A Novel Level Set Based Echocardiographic Contour Extraction Method with Prior Knowledge

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Abstract

This paper presents a novel level set method with shape priors. The method keeps the level set deformations and the integration of the prior information as separate processes and hence it can be used with any level set formulation without complicating the level set functional. The method does not need any explicit training phase and by the addition of an appropriate deformable contour matching method, it can be used for any specific application. The system is tested and verified by the task of extraction of the inner and outer heart walls (endocardium and epicardium) from the echocardiographic images of the left ventricle.

1 Introduction

Level set methods [1] are introduced [2] to computer vision for recovering shapes of objects in two or three dimensions. The basic idea of level set methods is embedding the shape of the objects as the zero level set of a higher dimensional surface. The higher dimensional surface evolves under the influence of the ideal image and surface features without violating the surface regularity. While the surface evolves, the zero level set contours might develop singularities and sharp corners or they might change topology, which are not easily achievable by using classical deformable contours or snakes [3].

It is argued that [4] the main advantage of level sets over deformable contours comes from their ability to deal with very local image properties. The level set interfaces can deform to recover contours in pixel-wise detail. However, the very local nature of level sets becomes an obstacle in cases where global or prior information needs to be imposed. This problem with the level sets is amplified especially for medical imaging applications where the images are very noisy and expert knowledge about the desired contours needs to be integrated into the contour extraction process. For this reason, incorporating global or prior information into the level sets has been an active research area. Leventon *et al.* [5] have used prior knowledge by defining a Gaussian probability distribution over the variances of a set of training shapes without addressing the scale and pose variations.

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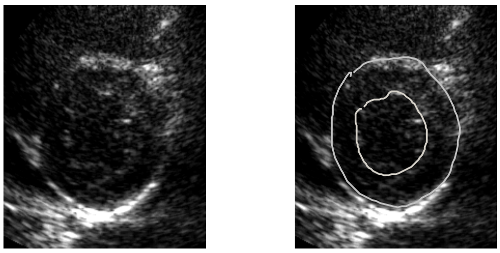
Chen *et al.* [7] used an average model as prior in its implicit functional. Shape priors for level sets [4] are also used where a prior is imposed by direct comparison between the level sets of prior models and the evolving interface. Most of the existing level set systems with shape priors test their systems on medical images such as brain [5] and cardiac [6] images.

The common technique used by the above methods seems to be the addition of a new functional into the level set formulation which would integrate the global or prior information. The level set front deformations are affected by the new functional in a way that the shapes are always similar to previously learned or trained contours. It can be argued that this approach is borrowed from deformable contours because almost every deformable contour with prior information adds a new energy term, e.g. [9], to the main functional or rewrites the main functional so that global or prior information is built into the functional, e.g. [8]. Although this borrowed method works up to a degree with the level sets, the overall level set surface functional becomes too complicated to impose scaling, translation and rotation based constraints at the same time. Therefore, it is difficult to design and formulate new prior functional terms with the level sets. In addition, the new terms added to the main surface formulation might have undesirable effects on the overall system such as numerical interference of the prior term and the other level set terms. Finally, the resulting systems are not efficient for computer implementation because level sets are already demanding in terms of computing power requirements. The newly added functional terms increase these power requirements even more.



(a) (b)

Figure 1: (a) Example short axis view echocardiographic image. The high levels of ultrasound noise, missing wall sections on the image and reflections from the unrelated structure are the main problems of images. (b) The same image with endocardium and epicardium marked by an expert.

In this paper, we present a novel prior shape based level set method that does not modify or rewrite the basic level set functional. Our method incorporates the prior information into the surface deformation process by regularly re-initializing the surface under the influence of the prior information. The re-initialized surface in turn affects the deformations of the level set front on the image, which results in a final boundary that shows the influence of the local image features as well as global or prior model characteristics. The method can be used with any level set formulation without complicating the overall level set functional. In addition, the method does not significantly increase the computational power requirements while maintaining the scale, rotation and translation independency using appropriate contour matching methods. Furthermore, no explicit training phase is required because the model contours are directly employed during the level set surface evolution process. Finally, the lack of explicit training phase makes it possible to incrementally add new model contours to the system without any penalty.

As the test bed application, we choose the recovery of the inner and outer heart walls (endocardium and epicardium) from the echocardiographic images of the left ventricular (LV) short-axis transthoracic views during the cardiac cycle (Figure 1). Recovery of the cardiac borders poses several challenges for the computerized automation due to high levels of ultrasound image noise, missing wall sections, and unrelated structure around the heart walls. As expected, the level set method without any prior or global information would recover incorrect wall positions and the recovered contours would go into topological changes which are not desirable for the task of heart contour extraction process. Most of these problems can be addressed by incorporating expert knowledge as prior information into the heart wall extraction process. The prior knowledge would help the system differentiate between related and unrelated structure. The prior information also makes it possible to fill the contours for the missing sections of the cardiac wall. Therefore, it would be a very good environment for testing and verification of the proposed ideas.

The paper is organized as follows: The level set method formulation is presented in Section 2. Integrating the shape prior into the level sets and level set re-initialization are introduced in Section 3. Section 4 includes the experiments performed to test the validity of our method. Finally, we provide concluding remarks in Section 5.

2 The Level Set Formulation

The level set approach evolves a 3D surface by embedding objects into the zero level of the surface. The proposed heart wall extraction system is based on two deformable contours evolving on the echocardiographic images. The surface is evolved in a way that the contours move towards each other until the contours stop at the boundary positions. Although this paper provides the formulations for extracting inner and outer heart walls, the system can be applied to other level set applications by modifying the formulations.

We define two closed contours $c_{endo}(t)$ and $c_{epi}(t)$ on $\Re^2$ that evolve with time t. $c_{endo}(t)$ is used for extracting endocardium and $c_{epi}(t)$ is used for extracting epicardium. Consider C as the set of points on $c_{endo}(0)$ and $c_{epi}(0)$. Let s be a signed distance function:

$$s(\mathbf{x}) = \begin{cases} 0, & \text{if } \mathbf{x} \in C \\ -d(\mathbf{x}), & \text{if } \mathbf{x} \text{ is outside } c_{endo}(0) \text{ but inside } c_{epi}(0) \\ d(\mathbf{x}), & \text{otherwise,} \end{cases} \tag{1}$$

where d is the shortest distance to C from point $\mathbf{x} \in \Re^2$. The time dependent surface $\phi(\mathbf{x}, t = 0)$ is defined by

$$\phi(\mathbf{x}, t = 0) = G(\alpha\,|s(\mathbf{x})|) * s(\mathbf{x}), \tag{2}$$

where $G(x, \sigma)$ is the two dimensional Gaussian with variance σ^2, $\alpha > 0$ is a weighting constant and * is the convolution operation. It can be seen from Equation 2 that the contours c_{endo} and c_{epi} are the zero level set of ϕ at $t = 0$.

$$C = (\mathbf{x} | \phi(\mathbf{x}, t = 0) = 0). \tag{3}$$

The surface ϕ moves under the influence of geometry, position and image data. While ϕ deforms, the contours c_{endo} and c_{epi} also move to find the desired wall boundaries.

In this study we used variational level set formulation presented in [10]. The variational level set formulation employs the 3D surface ϕ, the internal energy term $P(\phi)$ and the external energy term $\varepsilon_m(\phi)$ to make up the level set variational energy function $\varepsilon(\phi)$:

$$\varepsilon(\phi) = \mu P(\phi) + \varepsilon_m(\phi), \tag{4}$$

where μ is a parameter which controls the weight of the internal energy term in the overall contour extraction process. The internal energy term penalizes deviation of the level set function from signed distance function which is desired to satisfy $|\nabla\phi| = 1$ in $\Omega \subset \Re^2$. Internal energy term function is:

$$P(\phi) = \int_\Omega \frac{1}{2}(|\nabla\phi| - 1)^2 dxdy. \tag{5}$$

The external energy term is used for moving the contours towards the object boundaries. The external energy term employs length and area of the zero level set of ϕ by using edge indicator function defined by

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2}. \tag{6}$$

For details of the variational energy formulation, see [10]. Although we use the variational level set formulation described above because of its advantages like using large time steps and being incomplex, our system can also be used with any level set approaches with simple modifications.

3 Level Sets with Shape Priors

The classical level set methods employ the local image characteristics for pixel-wise deformations of surfaces. However, in many applications the local characteristics are not always sufficient to extract object boundaries because of the image noise and parts unrelated with object boundaries in the images. Therefore, the level set must also employ global or prior knowledge besides the local characteristics especially in medical imaging applications where the expert knowledge needs to be integrated into the contour extraction process.

Our level set with prior information method is based on the idea of regularly re-initializing the surface under the influence of the shape prior. The proposed method employs two repeating phases. In the first phase, the surface evolves on the echocardiographic image according to the classical level set method. In the second phase, the level set surface borrowed from the evolving process is re-initialized under the influence of prior information. These phases follow each other until the desired contours are found.

3.1 Integrating the Shape Prior into the Level Set Surface

Our method does not use any explicit training phase to incorporate prior knowledge into the level sets. The model contours are obtained from experts and these contours are directly used in a level set surface ϕ re-initialization phase. After the re-initialization, the new surface ϕ can be evolved with any level set algorithm to extract the desired contours on the images. The main advantage of this technique is that the operations of surface evolution and the incorporation of the prior information are completely separated, which makes our system applicable to any level set algorithm. Establishing scale, rotation, and translation independent constraints in the level set formulations is not a trivial task. By isolating the prior information integration from the level set surface deformations, our system becomes architecturally modular and simple to implement.

Our integration of the shape prior knowledge into the level set surface can be viewed as taking a level set surface ϕ^{input} with zero level set C^{input} and producing another level set surface ϕ^{output} with zero level set C^{output} such that the zero level set C^{input} is deformed under the influence of the expert contours. Therefore, our prior information integration is a form of establishing contour matches between C^{input} and the expert contours. In order to produce C^{output}, we also define the deformation procedures between C^{input} and the best matching expert contour. The final surface ϕ^{output} is simply the signed distance function produced with the zero level set C^{output}.

Let ϕ^{input} be a level set surface. Considering the heart wall extraction problem, let c^{input}_{endo} and c^{input}_{epi} be the inner and outer contours of the LV on the zero level set C^{input} of ϕ^{input}. Suppose e^{i}_{epi} is the epicardium contour and e^{i}_{endo} is the endocardium contour delineated by expert i, where $0 < i \leq n$ and n is the number of experts. We need to find the expert contours e^{i}_{epi} and e^{j}_{endo} that produce the smallest difference when compared to c^{input}_{endo} and c^{input}_{epi}. Unfortunately, this comparison with input contours cannot be directly done due to scale, rotation, and translation differences. However, by taking advantage of the convex nature of the heart walls, we can use a very practical deformable contour matching algorithm to find the closest expert contour-input contour pairs. Although this deformable contour matching algorithm is developed specifically for LV heart wall extraction task, it does not make our prior shape based level set approach specific for this task. Any deformable contour matching algorithm can be switched with our matching method to apply our level set method for other applications.

In order to perform the deformable contour matching between expert contours and the input contours, we first translate the center of gravity positions of all contours to origin and then we express the contours in Polar coordinates ((θ, r) space). We define two functions $R_k(c)$ and $\Theta_k(c)$ that returns the r value and θ value of the k^{th} point of contour c, respectively. Figure 2(a) shows the Polar representation of c^{input}_{endo} and e^{j}_{endo} for $j = 1, 2$, and 3. These steps remove the translation differences between the contours.

For the heart wall extraction task, the rotational differences between the contours can be neglected because the short axis LV images of the heart are formed by holding the ultrasound transducer at a specific angle. For this reason, the ultrasound LV images are rotationally registered automatically and no explicit rotational matching is required.

In polar coordinates, the scale matching between the contours can be done by formulating a match function between the r components of the contours. If there is a uniform scaling between c^{input}_{endo} and e^{j}_{endo}, we then find the average values of $R_k(c^{input}_{endo})$ and $R_k(e^{j}_{endo})$ for all available k values. The ratio of average r values between these contours would produce the uniform scale difference.

In order to use a more flexible scaling algorithm, we take a piecewise uniform scaling approach. Instead of calculating the average r values for the whole contour, we use only a neighborhood of contour positions of size m. These local average r values are then compared between the contours to find the local scaling amount.

$$S(c_1,c_2,\theta) = \frac{\sum_{i=-m/2}^{m/2} R_i(c_1)}{\sum_{i=-m/2}^{m/2} R_i(c_2)} \tag{7}$$

where $\theta = \Theta_k(c_1) = \Theta_j(c_2)$.

Once the local scaling factors are calculated between two contours, one contour can be transformed to the other by multiplying the r positions of the contour with the local scaling factors. Given two contours c_1 and c_2, we can produce the transformed contour T by deforming c_2 to c_1 using formula

$$R_k(T) = R_j(c_2)S(c_1,c_2,\theta), \tag{8}$$

where $\theta = \Theta_k(t) = \Theta_j(c_2)$ for $\theta = 0...2\pi$.

Each expert contour e^j_{endo} and e^j_{epi} is deformed to c^{input}_{endo} and c^{input}_{epi} respectively using the transformation Equation 8. Figure 2(b) shows expert contours e^j_{endo} deformed to c^{input}_{endo} for $j = 1,2,$ and 3.

The transformed contours are compared against the input contours and the ones that produce the smallest difference are chosen as the C^{output} contours. The comparison between two contours is done in the Polar coordinates using the formula

$$D(c_1,c_2) = \sum_{\theta=0}^{2\pi} \left| R_k(c_1) - R_j(c_2) \right|, \tag{9}$$

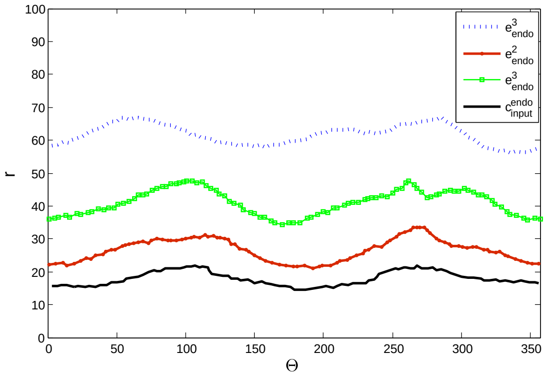
where $\theta = \Theta_k(c_1) = \Theta_j(c_2)$.

Finally, we construct the surface ϕ^{output} by embedding the contours C^{output} into the zero level of the surface according to the Equation 1.

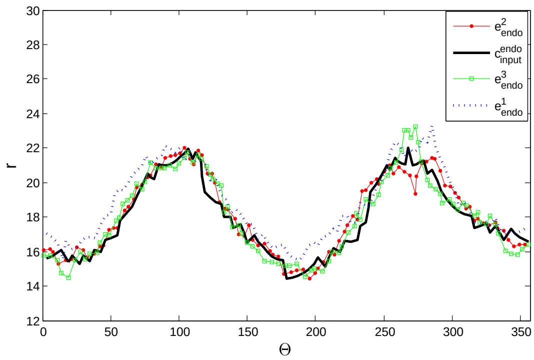
3.2 The Level Set Algorithm

Given the echocardiographic image I, $c^{input}_{endo}(0)$ and $c^{input}_{epi}(0)$ are initialized on I at t=0. c^{input}_{endo} should be placed inside the endocardium and c^{input}_{epi} should be placed outside the epicardium. Although we place them manually, it can be done automatically by performing optic flow analysis of the heart walls.

In the first phase of the system, the surface ϕ is constructed using Equation 1 by embedding c^{input}_{endo} and c^{input}_{epi} into the zero level of ϕ. Then ϕ is evolved on echocardiogram I by calculating the level set functional including the internal and external energy terms (Equation 4) until t reaches a threshold value (Figure 3(a)) . The two new closed contours $c^{input}_{endo}(t)$ and $c^{input}_{epi}(t)$ are the zero level set of the evolved surface.



(a)



(b)

Figure 2: (a) The endocardium contours of experts e^j_{endo} and the zero level inner contour c^{input}_{endo} (b) The deformed expert contours e^j_{endo} and the zero level inner contour c^{input}_{endo}

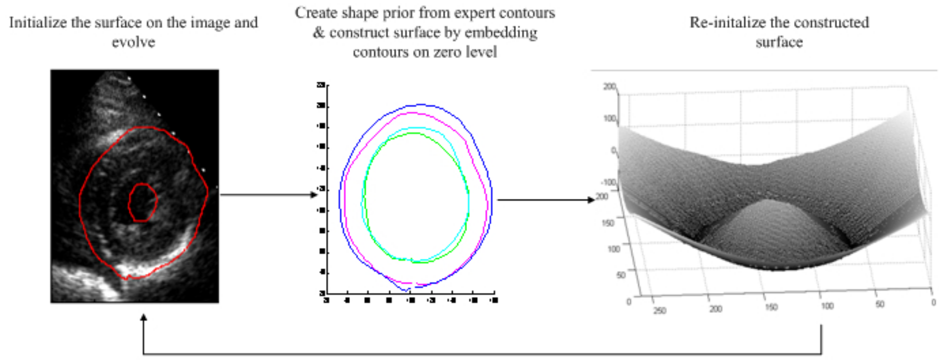
Phase 2 takes the newly formed surface ϕ with its zero level C and uses them as the input surface and the input contours for the shape prior integration process defined in Section 3.1 and creates the new surface ϕ^{output} using Equation 1 (Figure 3(b)).

The surface ϕ^{output} is used to re-initialize two new contours on image I and phase 1 repeats. If the contours stop deforming, the evolution is complete and the cardiac contours are the zero level set of the final ϕ; otherwise phase 2 repeats.

4 Experiments and Validation

To validate and verify our system, we used real echocardiographic images. The system is tested on 20 different echocardiogram images. Four different epicardium and endocardium contours for each image are traced by four different human experts without seeing each others results. The images are 190 by 240 pixels in size.

The results we have found are compared with the experts' delineations because it is not easy to obtain ground truth for echocardiograms. The delineations of experts are also



(a) (b) (c)

Figure 3: Shape prior based level set method

compared with each other to obtain the variation between experts. The average pixel errors of 20 different endocardium and epicardium contours are shown in Table 1.

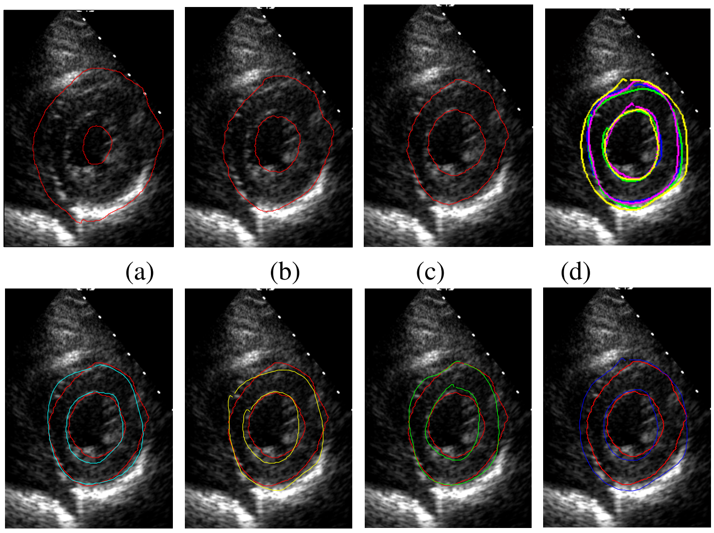
Table 1: Average pixel errors for endocardium and epicardium of 20 different echocardiograms

	Endocardium Errors				Epicardium Errors			
	Exp 2	Exp 3	Exp 4	Auto	Exp2	Exp3	Exp 4	Auto
Exp 1	3.49	3.07	4.21	4,66	3.16	3.13	7.08	5.44
Exp 2		3.31	4.07	5.03		3.20	7.11	6.18
Exp 3			3.66	4.85			7.00	5.59
Exp 4				5.03				5.80

Figure 4 shows the contours detected by our system for a typical LV image and Table 2 shows the average pixel errors between the experts and our contours for the same image. The average pixel errors of experts vary between 1.47 and 2.73 for endocardium and 1.92 and 6.75 for epicardium. The automatically extracted outer contours are similar to expert detected contours and automatically extracted inner contour is nearly within 1 pixel distance from the inter expert variation. We found the results very close to expert detected contours and they are very encouraging.

Table 2: Average pixel errors for the Figure 4

	Endocardium Errors				Epicardium Errors			
	Exp 2	Exp 3	Exp 4	Auto	Exp2	Exp3	Exp 4	Auto
Exp 1	2.08	3.63	1.82	4,07	2.57	1.92	6.18	3.81
Exp 2		2.73	1.47	3.89		3.03	6.17	4.31
Exp 3			2.27	3.51			6.75	4.49
Exp 4				3.32				4.65



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 4: (a) The initial contours; (b) Evolving contours; (c) Extracted contours at the end of evolution (d) All of the Expert contours; (e,f,g,h) Red contours are the automatically detected contours, other contours are expert detected contours

5 Conclusions

We presented a novel level set based contour extraction method with prior knowledge. The proposed method deals with both local and global image properties by incorporating the prior information into the surface deformation process and by regularly re-initializing the surface under the influence of the prior information. Our method does not modify the level set formulation, so the system can be used with any level set method. Moreover, the method does not significantly increase the computational cost while making it possible to keep scale, rotation and translation independence features.

We applied our system to the echocardiographic images for extracting cardiac walls. We presented a double evolving contour approach in which the expert contour knowledge is used as shape prior. The presented system is not specific for heart wall extraction. By providing application specific contour matching methods, the system can be ported to any challenging applications. The system is validated on real echocardiographic images and we compared our results with expert detected contours. The results are very promising and we plan to apply our system to other medical imaging applications.

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