta.*

1 INTRODUCTION

Deformable models are highly appropriate in the segmentation of the human aorta since they can naturally adapt to local image structures. However, explicit or parametric models are not suitable in our case since they generally have difficulties in dealing with topological changes and reaching into deep concavities such as tubular structures. Implicit deformable models based on the level set technique are introduced by Caselles et al. [1] and Malladi et al. [4] to address some of the limitations of parametric deformable models. In this approach, the evolution of curves and surfaces are represented implicitly as a level set of a higher-dimensional scalar function and the deformation of the model is based on geometric measures such as the unit normal and curvature. The evolution of the model is therefore independent of the parameterisation, and topological changes can be handled automatically.

Conventional image gradient based methods are generally prone to local minima that often appear in real images. The balloon force [4] can monotonically expand or shrink the contours, but has great difficulties in dealing with weak edges and cross boundary initialisations. The bidirectionality of the gradient vector flow (GVF) model [7] allows more flexible initialisation and its diffused force field handles image noise interference in a much better manner. However, it has serious convergence issues [6]. More recent works, such as [2, 5, 3], showed promising but limited success.

In this paper, we present a new external force field which is based on the relative position and orientation between deformable model and the image object boundaries. The geometrically induced force field can easily deal with arbitrary cross-boundary initializations and weak image edges due to its bidirectionality. In addtion, the dynamic interaction forces between the geometries of the deformable model and image object can greatly improve the performance of the deformable model in acquiring complex geometries and highly concave boundaries.

2 PROPOSED METHOD

The new external force field proposed in this paper is created based on the hypothesized geometrically induced interactions between the relative geometries of the deformable model and the object boundaries (characterized by image gradients). In other words, the magnitude and direction of the interaction forces are based on the relative position and orientation between the geometries of the deformable model and image object boundaries, and hence, it is called the *geometric potential force (GPF)* field.

2.1 Geometric potential force

Consider two area elements dA_1 and dA_2 on two surfaces, with unit normals $\hat{\boldsymbol{n}}_1$ and $\hat{\boldsymbol{n}}_2$ respectively. The hypothesized interaction force acting on dA_1 due to dA_2 is defined as

$$d\boldsymbol{F} = dA_1 \hat{\boldsymbol{n}}_1 d\boldsymbol{G} \tag{1}$$

where dG is the corresponding geometrically induced potential created by element dA_1, and is given as

$$d\boldsymbol{G} = \frac{|\boldsymbol{n}_2| dA_2}{r^3} (\hat{\boldsymbol{r}}_{12} \cdot \hat{\boldsymbol{n}_2}) \tag{2}$$

Here, $|\boldsymbol{n_2}|$ is the magnitude of the normal at element dA_2, r is the distance between dA_1 and dA_2, and $\hat{\boldsymbol{r}}_{12}$ is the unit vector pointing from dA_1 to dA_2.

The geometric potential dG can be seen as a induced scalar field, in which the strength of depends on the relative position of the two elements dA_1 and dA_2. The magnitude and direction of the geometrically induced vector force dF is therefore handled intrinsically by the relative postion and orientation between the geometries of the deformable model and object boundary.

2.2 Deformable model based on geometric potential force

Let the 3D image be described by function $u(\boldsymbol{x})$ where $\boldsymbol{x}$ is a pixel or voxel location in the image domain, and ∇u be its gradient. Let dA_1 belongs to the deformable surface whereas dA_2 belongs to the object boundary. To compute the force acting on dA_1 from dA_2, we substitute $|\boldsymbol{n}_2| = |\nabla u|$, $\hat{\boldsymbol{n}_2} = \nabla u / |\nabla u|$ into (2) and treat $\boldsymbol{n}_2$ as a normal to the object boundary. Then we compute the total geometric potential field strength $G(\boldsymbol{x})$ at every voxel. Note that only voxels on the object boundary will contribute to the geometric interaction field. Let S denote the set containing all the edge voxels, and $\boldsymbol{s}$ denote a boundary voxel, the total geometric interaction at $\boldsymbol{x}$ can then be computed as:

$$G(\boldsymbol{x}) = V.P. \oiint_{\boldsymbol{S}} \frac{\hat{\boldsymbol{r}}_{\boldsymbol{xs}}}{r^3_{\boldsymbol{xs}}} \cdot \hat{\boldsymbol{n}_2}(\boldsymbol{s}) |\boldsymbol{n}_2|(\boldsymbol{s}) \, dA_{\boldsymbol{s}} \tag{3}$$

where $\hat{\boldsymbol{r}}_{\boldsymbol{xs}}$ is the unit vector from $\boldsymbol{x}$ to $\boldsymbol{s}$, and $r_{\boldsymbol{xs}}$ is the distance between them. Computation of ((**??**)) can be performed efficiently using fast fourier transform (FFT).

The force acting due to the geometrically induced potential field on the deformable surface $\mathcal{C}$ at the position $\boldsymbol{x} \in \mathcal{C}$ can then be given as:

$$\boldsymbol{F}(\boldsymbol{x}) = dA_{\boldsymbol{x}}\, \boldsymbol{n}(\boldsymbol{x})\ G(\boldsymbol{x}) \tag{4}$$

Given the force field $\boldsymbol{F}(\boldsymbol{x})$ derived from the hypothesized interactions based on the relative geometries of the deformable model and object boundary, the evolution of the deformable model $C(\boldsymbol{x}, t)$ under this force field can be given as:

$$C_t = \big(\boldsymbol{F} \cdot \boldsymbol{n}\big)\, \boldsymbol{n} \tag{5}$$

Since contour or surface smoothing is usually desirable, the mean curvature flow is added and the complete geometric potential deformable model evolution can be formulated as:

$$C_t = \alpha g(\boldsymbol{x})\kappa\boldsymbol{n} + (1-\alpha)(\boldsymbol{F} \cdot \boldsymbol{n})\boldsymbol{n} \tag{6}$$

where $g(\boldsymbol{x}) = \dfrac{1}{1 + |\nabla u(\boldsymbol{x})|}$ is the edge stopping function. Its level set representation can then be given as:

$$\Phi_t = \alpha g\kappa|\nabla\Phi| - (1-\alpha)(\boldsymbol{F} \cdot |\nabla\Phi|) \tag{7}$$

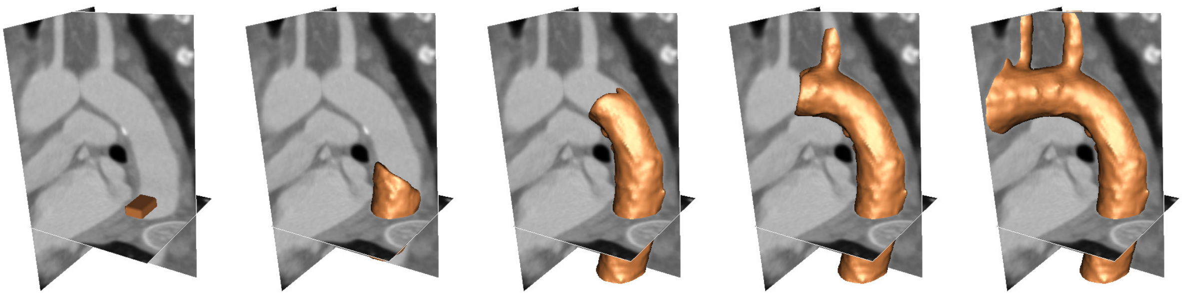

Figure 1: Segmentation process of the human aorta using the GPF deformable model.

3 RESULTS

The new deformable model based on the geometric potential force is applied in the segmentation of the human aorta from a 3D image dataset acquired using computed tomography (CT) imaging. The image dataset is cropped to obtained the region of interest. This is done so as to reduce the computational expenses in using the level set method. Figure 1 portrays the results of the segmentation process using the proposed method. The different views of the segmented aorta model is then shown in Figure 2.

As shown in Figure 1, an initial level set surface is used for the segmentation process. In particular, the level set surface is initialised across object boundaries (i.e. across different structures) in the image to demonstrate the capability of the new deformable model to deal with arbitrary cross-boundary initialisations. The evolution process of the level set surface and the converged deformable model is also shown in the figure.

The example demonstrates that the proposed deformable model can efficiently segment complex geometries such as the human aorta. In addition, it can resolve intensity inhomogeneity in image structures such as those of the human aorta.

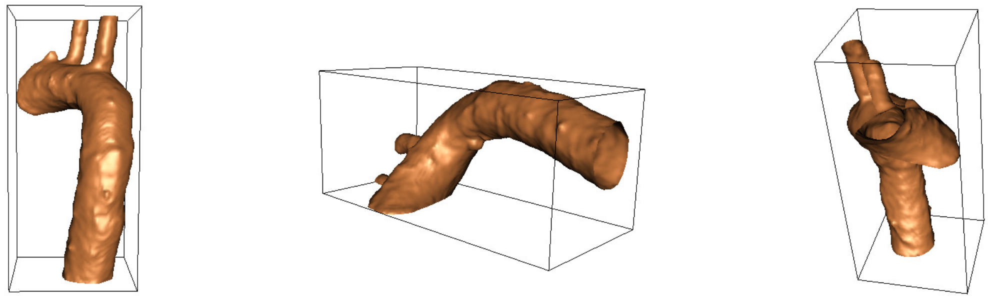

Figure 2: Three different views of the segmented human aorta.

4 CONCLUSIONS

In this paper, we presented a new external force field for image segmentation which is based on hypothesized geometrically induced interactions between the deformable surface and the image object boundary. The proposed deformable model is applied in the segmention of the human aorta from a 3D image dataset. It is shown that by using this approach, complex topologies such as those of the human aorta can be efficiently reconstructed. Accordingly, the new external force is dynamic in nature as it changes according to the relative position and orientation between the evolving deformable model and object boundary. It can thus be used to attract the deformable model into deep boundary concavities that exists in some image objects. In addition, the new deformable model can handle arbitrary cross-initialisation which is a desirable feature to have, especially in the segmentation of complex geometries. Quantitative analysis and comparison to other gradient based methods are necessary to further study the performance of the proposed model. However,this preliminary work illustrates the efficiency of this approach in resolving intensity inhomogeneity and in handling complex 3D geometries, which are often found in biomedical image datasets.

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