Cardiac Segmentation from MRI-Tagged and CT Images

D. METAXAS[1], T. CHEN[1], X. HUANG[1] and L. AXEL[2]
Division of Computer and Information Sciences[1] and Department of Radiolgy[2]
Rutgers University, Piscataway, NJ[1] and New York University, New York, NY[2]

Abstract: - We present new developments in the formulation of a new class of deformable models, which we term *MetaMorphs*, and demonstrate the effectiveness of the method in cardiac image segmentation and motion analysis. The formulation of the MetaMorphs naturally integrates both shape and interior texture, and the model deformations are derived from both boundary and region information based on a variational framework. Previously we have shown the general framework in *[3]*. In this paper, in order to address the difficulties in cardiac image segmentation, we describe an automatic and robust way to initialize the metamorph models. A variation of the framework using the parametric curve/surface representation and a hierarchy of global and local deformations is also presented. In our experiments, we demonstrate the application of the MetaMorph models to segment the epicardium and endocardium surfaces of the RV and LV using CT and MRI-tagged cardiac images. Large-scale textures, such as tag lines in MRI-tagged images, are naturally dealt with in our framework by coupling with the gabor filter banks.

Key-Words: - **MetaMorphs, Deformable models, Cardiac segmentation**

1 Introduction

The leading cause of death in the Western World is heart disease and consequently study of normal and pathological heart behavior has become the topic of rigorous research. In particular the study of the shape and motion of the heart is important because many heart diseases are thought to be strongly correlated to the shape and motion of the heart. Important examples of such heart diseases include ischemia and right ventricle (RV) hypertrophy.

An automated analysis must address the following tasks: 1) Extraction of 3-D information from the 2-D slices, 2) Computation of correspondence - the exact motion of the living tissue over time, 3) Generation of the anatomically correct model, 4) Provisions for normal variations with underlying geometric model, 5) Relation of the acquired geometric and motion data to specific diseases.

Our group has developed several methods over the past several years towards the automated analysis of the heart's motion. Due to the common presence of cluttered objects, complex backgrounds, high noise and intensity inhomogeneities in cardiac images, the segmentation problem remains a very difficult task. To address these difficulties, deformable models [1,2,4,5,6,7,9] have been extensively studied and used as a model-based segmentation approach. In traditional deformable models, image forces come primarily from edge (image gradient) information. Such reliance on edge information, however, makes the models sensitive to noise and highly dependent on the initial estimate.

In the past few years, there have been significant efforts to integrate region information into deformable models [1,10,5,4]. To address the limitations in previous efforts to incorporate region information in deformable models, we introduced [3] a new class of deformable models, which we term "MetaMorphs". The new models possess both shape and interior texture, and integrate boundary and region information coherently in a common variational framework. This framework represents a generalization of previous model-based segmentation approaches. The shape of the new model is represented implicitly as an ``image" in the higher dimensional space of distance transforms. The interior texture is captured using a nonparametric kernel-based approximation of the intensity probability density function (p.d.f.) inside the model. The deformations that the model can undergo are defined using a space warping technique - the cubic B-spline based Free Form Deformations (FFD). When using the models for boundary finding in images, we derive the model dynamics from an energy functional consisting of both edge energy terms and texture energy terms. This way, the models deform under the influence of force derived from both boundary and region information.

In this paper, we present variations and improvements to the general MetaMorphs framework, so that it can be used more effectively in cardiac image segmentation problems, and achieve faster and better convergence. The first problem we address is how to use MetaMorph models with their shape represented by traditional parametric deformable curves, since this representation is more common in the deformable model community, and many related tools and implementations are readily available. Based on this formulation we also parameterize the model deformations in a hierarchical way. The global transformation is described by a few parameters such as translation, rotation and scaling. And the local deformation is represented by the local deformation tensor. The second problem we address is how to automatically initialize a model using an initial shape that closely approximates the shape of the actual object boundary. With this new model initialization scheme, a MetaMorph model can converge to an optimal solution more efficiently. It also enables the model to escape the trap of many small spurious edges inside an object of interest in the very beginning, hence makes the boundary finding more robust to image noise and intensity inhomogeneities. In the remainder of the paper we present our approach and show its application to heart boundary segmentation.

2 Methodology

In [3], we presented the shape and texture representations and the deformation dynamics of MetaMorphs. In this section, we present several new extensions to the framework, in order to deal with the difficult cardiac image segmentation problem.

2.1 Model formulation using parametric deformable curves

Instead of using free form deformations, we can use a parametric formulation in the MetaMorph framework for cardiac segmentation. Using this approach, the deformable model is represented by a group of nodes on a deformable curve (or on a deformable surface in 3D), in its object centered coordinate system. Then a hierarchy of local and global transformations can be applied on the model to move and deform the model in space.

2.1.1 Hierarchical Deformations

A hierarchy of both global and local deformations parameterizes the model geometry. In the 2D case, the global transformation is defined as:

$$\mathbf{q}_g = [t_x, t_y, \theta, s_x, s_y]^T$$

where t_x, t_y are the translations along x and y directions, θ is the rotation angle, and s_x, s_y are the scaling factors along x and y directions, respectively. The local deformation of the model is represented by the local deformation tensor:

$$\mathbf{q}_l = \{(d_{ix}, d_{iy})\}, i \in [1, N]$$

where i is the index of the nodes on the model surface, d_{ix}, d_{iy} are the local displacements of the ith node along x and y directions.

The overall parameter vector for the metamorph model is:

$$\mathbf{q} = [\mathbf{q}_g; \mathbf{q}_l] = [t_x, t_y, \theta, s_x, s_y; (d_{1x}, d_{1y})...(d_{Nx}, d_{Ny})]$$

For each node on the model surface, its transformed position in the image space can be expressed as:

$$D(\mathbf{q}; \mathbf{x}) = \mathbf{t}(t_x, t_y) + \mathbf{R}(\theta)\mathbf{S}(s_x, s_y)\mathbf{x} + \mathbf{d}(d_{ix}, d_{iy})$$

where $\mathbf{t}$ is the translation vector, $\mathbf{R}$ is the rotation matrix, $\mathbf{S}$ is the scaling matrix, $\mathbf{x}$ is the location of the node in the model space, and $\mathbf{d}$ is the local displacement vector.

The formulation can be easily extended into 3D by adding parameters that account for global and local deformation in the z direction.

2.1.2 Model dynamics

For the global deformation, our parametric formulation uses a similar form of the energy functional as in [3] which includes both shape/edge energy terms and intensity/texture energy terms. However, the control parameters are different.

During the global deformation, the global parameters evolve to their optimal values using the unified gradient descent method. In each step of the deformation, we calculate the partial derivatives of the image energy with respect to $\mathbf{q}_g$, and then change the values for these parameters in the opposite direction to achieve the global minimum solution of parameters.

The local deformations are computed using the external force formulation, in which the model evolves based on Lagrangian dynamics:

$$\dot{\mathbf{q}}_l + \mathbf{K}\mathbf{q}_l = f_{ext}$$

where $\mathbf{K}$ is the stiffness matrix, $\mathbf{q}_l$ is the local displacement vector and f_{ext} are the external forces.

In this extended MetaMorphs formulation, we use the combination of the edge map distance gradients, the region edge distance gradients, and the second order derivative of the original image as the external force. The form of the external force is shown below:

$$f_{ext} = -(a\nabla(M(I)) + b\nabla M(S(I)) + c\nabla(\nabla G(I)))$$

where I is the original image, $M(.)$ is the function that extracts the edge from the image and computes the distance transform of the edge map by calculating at every pixel in the image the distance to the nearest edge, ∇ is the gradient operator, $S(.)$ is the function that computes the binary mask of the object of interest, $G(.)$ is the Gaussian operator, and a, b, c are the weights for the edge map distance gradient, the region edge distance gradient, and the second order derivative gradient flow respectively. The first two terms of the external force have the same magnitude because they are both distance gradient flows. The second order derivative gradient flow has a different magnitude (because it is derived from the original image) so that the weight parameter c also functions as a normalize factor of the magnitude. To normalize the gradient flow magnitude, we calculate the mean of arbitrary value and the standard deviation of the second order derivative gradient flow and rescale it to have the similar magnitude and standard deviation of the distance gradient. The edge distance gradient and the second order derivative gradient flow do not change during the model evolution. The region edge distance gradient, however, will be updated every few loops during the deformation. A new binary mask of the object of interest will be created based on the statistics of the current model's interior. As the model evolves, the model's interior statistics will be more stable and more accurate so that the updated region edge map will provide more texture information of the object.

2.1.3 Model evolution

Using the hierarchical transformation model, the parametric deformable curve models deform globally and locally simultaneously. In the first few (normally the first 5 to 20) steps, the global deformation has a dominant weight so that the model can get close to the global shape and boundary features in the image very fast. When the model is close enough to the edges, the local deformations take over so that the model evolves under the influence of the gradient flow. In this way, the unique structures on the object surface will be well captured while local minimums are avoided.

The intrinsic advantage of the MetaMorphs framework, i.e., the natural integration of shape and texture information, is very important to help the model converge to the true object boundaries by taking into account the consistency of the interior texture statistics. As have mentioned in the last section, in the global deformation process, we combine the shape and texture information by forming and minimizing an energy function that integrates these information. During the local deformation stage, the shape and texture information are used to derive external forces that deforms the model. Notice that the texture information keeps updated during the whole deformation process.

2.2 Robust model initialization

A good initialization of the deformable model can greatly speed up the convergence of the model and decreases the chance of getting trapped in local minima. In our methodology, we developed two methods to tune the global parameters to find a very good initialization for the model shape. We can then use this initial model to deform to the object boundary.

One extension we make to the original MetaMorphs framework is that, after locating the "region of interest" (ROI) intensity energy term (see [3]), we use a morphological operation to find the skeleton of the estimated object region. The technique is based on Blum's grass-fire interpretation so that we keep removing pixels on the object's boundary but do not allow the object to break apart. The pixels remaining make up the skeleton. The coordinates of these skeleton pixels are used to compute the covariance matrix. We compute the eigenvalues and eigenvectors of the covariance matrix and use the result to construct an ellipsoid with its long and short axes in the direction of the two eigenvectors and the scaling equal to the two eigenvalues of the matrix. The value of the global parameters will be set as follows: let E_1 and E_2 denotes the two eigenvalues, where $E_1 > E_2$. We let $s_x = E_1$ and $s_y = E_2$ respectively, we use the direction of the long axis of the ellipsoid as the value of θ, and the center of the ellipsoid will be used as the value of (t_x, t_y).

For most cardiac objects, such as left ventricles, this ellipsoid provides a good initialization for the deformable model. This initialization is capable of providing us a close estimation of the values of all global parameters, which will dramatically shorten the global fitting process. Using this initialization also allows the model to efficiently use the image gradient flow, allowing it to evolve more efficiently and robustly toward the correct object boundary compared to models initialized with fixed parameter values. One example of the initialization and model evolution process can be seen in Figure 1.

Another initialization solution we provide is to use a 2D marching cube method to create curves from a binary mask of the object of interest. After we locate the ROI, we use the 2D marching cubes method to find a series of nodes on the boundary of the ROI. These nodes link in sequence to form a closed curve, which will be used as the initialization of the deformation model. This kind of initialization uses the texture information explicitly and counts on the boundary information to get out of possible local minima. This initialization method works especially well when the object shape is complicated. An example is shown in Figure 3.

3 Experimental Results

Figure 1 shows completely automated segmentation results from CT images, while Figure 2 shows segmentation results from MRI-tagged images. In both experiments we initialize the metamorph models using the first initialization method. Figure 3 also shows the segmentation results from the MRI-tagged data. However, we use the 2D marching cubes to initialize the deformable model in experiment 3. The size of the CT image is 128 by 128 pixels. We use the extended metamorph to segment the endocardiac surface of the left ventricle. The segmentation process stops after 50 iterations. The global deformation is turned off after 20 iterations. The segmentation time is within one minute. The MRI image size is 192 by 192 pixels. The tag lines have been previously extracted and removed using a tunable gabor filter technique [11]. The metamorph models have been used to segment the endocardiac surface of both left and right ventricles. The segmentation process stops after 30 iterations. The global deformation is turned off after 10 iterations. The whole segmenting time is about 35 seconds. The only user interaction during the segmentation process is to pick the initial seed points. A small neighborhood with the radius of 5 pixels is used to calculate the initial statistics of the object. In the 3rd experiment, we use the 2D marching cubes to initialize the metamorph model. The segmentation time is the same as that of the 2nd experiment.

The experimental results have been sent to cardiac experts for qualitatively validation. According to the validation results, the segmentation results have an excellent agreement with expert manual segmentations, while the segmentation time and labor are greatly decreased.

4 Conclusions

We have presented a novel approach towards the goal of automated cardiac segmentation based on variations and improvements of our novel class of deformable models, Metamorphs, which incorporate both texture and shape. Our aim is to integrate this approach with our already developed methods for cardiac shape and motion analysis towards the goal of a completely automated system for cardiac motion analysis and detection of disease.

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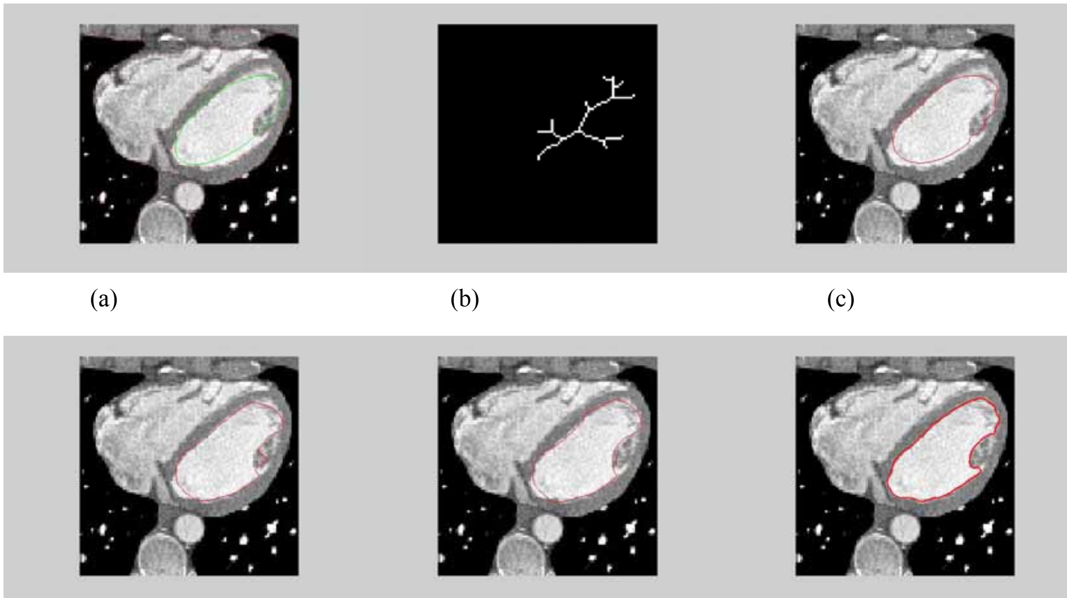
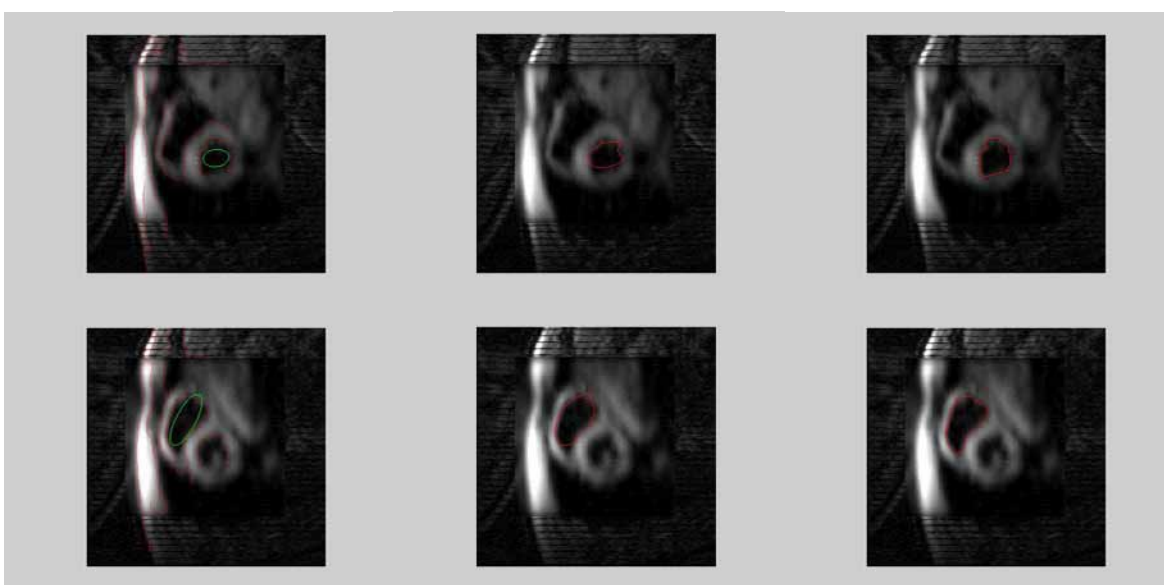


(a) (b) (c)

(d) (e) (f)

Figure 1: a) Original 256 by 256 high resolution CT data and the initial deformable model (green line) drawn based on preprocessing to compute the region of interest (ROI), b) ROI skeleton, c) model after 1 iteration (red), d) model after 10 iterations (red), e) model after 50 iterations (red), f) final result.



(a) (b) (c)

Figure 2: a) Original 192 by 192 MR data, preprocessed using Garber Filters to remove the tagging lines. Red lines are the estimated edges. Notice there are big gaps in the edges for both the left and right ventricles. Green curves represent the initial location of the model, b) model after global-local deformation, c) final results after

the local deformation refinement. Please note that in the Metamorph formulation the model evolves to a boundary whose interior statistics are consistent.

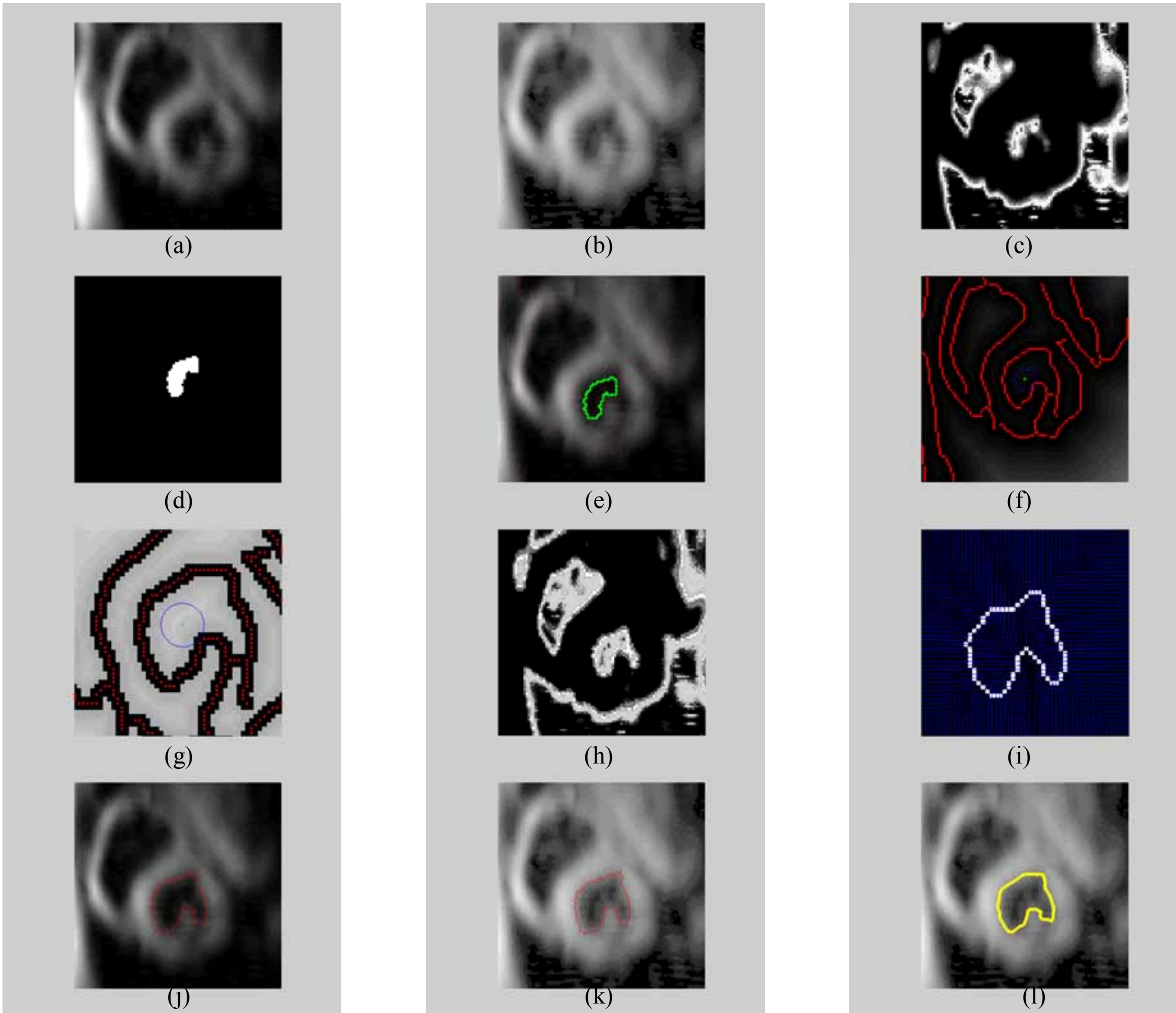


Figure 3: a) Original MRI image with tag lines removed, b) brightened original image, c) original nonparametric p.d.f distribution, d) the binary created by the initial statistics in the seed pixel's neighborhood, e) initial model created by 2D marching cubes (the green curve), f) the edge map of the original image (the red lines), g) edge distance map, the green point is the seed, the blue circle is the original neighborhood in which the statistic has been used to initialize the model, h) final p.d.f distribution, i) final region edge, j) and k) the model location (red curve) when the global deformation turns off, in k) we lighten up the original image so that we can see the convergence of the model to the boundary features, l) final segmentation results in yellow curve.