Hybrid Deformable Models for Medical Segmentation and Registration

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Abstract—Deformable models have had great successes over the past 20 years in medical applications. We have recently developed new classes of deformable models which we term hybrid deformable models to automate the model initialization process and make improvements in segmentation and registration. In this paper we present several hybrid deformable methods we have been developing for segmentation and registration. These methods include Metamorphs, a novel shape and texture integration deformable model framework and the integration of deformable models with graphical models and learning methods. We first present a framework for the robust segmentation and tracking of the heart from tagged MRI images and second applications involving brain tumor segmentation as well as brain and cardiac shape registration.

Keywords—hybrid deformable model, segmentation, registration

I. INTRODUCTION

We will first present the power of our hybrid segmentation methods through our framework for cardiac segmentation and tracking from tagged MRI images. Cardiovascular diseases are the main cause of death in the western countries. Many heart diseases, such as ischemia and RV hypertrophy are thought to correlate strongly to the shape and motion of the heart. Tagged cardiac magnetic resonance imaging is a well-known technique for non-invasively visualizing the detailed myocardium motion and deformation. It has the potential of early diagnosis and analysis of these cardiovascular diseases. This technique generates a set of equally spaced parallel tagging plains within the myocardium as temporary markers at end-diastole by spatial modulation of magnetization. Imaging planes are perpendicular to the tagging planes, so that the tags appear as parallel dark stripes in MR images and deform with the underlying myocardium during the cardiac cycle in vivo, which gives motion information of the myocardium normal to the tagging stripes. Some example images can be seen from [Fig. (1)].

A set of spatio-temporal(4D) tagged MRI images of the heart provides qualitative and quantitative information about the morphology, kinematic function and material properties of the heart. However, before this technique being used in the routine clinical evaluation, we need to solve the following image analysis tasks: 1. Extraction and tracking of the heart wall boundaries and tags. 2. LV-RV shape and motion analysis. 3. Myocardium strain analysis. 4. Modeling the intra-cavity flow, etc.

It has been noted by several researchers that the rate-limiting step which prevents tagged MR from clinical use is the robust extraction and tracking of the contours and tags. There have been a vast research efforts on the automated contour segmentation, however, it still remains a difficult task due to the common presence of cluttered objects, complex object textures, image noise, intensity inhomogeneity, and especially the complexities added by the tagging lines.

In [1], to address the difficulty added by tagging lines, before the segmentation process, a tunable Gabor filter bank technique is first applied to remove the tagging lines and enhance the tag-patterned region [2]. Because after the initial tagging modulation, the tag patterns in the blood are flushed out very soon, this de-tagging technique actually enhances the blood-myocardium contrast and facilitates the following myocardium segmentation.

Our segmentation framework is based on a newly proposed deformable model, which we call "Metamorphs" [3]. The key advantage of the Metamorph models is that it integrates both shape and interior texture and its dynamics are derived coherently from both boundary and region information in a common variational framework. These properties of Metamorphs make it more robust to image noise and artifacts than traditional shape-only deformable models.

A full set of conventional spatio-temporal(4D) tagged MRI consists of more than one thousand images. Segmenting every image individually is a time-consuming process that is not clinically feasible. We propose a new myocardium tracking technique which enables temporal propagation of the heart wall boundaries over the heart beat cycle. Through this propagation, we only need to do myocardium segmentation at one time, then it will be propagated both spatially and temporally to segment the whole set efficiently. This method is based on implementing a tunable Gabor filter bank to observe the deformations of the tagging lines over time [4]. This is possible because we
can approximate the displacements (or deformations) of the tagging patterns by estimating the changes in parameter values of the Gabor filters that maximize the Gabor response over time. The motion of the tagging lines indicates the underlying motion of the myocardium, and therefore, the motion of the heart wall boundaries. Spatial propagation of the heart wall boundaries is more difficult due to the complex heart geometry and the topological changes of the boundaries at different positions of the heart. Our solution is segmenting a few key slices first, which represent the topologies of the rest of the slices. Then we let the key frames propagate to the remaining slices.

The remainder of this paper is organized as follows: in Section II, we briefly introduce the Metamorphs segmentation on model shape, texture, deformations and dynamics. In Section 3, we present the theory of the tunable Gabor filter bank and its applications in tag removal and myocardium tracking. We introduce the integration of the Metamorphs and Gabor filter bank methods in Section 4 with our phototype system and some experimental results as this paper’s conclusion.

II. THE METAMORPH DEFORMABLE MODEL FOR TAGGED MR IMAGE SEGMENTATION

In our framework, the shape of an evolving model is implicitly embedded as the zero level set of a higher dimensional distance function using the Euclidean distance transform [5]. Let $\Phi : \Omega \to \mathbb{R}^+$ be a Lipschitz function that refers to the distance transform for the model shape $\mathcal{M}$. The shape defines a partition of the domain: the region that is enclosed by $\mathcal{M}$, $[\mathcal{R}_M]$, the background $[\Omega - \mathcal{R}_M]$, and on the model, $[\partial \mathcal{R}_M]$.

The model deformations are efficiently parameterized using a space warping technique, the cubic B-spline based Free Form Deformations (FFD)[6], [7]. The essence of FFD is to deform an object by manipulating a regular control lattice $F$ overlaid on its volumetric embedding space. In this paper, we consider an Incremental Free Form Deformations (IFFD) formulation using the cubic B-spline basis [8].

The interior intensity statistics of the models are captured using nonparametric kernel-based approximations, which can represent complex multi-modal distributions. Using this non-parametric approximation, the intensity distribution of the model interior gets updated automatically while the model deforms.

When finding object boundaries in images, the dynamics of the Metamorph models are derived from an energy functional consisting of both edge/boundary energy terms and intensity/region energy terms.

We used Metamorph models to segment heart boundaries in tagged MR images, both on original images with tags and on de-tagged images that have tags removed by gabor filtering. In [Fig. (2)], we show the Left Ventricle, Right Ventricle, and Epicardium segmentation using Metamorphs on de-tagged MR images. By having the tagging lines removed using gabor filtering, a Metamorph model can get close to the heart wall boundary more rapidly. Then the model can be further refined on the original tagged image.

![Fig. 2. Metamorph segmentation on de-tagged images. (1) segmentation at time 7, slice position 7. (2) segmentation at time 7, slice position 10. (a) original image. (b) image with tags removed by gabor filtering. (c) cardiac contours segmented by Metamorphs on detagged image. (d) contours projected on the original image.](image-url)
At each pixel in the input image, we apply the tunable Gabor filter bank and find out a set of optimal filter parameters that maximize the Gabor filter response. From the optimal \( m \) and \( \omega \) values, we can learn the current pixel’s relative distance with respect to the nearby tagging lines. Thus the change of \( \omega \) coupled with \( m \) can approximately tell the displacement of the underlying tissue. For conventional short axis (SA) tagged MRI sequences, we have two sets of data whose tagging lines are initially perpendicular to each other. When we combined the horizontal and vertical deformations from the two data sets, we get the deformation of the myocardium.

**IV. INTEGRATION AND THE PROTOTYPE SYSTEM**

We integrate the above two major techniques, the tunable Gabor filter bank and the Metamorphs segmentation, to construct our 4D spatio-temporal integrated MR analysis system. By using the two techniques in a complementary manner, exploiting specific domain knowledge about the heart anatomy and temporal characteristics of the tagged MR images, we can achieve efficient, robust segmentation with minimal user interaction. The algorithm consists of the following main steps. (The illustration of the spatio-temporal propagation can be found in [Fig. (6)].)

1. Tag removal for images at the mid-systolic phase. Given a 4D spatio-temporal tagged MRI dataset of the heart, we start by filtering using a tunable Gabor filter bank on images of a 3D volume that corresponds to a particular time in the middle of the systolic phase, which we term ‘center time’. For a typical dataset in which the systolic phase is divided into 13 time intervals, we apply the Gabor filtering on images at time 7, when tag patterns in the endocardium are flushed out by blood but tag lines in the myocardium are clearly visible.

2. Metamorphs segmentation using the de-tagged images. Given the de-tagged Gabor response images at time 7, we use Metamorphs to segment the cardiac contours including the epicardium, the LV and RV endocardium. Since the formulation of Metamorphs naturally integrates both shape and interior texture, and the model deformations are derived from both boundary and region information, the Metamorph models can be initialized far-away from the object boundary and efficiently converge to an optimal solution. For each image, we first segment the LV and RV endocardium. To do this, the user initializes a circular model by clicking one point (the seed point) inside the object of interest, then the surrounding region intensity statistics and the gradient information automatically drive the model to converge to the endocardium boundaries. We then automatically initialize a metamorphs model for the epicardial contour by merging the endocardial contours and expanding the interior volume according to myocardium thickness statistics. The model is then allowed to evolve and converge to the epicardium boundary.

3. Spatial propagation at the mid-systolic center time. At the mid-systolic phase, we do the segmentation at several key frames which represent the topologies of the rest of the frames, then let the segmented contours propagate to their nearby frames. In short axis cardiac MR images, from the apex to the base, the topology of the boundaries goes through the following variations: 1. one epicardium; 2. one epicardium and one LV endocardium (in some cases of the RV hypertrophy patients, one epicardium and one RV endocardium are also possible); 3. one epicardium, one LV endocardium and one RV endocardium; 4. one epicardium, one LV endocardium and two RV endocardium. The key frames consist of one center frame of the third topology and three transition frames. This spatial propagation actually provides a quick initialization method (rather than manually clicking the seed points as mentioned in step 2) for the rest of the non-key frames from the key frames.

4. Boundary tracking using tunable Gabor filters over time. Once we have segmented the cardiac contours at time 7, we keep tracking the motion of the myocardium and the segmented contours over time. This temporal propagation of the cardiac contours significantly reduces computation time, since it enables us to do supervised segmentation at only one time, then fully automated segmentation of the complete 4D dataset can be achieved. It also improves segmentation accuracy because we capture the overall trend in heart deformation more accurately by taking into account the temporal connection between segmented boundaries.

5. Boundary refinement using Metamorphs. In practice, we provide the option to further refine the boundaries using Metamorph deformable models. We also provide the manual correction option to doctors during the whole segmentation process to ensure satisfiable results.

6. Tagging lines tracking within the heart wall. Tagging lines are straight lines and equally spaced at time 0. Starting from time 0, we keep tracking the tagging lines only within the heart wall from the results of the boundary segmentation.
and boundary tracking steps above. The tagging lines’ model is basically a set of Snakes whose external forces are from the original intensity images and the tag-enhanced images.

The prototype of our 4D segmentation system is developed in a Matlab 6.5 GUI environment. The user need to load in the raw MRI data of the short axis and long axis volumes first ((Fig. (4-1a))). Then the user is allowed to examine the whole data sets, which consist of two short axes and one long axis, and determine the slice index of the center time ((Fig. (4-1b,1c))). The tag removal step is done on the 3D volume at the center time ((Fig. (4-2a))). Then the user has an option to determine the indices of the key frames and do Metamorphs segmentation on these key frames ((Fig. (4-2b,2c))). The segmented contours are propagated spatially (optional) and then temporally ((Fig. (4-3a,3b))). Practically the spatial propagation step is optional because for most clinical analysis one typical slice is enough unless a fully 4D model is required. Manual interaction is always available during the whole segmentation and propagation process to make corrections in time. Based on the boundary segmentation results, the user are able to track the tagging lines from time 1 ((Fig. (4-3c))). The initialization and tracking of the tag tracking is totally automatic. However, manual corrections is also available. Figure 5 is a set of contour segmentation and tagging lines tracking results generated by this system.

V. OTHER HYBRID SEGMENTATION METHODS

We have also developed other hybrid deformable models based on the integration of deformable model with graphical models and learning methods[13], [14], [15], [16], [17], [18]. Region-based and edge-based segmentation are the two major classes of segmentation methods. Though one can label regions according to edges or detect edges from regions, these two kinds of methods are naturally different and have respective advantages and disadvantages. A hybrid segmentation method that combines region based and edge-based methods will improve the segmentation results over the two methods alone. We have proposed a hybrid segmentation framework to combine the Markov Random Field (MRF)-based and the deformable model-based segmentation methods. To tightly couple the two models, we construct a graphical model to represent the relationship of the observed image pixels, the true region labels and the underlying object contour. As seen in Figure 6, we used a hybrid segmentation framework for locating tumors in the brain before surgery. First, a group of high-order Gibbs models have been designated for image slices based on the image data and prior information. We segmented the region of interest in 2D images by minimizing the energy function of the Gibbs model. Those 2D segmentation results are then combined to form a 3D binary mask for the creation of a 3D deformable mesh using the marching cubes method. The deformable mesh is first fit to the image features, guided by image forces and internal shape constraints. Its result is then used to recalculate the parameters of the Gibbs Prior models. Finally, in Figure 7 we present registration results using a shape registration method which is based on information theory and free form deformations [16].

VI. CONCLUSION

We have presented a series of hybrid deformable models whose power stems from the integration of region information into traditional shape-based deformable models. Using this new hybrid approach we have been able to address in an automated way difficult segmentation and registration problems in medical image analysis. We are currently continuing our efforts in this direction through the addition of priors in our framework and improved learning methods.

REFERENCES

Fig. 4. Screen snapshots of our segmentation and tracking system. (1a) read in the SA and LA volumes. (1b,1c) examine the data sets. (2a) de-tagged image at the center time. (2b) Metamorphs segmentation based on de-tagged images. (2c,3a) segmentation results. The papillary muscle is excluded from the myocardium by manual interaction. (3b) temporal propagation. (3c) tagging lines tracking.

Fig. 5. Contour and tag results generated by our system for a SA horizontal-tagged data set at position 7 at time 1, 3, 5, 7, 9, and 11.
Fig. 6. a) one slice in the 3D volume of a brain with a tumor region (darker region); b) the segmentation result of the Gibbs Prior model in the first iteration; c) the segmentation result of the Gibbs Prior model in the second iteration; d) final segmentation result of the deformable model on the same slice; e) projection of the segmentation result onto the original image (on one slice); f) the initial deformable created by marching cubes method in the second iteration; g, h) the final 3D deformable model fitting result (view from two directions).

Fig. 7. First row: incremental B-spline FFD local registration for Brain Structure. (a) Initial conditions (source shape in blue, target shape in red), (b) Result after global registration, (c) Established correspondences after local registration; only the zero level set (i.e., shape) correspondences are shown, (d) Locally deformed source shape (in green) overlaid on the target (in red), (e) Final IFFD control lattice configuration depicting the space warping to achieve local registration.
2nd-5th rows: Applications in cardiac contours. Established correspondences using IFFD. (red) source shapes after global transformations, (blue) target mean shape, (dark lines) correspondences for a fixed set of points on the mean shape.