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Segmentation of Cardiac Images by the Force Field Driven Speed Term

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***Abstract*—The class of geometric deformable models, so-called level sets, has brought tremendous impact to medical imagery. In this paper we present yet another application of level sets to medical imaging. The method we give here will in a way modify the speed term in the standard level sets equation of motion. To do so we build a potential based on the distance and the gradient of the image we study. In turn the potential gives rise to the force field: $\vec{FF}(x,y) = \sum_{\forall(p,q)\in I}((x,y)-(p,q))\frac{|\nabla I(p,q)|}{|(x,y)-(p,q)|^2}$. The direction and intensity of the force field at each point will determine the direction of the contour's evolution. The images we used to test our method were produced by the Univesité de Sherbrooke's PET scanners.

***Keywords*—PET, Cardiac, Heart, Mouse, Geodesic, Geometric, Level Sets, Deformable Models, Edge Detection, Segmentation.

I. INTRODUCTION

IN the past decades, image segmentation has played an important role in medical imaging. Segmented images are now used routinely in a huge number of different applications, such as the quantification of tissue volumes [7], diagnosis [8], localization of pathology [9], study of anatomical structure [10], [11], treatment planning [12], partial volume correction of functional imaging data [13], and computer-integrated surgery [14]. However, image segmentation remains a challenging task, mostly due to the unpredictability of object shapes and also the inconsistency in image quality. Also, medical images are often corrupted by noise and sampling artifacts, which can make the classical segmentation techniques such as edge detection and thresholding almost useless. Consequently, when using these techniques one usually must apply some kind of post processing step in order to discart unsound object boundaries in the obtained segmentation results.

In order to deal with those difficulties, deformable models have been widely studied and broadly used in medical image segmentation, with generally satisfying results. Deformable models are curves or surfaces defined within an image domain that can move under the influence of internal forces and external forces. Internal forces are defined within the curve or surface itself, and can be computed from the image. The internal forces are designed to keep the model smooth during deformation. The external forces are defined to move the model toward an object boundary or other desired features within an image.

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In particular, the class of geometric deformable models(GDM) introduced in [1], [2], [3] are deforming contours (curves and surfaces) represented implicitly as level sets of some higher dimensional scalar function. This level sets representation allows these models to have numerous advantages such as providing efficient computational schemes, automatically handling topology changes of the evolving contours and simple implementation. These numerous advantages can be used profitably to provide a very efficient framework for image segmentation, edge detection, shape modeling, visual tracking etc.

Using the classical level sets implementation of the geodesic deformable model it would be challenging to segment a cardiac image. The reason is because if only one contour is initialized the interior or the exterior of the heart would not be detected. On the other hand if two contours are initialized (one inside and one outside of the heart) the constant speed term c would force the contours to expend or shrink making it impossible to detect the compleat boundary. In order to benefit from all the advantages that come with the geodesic deformable model and yet be able to properly segment the cardiac image we develop a new method, based on the geodesic deformable models, for segmentation of medical images in particular, the PET images of a mouse's heart. We develop a force field that will influence the speed term in the evolution equation. The evolving curve will act as if placed in a potential that is proportional to gradient and inversely proportional to the distance. This framework will allow the curve to move forward and backward depending on the force field.

For cardiac images it is important to have a segmentation method in order to be be able to make an accurate diagnostic. For example the volume of the blood that is being pumped can be well approximated if the segmentation is done properly. The segmentation also allows us to measure the muscle thickness at various places.

This paper is organized as follows. In Section II, we briefly introduce the geometric and geodesic deformable models. In section III we discuss the the creation of the force field that will later govern the evolution of the evolving contour. In Section IV, we explain how the constant speed term c can be modified to accommodate our need for the contour to be free to shrink and to expend. Some experimental results are also presented. A brief conclusion is given in Section VI.

II. Geometric Deformable Models

Geometric models for active contours have brought tremendous impact to classical problems in imagery such as providing ways to devise efficient computational algorithms for automatic segmentation. This is achieved by using the level set methods, which allow handling automatic changes in topology while providing a framework for very fast numerical schemes.These models are based on the theory of curve evolution and geometric flows. The curve/surface is propagating (deforming) by an implicit velocity that contains two terms, one related to the regularity of the deforming shape and the other attracting it to the boundary. The model is given by a geometric flow(PDE), based on mean curvature motion, therefore it's completely intrinsic. When implemented using the level set based numerical algorithm, the model handles topology changes automatically.

The geometric model proposed by Caselles *et al* [1] is based on the mean curvature motion equation which describes the propagation of the level set function following the normal direction with speed depending on the mean curvature. Let u be a level set function $u : R^2 \times [0, +\infty) \rightarrow R$ and curve C is a level set of u, such that $C = \{x \in R^2 : u(x,t) = r\}, r \in R$. The geometric model is defined as follows:

$$\frac{\partial u}{\partial t} = g\left(I\right)\left(c + k\right) \mid \nabla u \mid = F_1 \mid \nabla u \mid \tag{1}$$

$$u(x, 0) = u_0(x) \tag{2}$$

where u_0 is the initialized curve. A similar formulation called the geodesic model gives:

$$\frac{\partial u}{\partial t} = \left(g(I)(c + k) - \nabla g \cdot \vec{N}\right) \mid \nabla u \mid = F_2 \mid \nabla u \mid \tag{3}$$

where $g(I)$ is the stopping function,

$$g(I) = \frac{1}{1 + \mid \nabla \hat{I} \mid^2}$$

which will stop the propagation when the evolving front reaches the desired position, the boundary detected. $\hat{I}$ is a convolved image that ensures the motion of C is less affected by the noise in the image. k is the mean curvature. And $\vec{N}$ is computed on the evolving front. For the added constant term c, we can think $cg(I) \mid \nabla u \mid$ as an extra speed in the geodesic problem to increase the speed of the convergence. The gradient term $\mid \nabla u \mid$ controls what happens at the interior and exterior of the interface. $\nabla g \cdot \nabla u$ denotes the projection of an attractive force vector on the normal to the moving interface. This term allows to accurately track boundaries with high variation in their gradient, including boundaries with small gaps.

There are many algorithms for numerical implementation of GDM using level sets. Narrow band method and fast marching method are two simple, computationally fast and widely used algorithms. Instead of computing the evolution of all the level sets, which means all the grid points, narrow band method just updates a small set of points in the neighborhood of the zero level set for each iteration.

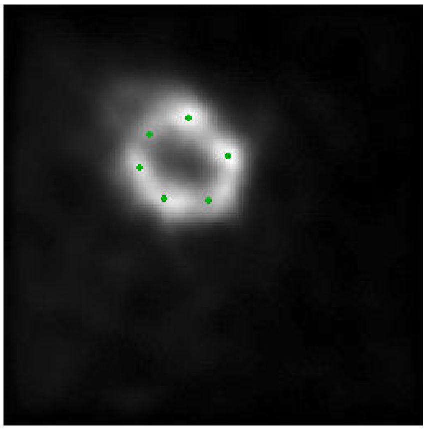

Fig. 1. *Points of reference.*

III. Force field

If the classical level sets implementation of the geodesic deformable model is used to segment a cardiac image it would be a challenge for at least two reason. The first reason is that if only one contour is initialized in the interior or in the exterior of the heart only partial boundaries would be detected. If the contour was to be initialized in the regions representing the heart's muscle the contour would easily leek producing incorrect boundaries. The second reason is that if two contours are initialized (one inside and one outside of the heart) the constant speed term c would force the contours to expend only or shrink only, making it impossible to detect the compleat boundary. With the desire to benefit from all the advantages that come with the geodesic deformable model and yet be able to properly segment the cardiac image we develop a new method, based on the geodesic deformable models, for segmentation of medical images, in particular the PET images of a mouse's heart. We develop a force field that will influence the speed term in the evolution equation. The evolving curve will act as if placed in a potential that is proportional to gradient and inversely proportional to the distance. This framework will allow the curve to move forward and backward depending on the force field.

Before we start the segmentation the user is asked to create about five points of reference. Those points should be placed inside the heart muscle as illustrated in the figure 1.

After the points of reference were acquired we proceed to estimation of the curve that will later be responsible for the existence of the force field. What is important is that this curve passes through all the points of reference and that it always stays in the heart muscle which is represented by the bright regions. There are numerous ways of creating such curve using the image information and also the knowledge of what a mouse's heart, for example, looks like. One possible instance of such a curve is shown in the figure 2.

From the image in the figure 2 we create the image in the figure 3.

To calculate the force field we use the image shown in the figure 3 and the following equation:

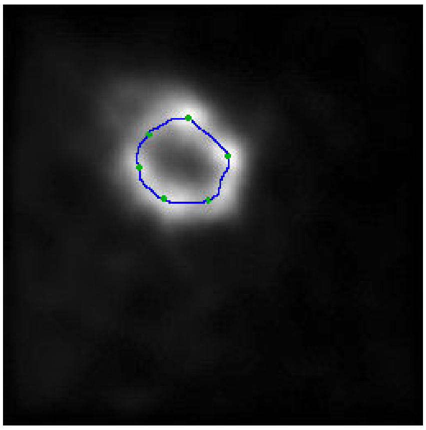

Fig. 2. *Force field curve step I.*

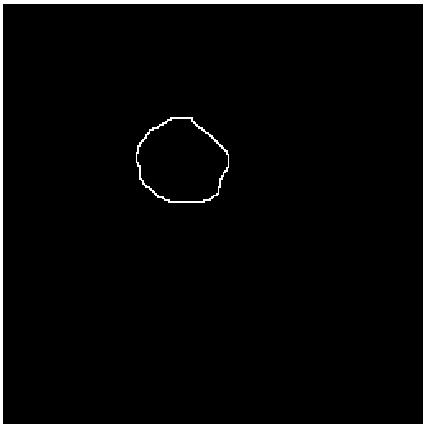

Fig. 3. *Force field curve step II.*

$$\vec{FF}(x,y)=\sum_{\forall(p,q)\in I}((x,y)-(p,q))\frac{|\nabla I\,(p,q)\,|}{|(x,y)-(p,q)|^2} \quad (4)$$

The force field created here is very similar to the one created by gravitational potential. In the case of gravity, the points in space that contain some matter (have some mass) will be the only ones that exert the force. Similarity, only the pixels that have non-zero gradient will exert the force. So the evolving contour acts as a "massless" string attracted by the pixels with high gradient.

IV. Adapting the Geodesic Deformable Model

In both geometric and geodesic deformable models the constant c is responsible for the direction of the evolution and the speed of the evolution of the evolving front. In this section we develop a way to calculate c that depends on the information provided to us by the image we are working on.

In order if the contour should expend or contract, that if the constant c should be positive or negative, we consider the dot product between the normal vector to the evolving front and the force field vector at the same point. As illustrated in the figure 4

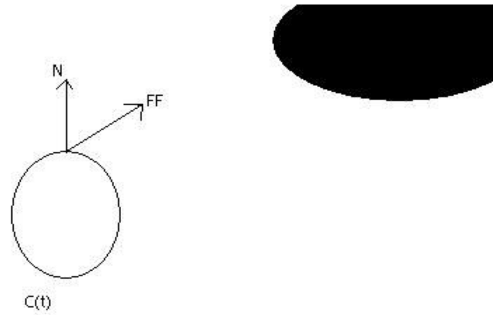

Fig. 4. *The normal N and the force field vector FF.*

Therefore, we define c which will no longer be a constant as:

$$c(\vec{FF}(x,y))=\begin{cases} c & if\vec{N}\cdot\vec{FF}\geq 0\\ -c & if\vec{N}\cdot\vec{FF}\leq 0\end{cases} \quad (5)$$

So now c can be moving the contour in either direction, forward or backward.

The new equation of motion is now:

$$\frac{\partial u}{\partial t}=g\,(I)\left(c(\vec{FF}(x,y))+k\right)|\,\nabla u\,| \quad (6)$$

for the geometric model and

$$\frac{\partial u}{\partial t}=\left(g(I)(c(\vec{FF}(x,y))+k)-\nabla g\cdot\vec{N}\right)|\,\nabla u\,| \quad (7)$$

for the geodesic model, where $c(\vec{FF}(x,y))$ is calculated using the equation 5 and the equation 4

V. Experimental Results

In this section, we show a few results that were obtained this new modified deformable model.

The following image is an image of a mouse's heart.

We initialize two contours. The first one is placed in the middle of the force field curve shown in the figure 3 and it should be as small as possible. The second one is a circle with center in the middle of the force field curve and its size should be big enough to encompass most of the pixels representing some radioactivity. The initialization is shown it the figure 6.

The evolution of our deformable model is shown in the figure 7.

VI. Summary and Conclusions

In this paper we have presented a new method for segmenting a particular class of medical images. The method is based on geometric and geodesic deformable model. The modification we made to the speed term allows the evolving contour to move in the direction normal to itself and also in the direction of its negative normal depending on the direction of the force field. The method was tested using the PET scanner images.

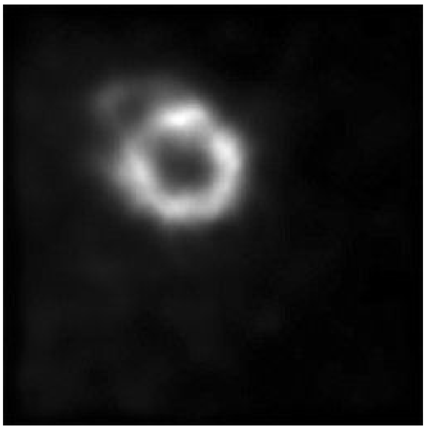

Fig. 5. *Mouse's heart.*

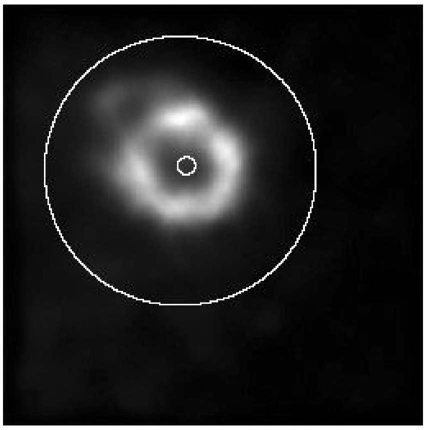

Fig. 6. *Mouse's heart: Contours initialization.*

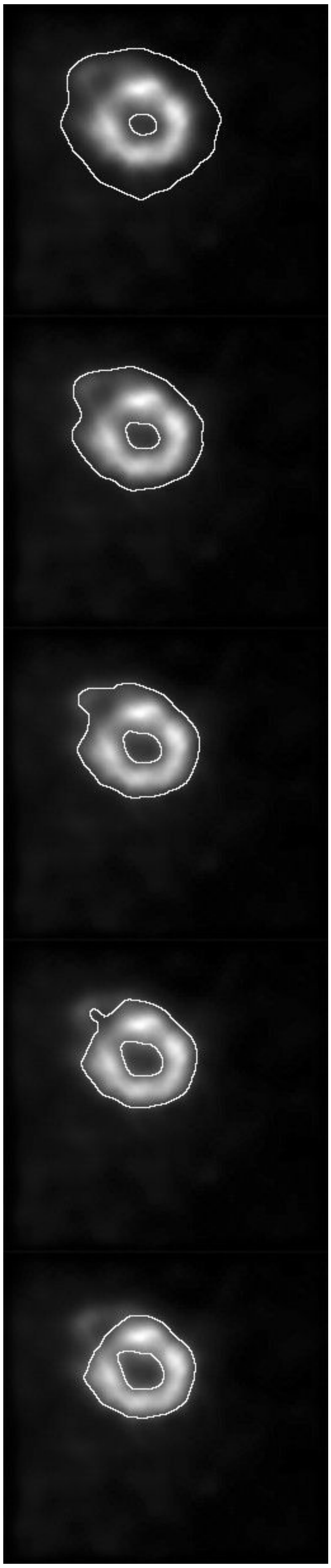

Fig. 7. *Evolution of the contour at different iterations.*

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