

TRACKING OF LEFT VENTRICLE USING LEVEL SET METHOD WITHOUT INITIALIZATION

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Abstract— In this paper our objective is to track left ventricle endocardium and epicardium while preserving the ability of dealing with local deformation using variational level set method. We present a new formation for geometric active contour, propagation of two curves endocardium and epicardium required two energy i.e. internal energy and external energy for each curve. Internal energy will force the deviation of the level set function from the signed distance function and external energy will force the motion of the zero level set method towards the desired image boundaries .For clinical diagnosis parameter such area, perimeter, cross correlation, variance are needed to analyze condition of heart. The proposed algorithm has been applied to real image with promising result show in paper with graphs.

Index Terms—Level Set Method, Cardiac, MRI, Image Segmentation, Active contour.

I. INTRODUCTION

In most part of the world the major reason for death is due to cardiovascular diseases as per statistic. Hence there is a urgent need for cardiac analysis techniques. In this paper a new variation level set method [1] as proposed by *Chunming Li* has been used with morphological filter. The cardiac MRI is taken from base to apex images in approximately 8 to 10 levels and each of these levels consist of 20 to 24 frames hence total frames 150 to 200 images. This method is proposed because manual segmentation is extremely time consuming and manual error.

The level set method is used for automatic topology adaption. We present a new formation for geometric active contour, propagation of two curves endocardium and epicardium required two energy i.e. internal energy and external energy for each curve. Internal energy will force the deviation of the level set function from the signed distance function and external energy will force the motion of the zero level set method towards the desired image boundaries and therefore completely eliminate the need of the costly re-initialization procedure.

Magnetic resonance imaging (MRI) provides time varying two-dimensional imagery of the heart. To help in the diagnosis of disease, the physicians are interested in identifying the heart chambers, the endocardium and the epicardium, and measuring the ventricular blood volume, the ventricular wall mass, the ventricular wall motion and wall thickening properties over various stages of the cardiac cycle. The left ventricle is of particular interest because it pumps oxygenated blood out to distant tissue in the entire body.

The main aim of paper is to track the left ventricle using morphology operation i.e. filter contour

only lead to satisfying results when applied to qualitatively good images.

With “qualitatively good” we mean images that do not contain too much noise and depicted objects are represented by more or less homogeneous regions. If this is the case structures in an image (e.g. edges) can be identified easily. In fact most medical images do not have such friendly properties. Noise, acquisition artifacts, complexity, and fuzziness of anatomical structures make it hard even for the human observer to correctly distinguish between different organs, blood vessels, tissues, etc. One great drawback of conventional segmentation methods is that they heavily rely on local image features. No information about the general appearance of segmented objects is used. Especially in the medical domain structures and appearances of anatomical objects are known very well. This makes it especially interesting to exploit prior knowledge for the design of robust algorithms for segmentation of medical images.

Snakes method or active contours originally has been introduced by *Kass*. It is a method that has been applied to many different tasks related to segmentation and tracking. The idea behind snakes is to initially place a curve close to some edge in a given image. Then the curve or snake deforms according to internal and external forces so that it optimally approaches the edge.

Active Appearance Models (AAMs) method These deform according to statistical features computed by analysis of a representative training set. In order to derive deformations the standard AAM makes use of a prediction scheme based on linear regression. This introduces prior knowledge not only about the appearance of the model but also about how to match the model to unknown data. AAMs have been introduced under this name first by

Cootes and Taylor in 1998.

Traditional Level Set Method

II. BACKGROUND

Approaches for segmentation based on region growing, threshold or edge detection in most cases

In level set formulation of moving fronts (or active contours), the fronts, denoted by C , are represented by the zero level set

$$C(t) = \{(x, y) | \emptyset(t, x, y) = 0\} \quad (1)$$

of a level set function $\emptyset(t, x, y)$. The evolution equation of the level set function \emptyset can be written in the following general form:

$$\frac{\partial \emptyset}{\partial t} + F |\nabla \emptyset| = 0 \quad (2)$$

which is called [1] *level set equation*. The function F is called the speed function. For image segmentation, the function F depends on the image data and the level set function \emptyset . In traditional level set methods, the level set function \emptyset can develop shocks, very sharp and/or flat shape during the evolution, which makes further computation highly inaccurate. To avoid these problems, a common numerical scheme is to initialize the function \emptyset as a signed distance function before the evolution, and then “reshape” (or “re-initialize”) the function \emptyset to be a signed distance function periodically during the evolution. Indeed, the reinitialization process is crucial and cannot be avoided in using traditional level set methods.

III. TRACKING OF LEFT VENTRICLE

Tracking of the left ventricle is main aim of this paper. Cardiac MRI data is filter using morphological operation converting into gray scale then apply threshold techniques. In threshold techniques segment having pixels with similar intensities can be mark for only one segment for each frame, then tracking left ventricle using region property such as fill the opening, solidity of object to select, then marking centroid as per fig shown. This centroid will be use to start the first phase of evolution of zero level set.

IV. VARIATION LEVEL SET METHOD

Level Set Formulation for inner and outer contour formation with penalizing energy

After plotting the centroid marking the inner contour with zero level set keep the evolving level set function as an approximate signed distance function, especially in a neighborhood around the zero level set. It is well known that a signed distance function must satisfy a desirable property of $|\nabla \emptyset| = 1$. Conversely, any function \emptyset satisfying $|\nabla \emptyset| = 1$ is the signed distance function plus a constant [1]. Naturally, we propose the following integral

$$\mathcal{P}(\emptyset) = \int_{\Omega} \frac{1}{2} (|\nabla \emptyset| - 1)^2 dx dy \quad (3)$$

as a metric to characterize how close a function \emptyset is to a signed distance function in Ω . This metric will play a key role in our variational level set formulation. With the above defined functional $\mathcal{P}(\emptyset)$, we propose the following variational formulation

$$\mathcal{E}(\emptyset) = \mu \mathcal{P}(\emptyset) + \mathcal{E}_m(\emptyset) \quad (4)$$

where $\mu > 0$ is a parameter controlling the effect of penalizing the deviation of \emptyset from a signed distance function, and $\mathcal{E}_m(\emptyset)$ is a certain energy that would drive the motion of the zero level curve of \emptyset . In this paper, we denote by $\partial \mathcal{E} / \partial \emptyset$ the Gateaux derivative (or first variation) of the functional, and the following evolution equation:

$$\frac{\partial \emptyset}{\partial t} = -\frac{\partial \mathcal{E}}{\partial \emptyset} \quad (5)$$

is the *gradient flow* [1] that minimizes the functional \mathcal{E} . For a particular functional $\mathcal{E}(\emptyset)$ defined explicitly in terms of \emptyset , the Gateaux derivative can be computed and expressed in terms of the function \emptyset and its derivatives.

In this paper focus is on applying the variational formulation in to active contours for image segmentation, so that the zero level curve of \emptyset can evolve to the desired features in the image. For this purpose, the energy \mathcal{E}_m will be defined as a functional that depends on image data, and therefore we call it the *external energy*. Accordingly, the energy $\mathcal{P}(\emptyset)$ is called the *internal energy* of the function \emptyset , since it is a function of \emptyset only.

During the evolution of \emptyset according to the gradient flow that minimizes [1] the functional, the zero level curve will be moved by the external energy \mathcal{E}_m . Meanwhile, due to the penalizing effect of the internal energy, the evolving function \emptyset will be automatically maintained as an approximate signed distance function during the evolution according to the evolution. Therefore the re-initialization procedure is completely eliminated.

Without re-initialization forming active contour using track left ventricle.

In image segmentation, active contours are dynamic curve that moves toward the object [1, 2] boundaries. To achieve this goal, we explicitly define an external energy that can move the zero level curve towards the object boundaries. Let I be an image, and ‘ g ’ be the *edge indicator function* defined by

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2},$$

where G_σ is the Gaussian kernel with standard deviation σ . We define an external energy for a function $\emptyset(x, y)$ as below

$$\mathcal{E}_{g, \lambda, \nu}(\emptyset) = \lambda \mathcal{L}_g(\emptyset) + \nu \mathcal{A}_g(\emptyset) \quad (6)$$

where $\lambda > 0$ and ν are constants, and the terms $\mathcal{L}_g(\emptyset)$ and $\mathcal{A}_g(\emptyset)$ are defined by

$$\mathcal{L}_g(\emptyset) = \int_{\Omega} g \delta(\emptyset) |\nabla \emptyset| dx dy \quad (7)$$

and

$$\mathcal{A}_g(\emptyset) = \int_{\Omega} g H(-\emptyset) dx dy, \quad (8)$$

respectively, where δ is the univariate Dirac function, and H is the Heaviside function.

Now, we define the following total energy functional

$$\mathcal{E}(\emptyset) = \mu P(\emptyset) + \varepsilon_g \lambda, v(\emptyset) \quad (9)$$

The external energy drives the zero level set toward the object boundaries, while the internal energy $\mu P(\emptyset)$.

penalizes the deviation of \emptyset from a signed distance function during its evolution. To understand the geometric [1] meaning of the energy $Lg(\emptyset)$, we suppose that the zero level set of \emptyset can be represented by a differentiable parameterized curve $C(p)$, $p \in [0, 1]$. It is well known that the energy functional $Lg(\emptyset)$ in (7) computes the length of the zero level curve of \emptyset in the conformal metric $ds = g(C(p))|C_p(p)|dp$. The energy functional $Ag(\emptyset)$ in (8) is introduced to speed up curve evolution. Note that, when the function g is constant 1, the energy functional in (8) is the area of the region $\Omega \emptyset = \{(x,y) | \emptyset(x, y) < 0\}$. The energy functional $Ag(\emptyset)$ in (8) can be viewed as the weighted area of $\Omega \emptyset$. The coefficient v of Ag can be positive or negative, depending on the relative position of the initial contour to the object of interest. For example, if the initial contours are placed outside the object, the coefficient v in the weighted area term should take positive value, so that the contours can shrink faster. If the initial contours are placed inside the object, the coefficient v should take negative value to speed up the expansion of the contours.

V. RESULTS

In this paper, some of the results obtained by running the level set method on short-axis MRI data sets are shown. Each complete data set contains 8 levels of short-axis MR images, each level consisting of 20 frames i.e. 160 short axis MRI real images. The presented results are generated using the first level of the MRI data set. The original size of each 2D scan is 257×257 pixels; however, cropped in the region of interest yields image sizes of roughly 101×101 pixels. Processing each frame is done with around 80 iterations. All simulations are in Matlab.

Image filtering is done by morphological operation then gray scale image is converted to binary image using gray scale threshold function. Result of tracked left ventricle binary image is shown with centroid. Segmentation is applied to left ventricle using level set method to mark endocardium. The proposed variational level set method has been applied to real images of cardiac left ventricle MRI data, all the experimental results shown in this section. For example, Figure shows the result on a 257×257 pixel image of a cardiac left ventricle. The initial level set \emptyset for each image is defined by the Level set function to a radius 10 centered at the image center, with point inside the circle having a negative values. For this image, we used the parameters $\lambda = 3.0$, $\mu = 0.02$, $\alpha = 1.5$, $\text{epsilon}=1.5$ and time step $\tau = 10$, which is significantly larger than the time step used for traditional level set methods. The curve evolution takes 80 iterations. As we can see, some parts of the

boundaries of the cardiac left ventricle are quite blurry. We have used this method to demonstrate the robustness of our method in the presence of weak object boundaries.

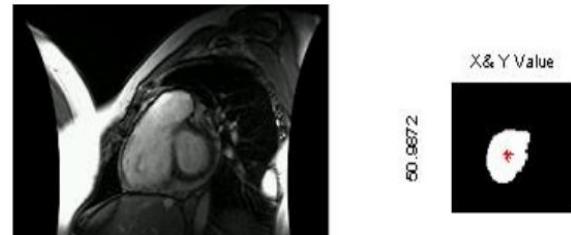


Figure 1
Figure 6 80 iteration for 20 frames

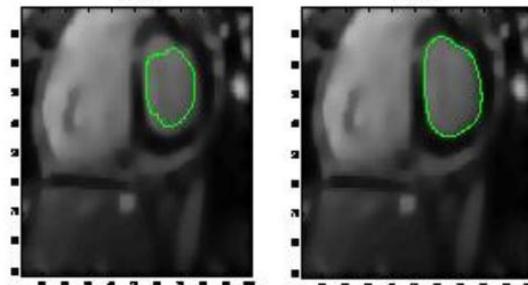


Figure 3 40 iteration
Figure 4 80 iteration

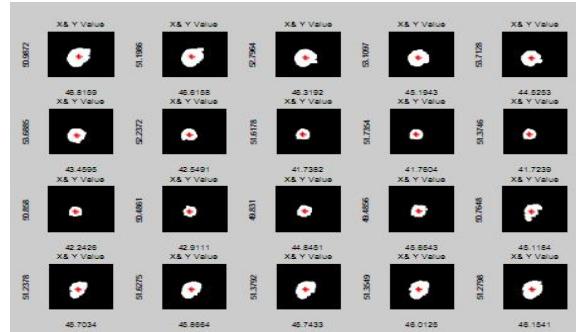


Figure 5 Centroid for 20 frames

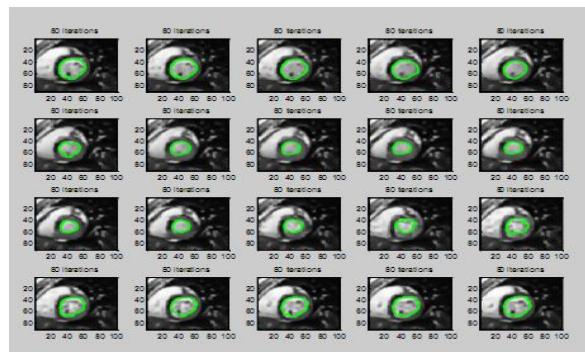


Figure 6 80 iteration for 20 frames

VI. CONCLUSION

Graph of Area v/s frames and Perimeter v/s Frames are plotted. The area of left ventricle varies for patient

1 normal, patient 2 Ischemia, patient 3 RVOT, as per the diastole and systole movement of heart. This process can be analyzed graphically.

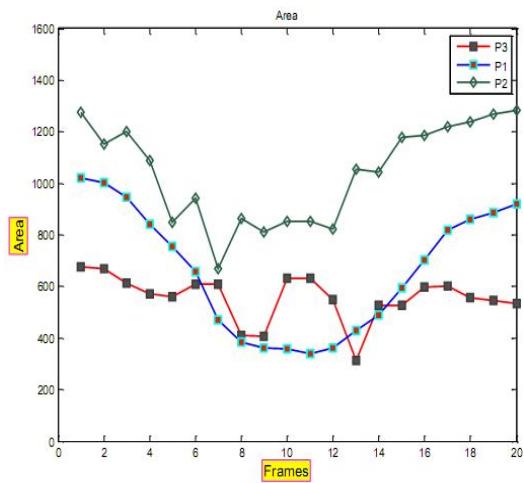


Figure 7 Area v/s Frames

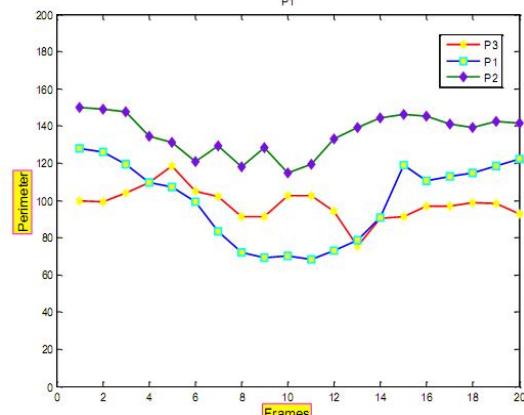


Figure 8 Parameter v/s Frames

REFERENCES

- [1]. Chunming Li , Chenyang Xu Changfeng Gui and Matrin D. Fox, "Level Set Evolutin without Re-initialization: A New Variational Formulation" IEEE Trans (CVPR'05) 1063-6919/05 \$20.00 © 2005
- [2]. Nikos Paragios "A Variational Approach for the Segmentation of the Left Ventricle in MR Cardiac Images" IEEE Trans 0-7695-1278-X/01\$10.000 2001.
- [3]. J.A.Sethian "Level Set Method: An act of violence" Evolving interface in geometry, Fluid Mechanics, Computer Vision & Material Science
- [4]. Qilong Zhang, Richard Souvenir, Robert Pless "On Manifold Structure of Cardiac MRI Data: Application to Segmentation" Washington University in St. Louis, Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06) 0-7695-2597-0/06 \$20.00 © 2006 IEEE
- [5]. Hongchuan Yu' Dejun Wangt Zesheng Tangt "Level Set Methods and Image Segmentation" Department of Computer Science and Technology, Tsinghua University 0-7695-1113-9/01\$10.000 2001 IEEE
- [6]. Li-jun Zhang Xiao-juan Wu Zan Sheng "A Fast Image Segmentation Approach based on Level Set Method" School of Information Science and Engineering, Shandong University, Jinan 250100, P.R.China 0-7803-9737-1/06/\$20.00 ©2006 IEEE
- [7]. Chunming Li , Ruai Huang , Zhaohua Ding, Chris Gatenby, Dimitris Metaxas and John Gore "A Variation Level Set Approach to segmentation and Bias Correction of Image with Intensity Inhomogeneity" MICCAI Part II LNCS 5242 pp1083-1091,2008
- [8]. S.P.Dakua and J.S.Sahambi "A Level set Method for cardiac Magnetic /resonance image Segmentation: An Adaptive approach" IEEE Trans. Imag. Proc., pp. 978-1-4244-2806-9/08/\$25.00@2008IEEE.
- [9]. Chieh-Ling Huang "Shape Based Level Set Method for Image Segmentation" IEEE Trans 978-0-7695-3745-0/09 \$25.00©2009 IEEE
- [10]. Chunming Li, Chenyang Xu, Changfeng Gui and Martin D Fox
"Distance Regularized Level Set Evolution and Its Application in Image Segmentation" IEEE Trans 1057-7149/\$26.00 ©2010 IEEE

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