Automatic Hybrid Segmentation of Dual Contrast Cardiac MR Data

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Abstract. Manual tracing of the blood pool from short axis cine MR images is routinely used to compute ejection fraction (EF) in clinical practice. The manual segmentation process is cumbersome, time consuming, and operator dependent. In this paper, we present an algorithm for the automatic computation of the EF that is based on segmenting the left ventricle by combining the fuzzy connectedness and deformable model frameworks. Our contributions are the following: 1) we automatically estimate a seed point and sample region for the fuzzy connectedness estimates, 2) we extend the fuzzy connectedness method to use adaptive weights for the homogeneity and the gradient energy functions that are computed dynamically, and 3) we extend the hybrid segmentation framework to allow forces from dual contrast and fuzzy connectedness data integrated, with shape constraints. Finally, we compare our method against manual delineation performed by experienced radiologists on the data from nine asymptomatic volunteers with very encouraging results.

1 Introduction

With the rapid development of cardiovascular MR, it is feasible to image the entire ventricle using 3D cine images. 3D cine imaging allows building a patient specific model of the ventricle for investigating the cardiac morphology and dynamics. However, the use of cine multi-slice or 3D techniques involves the delineation of structures on a large number of images. Manual tracing is labor intensive and can involve considerable inter- and intra-observer variations [7].

These limitations have motivated the development of automated segmentation techniques for more accurate and more reproducible left ventricle (LV) segmentation. Significant research has been performed in the last 20 years towards the analysis of medical images in general [2], and in automating the contour delineation process [13,11,15]. The most widely used active contour/surface model delineation technique [14,10,8] relies on user interaction for the initialization of the initial shape and location of cardiac boundaries. Research is ongoing in developing hybrid segmentation methods combining edge, region, and shape information [1,3,4]. Recently, statistics-based techniques following the active appearance-based model (AAM) have emerged showing improved results in terms of reliability and consistency [6]. However, these methods require an extensive training set.

In parallel with the research efforts for more reliable segmentation techniques, researchers are working towards improved imaging sequences. Recent developments in cine imaging using steady state free precession sequences (balanced FFE) provide high intrinsic myocardial and blood pool contrast. However, this high contrast by itself is not sufficient for appropriate segmentation of the three primary tissues (i.e., myocardium, blood, and fat). We propose a multi-spectral approach, where we choose two sequences that intrinsically have high contrast difference for the blood signal, i.e., double inversion black blood sequences (dual IR TSE), and the recently described bFFE for bright blood. In this paper, we present a new hybrid approach for the automatic computation of the EF (ratio of the stroke volume to the diastolic volume) of the LV from dual contrast short axis cardiac MR data, that combines the fuzzy connectedness region-based segmentation method with the deformable-model-based boundary segmentation method.

Our work is inspired by the work of Metaxas' and Udupa's research groups [16,5,12,3]. The most closely related work is [5]. Our approach differs from that work in the following: a) our algorithm does not need any manually selected seed area for the fuzzy connectedness; b) we employ adaptive weights for the fuzzy segmentation; d) we have developed a new class of forces derived from multi-valued data and fuzzy connectedness data; and d) segmentation of multi-valued as opposed to segmentation of scalar data is performed. Our contributions are the following: 1) we automatically estimate a seed point and sample region for the LV for the fuzzy connectedness estimates, 2) we extend the fuzzy connectedness method to compute dynamically changing weights for the homogeneity and the gradient energy functions, and 3) we extend the hybrid segmentation framework to allow forces from dual contrast and fuzzy connectedness data.

2 Methods

2.1 Adaptive Dual Contrast Fuzzy Connectedness

The Fuzzy Connected Image Segmentation framework developed by Udupa and his collaborators [16,12] assigns fuzzy affinities between two given pixels or voxels in an image or a volume based on a weighted function of the degree of coordinate space adjacency, degree of intensity space adjacency, and degree of intensity gradient space adjacency to the corresponding target object features. Specifically, the membership function of the fuzzy spel affinity is defined as: follows: $\mu_k(c, d) = \mu_\alpha(c, d)[\omega_1 h_1(I(c), I(d)) + \omega_2 h_2(I(c), I(d))]$, if $c \neq d$ and $\mu_k(c, c) = 1$, where $\mu_\alpha(c, d)$ is the membership function of the spatial adjacency between spels c and d , I denotes the intensity values, and ω_1 and ω_2 are free parameters satisfying: $\omega_1 + \omega_2 = 1$. For a dual contrast neighborhood, we used the functions as suggested in [16]:

$$\begin{aligned} h_1 &= \frac{1}{(2\pi)^{\frac{T}{2}} |\mathbf{S}_1|^{\frac{1}{2}}} e^{-\frac{1}{2} [\frac{1}{2}(\mathbf{I}(c) + \mathbf{I}(d)) - \mathbf{m}_1]^\top \mathbf{S}_1^{-1} [\frac{1}{2}(\mathbf{I}(c) + \mathbf{I}(d)) - \mathbf{m}_1]} \\ h_2 &= \frac{1}{(2\pi)^{\frac{T}{2}} |\mathbf{S}_2|^{\frac{1}{2}}} e^{-\frac{1}{2} [|\mathbf{I}(c) - \mathbf{I}(d)| - \mathbf{m}_2]^\top \mathbf{S}_2^{-1} [|\mathbf{I}(c) - \mathbf{I}(d)| - \mathbf{m}_2]} \end{aligned} \quad (1)$$

where $\mathbf{I}(c) = (I_{bFFE}(c), I_{TSE}(c))^\top$ is the two component intensity vector, $\mathbf{m}_1$ and $\mathbf{S}_1$ are the mean vector and covariance matrix of spels in the intensity

space, $\mathbf{m}_2$ and $\mathbf{S}_2$ are the mean vector and covariance matrix of spels in the gradient magnitude space. With ω_1 and ω_2 kept as free parameters, the results obtained from fuzzy connectedness remain highly sensitive to the selection of the sample region. To overcome this problem, we compute ω_1 and ω_2 as adaptive parameters depending on the ratio of homogeneity and gradient function values at each spel location as follows: $\omega_1 = \frac{h_1}{(h_1+h_2)}$ and $\omega_2 = 1 - \omega_1$. This method of weight assignment takes advantage of the fact that when the spels are closer to the center of the target object, then the degree of intensity space adjacency will be higher than when a spel is near the boundary of the target. As a spel moves towards the boundary, automatically more weight is given to the degree of adjacency in intensity gradient space, thus enabling more accurate boundary definition. In particular, this method enhances the difference in affinities attached to the pixels on either side of the boundary, and thus gives better defined fuzzy objects without involving a user to adjust the values of these parameters to find the best possible combination of ω_1 and ω_2 . To improve the accuracy of the boundary information, we incorporate information from both the imaging spectra to compute the fuzzy affinities. In Fig. 2 we present our results showing the improvements achieved by these extensions and modifications. Since our refined fuzzy connectedness attaches much higher affinities to the target object relative to rest of the image, the need for a complex algorithm to determine the appropriate threshold to segment the membership scene is eliminated. In addition, the edges of fuzzy affinity images are pronounced which is crucial for the integration with the deformable model.

2.2 Deformable Model

To extract and reconstruct the LV surface from the 3D dual contrast MR data, we employ an elastically adaptive deformable model [9]. We have defined a new class of forces derived from multi-valued volume data that localize salient data features. In order to attract our model towards significant 3D gradients of the multi-spectral data $\mathbf{I}(x, y, z) = (I_{bFFE}(x, y, z), I_{TSE}(x, y, z))^T$ and of the volume fuzzy connectedness data $\mathbf{F}$ derived with the techniques explained in the previous section, we construct a 3D potential function as follows: $\mathbf{P}(x, y, z) = \lambda_1 \|D_{MD} * \mathbf{I}\| + \lambda_2 \|D_{MD} * \mathbf{F}\|$, whose potential minima coincides with the LV surface. The 3D Monga-Deriche (MD) operator is applied to the multi-valued data and the fuzzy connectedness data to produce two gradient fields. A weighted combination of these terms is formed to force the model to drop into the deeper valleys and lock onto the LV surface boundary. Then, the following force distribution can be derived from this potential function: $\mathbf{f}(x, y, z) = c \frac{\nabla \mathbf{P}(x, y, z)}{\|\nabla \mathbf{P}(x, y, z)\|}$, where the variable c controls the strength of the force. Once the model converges towards the LV boundary, the smoothing effect of the model will allow it to ignore the data from the papillary muscle. Computation of the forces at any model point is achieved using tri-linear interpolation.

2.3 Ejection Fraction Computation Algorithm

Step 1 - Acquire and pre-process the data: Studies were performed in nine subjects (7m/2f) with normal sinus rhythm, with consent. Contiguous 10mm

short axis slices were obtained to cover the left ventricle (LV) from the apex of the ventricle to the mitral valve annulus within a breath-hold. For this study, it was assumed that respiratory motion with the breath-hold would be negligible. Scans were acquired using a dual IR black-blood sequence (TE/TR/TSE factor: 80/2hb/23, a single diastolic phase), and cine bFFE sequence (TE/TR/flip: 3.2/1.6/55 deg; 38-40 msec temporal resolution) using VCG gating at 1.5T. A TSE scan can be performed in just a single additional breath-hold and thus does not have any significant effect on the total scan time. All the images were stored in standard DICOM format. Figs. 1(a,b) depict the data from the 6th bFFE and TSE slice (subject-1). The data were analyzed manually by experienced radiologists and using the automated analysis in a post-processing workstation. 3D registration of the diastolic bFFE and TSE volumes is achieved using the Normalized Mutual Information algorithm. Figs. 3(a-h) illustrate a sample set of diastolic bFFE and TSE images from the apex to the base of the LV.

Step 2 - Construct spatio-dual-intensity 4D vector space: The promise of dual contrast acquisition is that the dimensionally expanded measurement space will allow differentiations about the different tissues to be made, which are impossible in any of the component images. To that end, we construct a four dimensional measurement space, which combines the spatial and dual contrast intensity information. The basis components of our 4D vector are the (x,y) Euclidean coordinates of the pixels and their signal intensities in bFFE and TSE scans. Tissue types due to their signal intensity responses (Fig. 1(c)) and organs due to their spatial adjacency (Fig. 1(d)) form 4D clusters in this measurement space, thus providing clues for tissue and organ classification.

Step 3 - Estimate the cluster center and the corresponding region for the LV: The three major tissue types present in the MR scans are blood, myocardium, and fat. For example in Fig. 1(c), we do observe a distinct cluster for blood, a number of clusters where the myocardium cluster is expected, and a cluster due to background. In this specific case, fat being almost negligible doesn't appear as a distinct cluster. We employ a conventional Fuzzy C-means clustering to estimate these clusters. Figs. 1(c,d) depict the results of estimating these clusters. Having identified the blood cluster (Fig. 1(e)) we can easily classify the blood in the scan (Fig. 1(f)) as the projection of the blood cluster on the spatial (x-y) plane. Since the LV contains the more oxygenated blood, it appears brighter compared to RV blood in the bFFE. This fact is used to split the blood cluster into two clusters - one for the LV and one for the RV (Fig. 1(g)). The cluster to the right on the bFFE-TSE plane corresponds to the LV. Projections of these clusters on the spatial (x-y) plane give the centroids and regions for LV and RV (Fig. 1(h)). Once the LV is identified this estimation is further rectified by using region growing to keep only the LV region and then we recompute its centroid. Fig. 3(x) depicts the estimated centroids for nine subjects mapped on a normalized circle fitted to the LVs. Note that the LVs of all the nine subjects were identified correctly with the estimated centroids always well within the LV blood pool.

Step 4 -Perform Fuzzy Connected LV blood pool segmentation: The estimated LV centroid and region are used as seed and sample statistics for our

Fig. 1. (a,b) Slice 6 from the bFFE and TSE scans of Subject-1, (c) projection of the 4D measurement space on bFFE-TSE, and (d) x-y planes, respectively. Projection of the identified blood cluster on the (e) TSE-bFFE and (f) x-y planes, respectively. Projection of the identified LV and RV clusters and centroids on the (g) TSE-bFFE and (h) x-y planes, respectively.

3D adaptive dual contrast fuzzy connectedness algorithm. The average intensity of the LV blood pool drops off as we move towards the apex of the heart, due to coil intensity fall off (Fig. 3(y)). We begin with the central slice and FCM-based LV estimation followed by LV segmentation; then we use the same statistics for the next slice and update the seed (centroid), the threshold of the membership scene, and the intensity and gradient statistics to refine the segmentation. The new threshold for the scene membership is computed as:

$$\begin{aligned} expoI &= \frac{(prevSliceMeanLVIntensity - currSliceMeanLVIntensity)}{prevSliceMeanLVIntensity}, \\ thresh &= thresh \times e^{-\sqrt{expoI}}. \end{aligned} \quad (2)$$

In this way, we adaptively propagate the LV blood pool segmentation along the volume and time.

Step 5 - Fit a Deformable Model: An elastically adaptive LV deformable model [9] is fitted to the fuzzy connectedness and dual contrast data using shape constraints. The domain specific prior knowledge that LV boundary is non-intersecting, closed and includes the papillary is incorporated to optimize fitting of deformable model to LV boundary (Fig. 3(q-w)). The elasticity parameters of the deformable model are changed adaptively depending on the gradient values allowing us to overcome spurious boundaries.

Step 6 - Compute the EF: Compute the EF by computing the volumes of the fitted deformable models at the end of systolic and diastolic phase.

Fig. 2. Images from a phantom data set. (a) Synthetic image and (b-e) synthetic image contaminated with blur, noise, blur + noise, and blur + noise + background variation, respectively. (f) Robustness of adaptive fuzzy connectedness over noise and blur variations with the mean intensity values of the segmented region of interest mapped to gray scale (0-255). Plots (g-j) depict the results of a comparative study between the adaptive and the conventional fuzzy connectedness with $w_1 = w_2 = 0.5$ for various levels of: (g) blur, (h) noise, (i) blur + noise, and (j) blur + noise + background variation.

3 Results, Discussion and Conclusion

We have performed a number of experiments to assess the accuracy, limitations and advantages of our approach. The processing time on an Intel Pentium III 900Mhz workstation with 0.5GB RAM ranged from 30-45s for each dual contrast dataset comprised of 20 images.

For the first experiment, we designed a number of synthetic 3D dual contrast datasets with different levels of noise, blurring, and gradual intensity change effects (Fig. 2), in order to assess the benefits from adapting the weights for fuzzy connectedness dynamically. The membership scene for spels belonging to the target object is defined as the square region of 100 pixels in the target of the central c_1c_2 slice. We use the mean values of strength of connectedness attached to the ground truth as metric to compare the performance of adaptive fuzzy connectedness-based segmentation with respect to the conventional fuzzy connectedness-based segmentation. Fig. 2 depicts the results of the comparison study of the two methods on a phantom dataset.

Next, we present the results from the segmentation of the data acquired from Subject-1. Figs. 3(a-h) illustrate a sample set of diastolic short-axis bFFE and TSE images. Corresponding FCM based LV region and centroid estimates are shown in Figs. 3(i-l). The segmentation results using adaptively weighted Fuzzy Connectedness for the LV blood pool are depicted in Fig. 3(m-p). Figs. 3(q-t) depict projections of the fitted elastically adaptive shape-constrained deformable model on the corresponding slices. Figs. 3(u-w) depict the fitted deformable models for subjects 1, 4, and 9, respectively.

Fig. 3. Slices for the diastolic dataset from a single-breath-hold multi-slice cine (subject-1), acquired with (a-d) bFFE, and (e-h) TSE MR imaging. (i-l) FCM-based LV estimation with centroid and (m-p) resulting Fuzzy connectedness data. (q-t) Projection of the fitted elastically adaptive deformable model. Fitted deformable models of the LV blood pool for (u) Subject-1, (v) Subject-4, (w) Subject-9, respectively. (x) Estimated centroids for nine subjects mapped on a normalized circle fitted to the LVs obtained manually, (y) coil intensity fall off in MR, and (z) EFs for nine subjects using manual and automatic methods.

The EFs computed for nine volunteers using the manual method and automated blood segmentation method are shown in Fig. 3(z). Our initial validation results demonstrate the feasibility of using bFFE/TSE for automated segmentation of the LV.

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