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Medical Image Segmentation Using Deformable Model and Local Fitting Binary: Thoracic Aorta

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***Abstract*—**This paper presents an application of level sets for the segmentation of abdominal and thoracic aortic aneurysms in CTA datasets. An important challenge in reliably detecting aortic is the need to overcome problems associated with intensity inhomogeneities. Level sets are part of an important class of methods that utilize partial differential equations (PDEs) and have been extensively applied in image segmentation. A kernel function in the level set formulation aids the suppression of noise in the extracted regions of interest and then guides the motion of the evolving contour for the detection of weak boundaries. The speed of curve evolution has been significantly improved with a resulting decrease in segmentation time compared with previous implementations of level sets, and are shown to be more effective than other approaches in coping with intensity inhomogeneities. We have applied the Courant Friedrichs Levy (CFL) condition as stability criterion for our algorithm.

***Keywords*—**Image segmentation, Level-sets, Local fitting binary, Thoracic aorta.

I. INTRODUCTION

IMAGE segmentation commonly utilises one of two main approaches to classify pixels belonging to a particular object or region, either edge-based or region-based. Edge-based segmentation looks for discontinuities in image intensity [4-6], whilst region-based methods look for uniformity within an image sub-region, based on some consistent property such as intensity, colour or texture [2, 6, 9, 10].

Active contours methods, also referred to as deformable models, evolve an image contour from an initial guess using image forces derived from region properties to drive the search to locate the boundaries of the desired objects. Level sets provide an implementation of an active contour method based on regions or edges. A local energy functional has been defined in terms of a contour and two fitting functions that locally approximate the image intensities on either side of the contour. An important characteristic of active contour methods is to identify the appropriate stopping condition for the curve evolution. In this paper we have used the Courant Friedrichs Levy (CFL) condition to establish the necessary conditions for numerical convergence of the level set PDE's, which also satisfies a criterion for algorithmic stability.

The method is applied to the detection of aneurysms in the cardiovascular system imaged by computed tomography angiography (CTA), which uses a contrast dye to enhance detection of the vasculature. The aorta is the major artery which carries blood from the heart and distributes it via many branches to all the organs of the body. The aorta is divided into four sections: the ascending aorta, the aortic arch, the thoracic (descending) aorta and the abdominal aorta. Blockage or weakness in the artery walls can lead to aneurysm, a distension of the vessel wall that is prone to rupture and su bsequent haemorrhage in severe cases.

Reliable detection of aortic aneurysm must overcome problems of intensity inhomogeneities and image noise. Level sets are part of an important class of methods that utilize partial differential equations (PDEs) and have been extensively applied in image segmentation. The approach uses a kernel function to aid noise suppression and then guides the search motion of the evolving contour, particularly for the detection of weak boundaries. Segmentation time can be significantly reduced by improving the convergence criteria, for which we have applied the CFL condition.

The rest of the paper is organized as follows. Section II reviews the level set method, edge based and region-based active contours and introduces the proposed computational methods. Section III describes the numerical implementation and experimental results and conclusions are presented in section IV.

II. LEVEL SET METHOD AND LOCAL FITTING BINARY

The level set method developed by Osher and Sethian [6] has been used in the formulation of several region or boundary based approaches for image segmentation and offers highly robust and accurate techniques for tracking interfaces moving under complex motions. Level set segmentation involves solving the energy-based active contour minimization problems by the computation of geodesics or minimal distance curves [6, 7]. The main idea of the level set method is to represent a closed curve on the plane as a zero level set of a higher dimension function. The motion of the curve is then embedded within the motion of the higher dimension surface. Basically, this means that the closed curves in a two-dimensional surface are regarded as a continuous surface of a three-dimensional space. The definition of a smoothing function $\phi(x, y, t)$ represents the surface while the set of definitions $\phi(x, y, t)$ = 0 define curves. Thus the evolution of a curve can be transformed into the evolution of a three-

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dimensional level set function. Given a level set function $\phi(x, y, t = 0)$ whose zero level set corresponds to a curve, with the curve as the boundary; the whole surface can be divided into an internal region and an external region of the curve.

The common movement formula of the level set is:

$$\phi_t(x, y, t) + V\left|\nabla \phi(x, y, t)\right| = 0$$
$$\phi(x, y, t = 0) = \phi_0\left(x, y\right)$$

Where V denotes a constant speed term to move forwards or inwards the contour. A special case is the motion by mean curvature [4] where $V = div(\frac{\nabla \phi}{|\nabla \phi|})$ is the curvature of the level-curve of ϕ passing through (x, y).

The level set method based on the local fitting binary is given by the equation [6]:

$$E(\phi, f_1, f_2) =$$
$$\sum_{i=1}^{2} \lambda_i \int (\int K_\sigma(x-y)|I(y) - f_i(x)|^2 M_i(\phi(y))dy)dx$$
$$+\nu \int \left|\nabla H(\phi(x))\right|dx + \mu \int \frac{1}{2}(|\nabla \phi(x)| - 1)^2 dx$$

K_σ is a kernel function (Gaussian kernel) that decreases and approaches zero as |x-y| increases. $f_1(x)$, $f_2(x)$ that approximate the image intensities inside and outside the contour.

For minimizing the LBF model, first the functional form of model is conformed with level set method, next in order to solve the level set equation, the implicit finite difference scheme is applied and gradient descent will employed to minimize the energy functional with respect to the level set function ϕ which shown as follows:

$$\frac{\partial \phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) +$$
$$\nu \delta_\varepsilon(\phi) div(\frac{\nabla \phi}{|\nabla \phi|}) + \mu(\nabla^2 \phi - div(\frac{\nabla \phi}{|\nabla \phi|})) \tag{1}$$

Where, δ_ε is the smooth Dirac deltas function and e_1, e_2 are the functions as follows:

$$e_i(x) = \int K_\sigma(y - x)|I(x) - f_i(y)|^2 dy \qquad i = 1,2$$

The term $-\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2)$ drives the active contour toward the object`s boundary and the second term has a length shortening (arc length) term [7], [8]. The third term is called a level set regularization term [9], which maintains the regularity of the level set function.

III. Implementation And Experimental Results

We have developed a code based on the LBF model to segment the object boundary in medical images. The active contour works well to detect the boundary images inhomogeneity intensity. And also we have applied CFL condition as stability criterion on our algorithm. CFL number is:

$$c = \left(\frac{v \Delta t}{\Delta x}\right)$$

Where v is the velocity, Δt is the time step, Δx is the length interval. CFL condition is a necessary condition for convergence while solving certain partial differential equations numerically. In consequence of, we have segmented the spine, ascending aorta and the descending thoracic aorta in CTA data.

The main steps of the algorithm can be expressed as follow:

1. Initialize the level set function ϕ to be binary function as follows:

$$\phi(x, y, t = 0) = \begin{cases} -c & x \in \Omega_0 - \partial\Omega_0 \\ 0 & x \in \partial\Omega_0 \\ c & x \in \Omega - \Omega_0 \end{cases}$$

Where c>0 is a constant, Ω_0 is a subset in the image domain Ω and $\partial\Omega_0$ is the boundary of Ω_0.

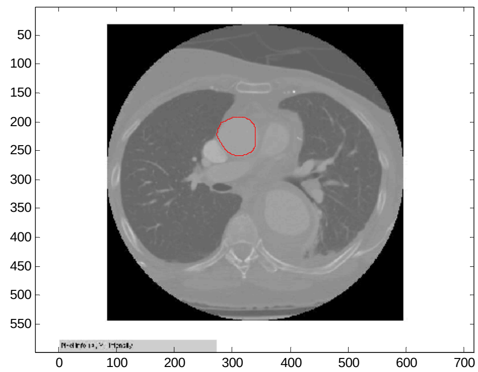
2. Evolve the level set function ϕ according to (1).
3. Check with iteration number whether the evolution is stationary or no.

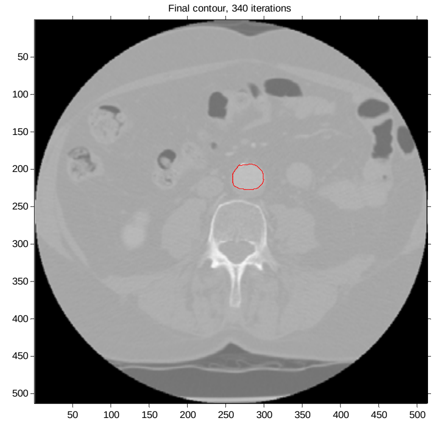
All partial derivatives can be discretized as central finite differences and also the temporal derivative is discretized as a forward difference. Therefore there are in total six convolutions, two convolutions $K_\sigma * I$ and $K_\sigma * 1$ can be computed only once before the iterations and four convolutions must be computed in each iteration.

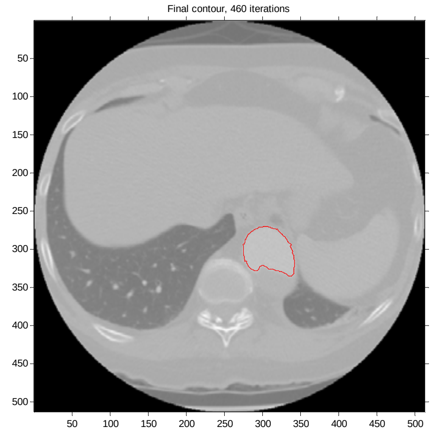
To validate and assess the robustness of the proposed method, we used computed tomography angiography (CTA) images to detect aorta and thoracic abdominal (AA and TA). The CTA images were collected at Lausanne University. This model is very encouraged. So, for the next work, we would like to validate this model in 3-D.

The methodology has been tested with several data with good result for images by intensity inhomogeneity, rather noisy and part of boundary is weak that are shown in figures.1, 2.

The PC model [2], [3] generally fails to segment images with intensity inhomogeneity. Therefore some part of the background/foreground is incorrectly identified as the foreground/ background, can be seen the difficulties in segmenting images with intensity inhomogeneity.







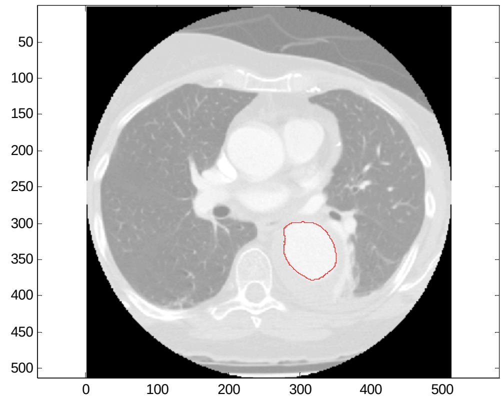


Fig. 1**.** Result of segmentation for the descending thoracic aorta with the final contour that are shown.

IV. Conclusion

We have presented an active contour model based on local binary fitting and which is better adapted to the problem of intensity inhomogeneities in the image. The method was demonstrated to segment the ascending and descending thoracic aorta and the abdominal aorta with desirable performance in the presence of intensity inhomogeneties and weak object boundaries. The time required for segmentation was significantly decreased through more effective convergence criteria. Finally, the effectiveness of the algorithm has been validated on a CTA dataset to assess its performance in terms of efficiency and accuracy. Further work will be to extend the level set algorithm to 3D which can then be applied to CTA voxel data.

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