Segmentation of the LV Wall with Trabeculations

Clément Beitone[1,2], Christophe Tilmant[1,2] and Frédéric Chausse[1,2]
[1] *Université Clermont Auvergne, Institut Pascal, BP 10448, F-63000 Clermont-Fd, France*
[2] *CNRS, UMR 6602, Institut Pascal, F-63171 Aubière, France*
clement.beitone@inria.fr

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Abstract: The evaluation of cardiac functional parameters for heart disease diagnosis requires to have an accurate segmentation result. We propose a method to efficiently and reliably segment both the endocardial and the epicardial borders of the left ventricle. We use MR short axis images acquired in SSFP mode. Our framework combines a threshold-based approach to produce an estimation of the shape of the cardiac wall and a level set approach that refine it. We assessed our method on two databases built for two MICCAI challenges. Our results would have positioned us at the third place of the 2009 challenges.

1 INTRODUCTION - STATE OF THE ART

According to the World Health Organization in 2012, cardiovascular diseases were responsible for 30% of the total number of deaths. Systolic function impairment and especially the left ventricle (LV) is one of the main characteristics reflecting that the heart is damaged. Quantitative analysis provides important cardiac functional parameters for heart disease diagnosis, for example the *strain* measure showed is a reliable prognostic value.

The evaluation of these parameters requires to have an accurate segmentation result. This step has been the subject of a large number of studies: a review and an evaluation of segmentation methods applied to MR images can be found in (Petitjean and Dacher, 2011).

Among all the methods, threshold-based have proven their efficiency. For example, the procedure proposed by Jolly (Jolly, 2009) combines a multi-seeded fuzzy connectedness approach and a registration algorithm to segment the wall of the left ventricle in sequences of MR images. This work was ranked as one of the best at the MICCAI 09 challenge for cardiac MR left ventricle segmentation. Nevertheless, one of the weakness of these strategies is that they are generally designed for a unique purpose. They tend to fail if the subject strays too far from the nominal value. Hence, they generally require an additional stage to refine their results.

The deformable models are another major category in cardiac segmentation. In particular, the level set framework has been extensively used to tackle this problem as it is convenient to implement specific constraints. For example, in (Feng et al., 2013) the authors represent the cardiac wall with two specified level contours of a level set function. These contours are maintained separated by a geometric constraint. More recently in (Ngo et al., 2016), the authors have mixed a deep learning approach with a level set method to segment the left ventricle in MR sequences. Here, the level set is used as a fine tuning method that completes the work produced by the deep learning algorithm. The drawback of the level set approaches is their need to be initialized close to the final solution in order to work properly.

In this article, we propose a method to efficiently and reliably segment both the endocardial and the epicardial borders of the left ventricle in MR short axis images acquired in SSFP mode. Unlike the work proposed in (Beitone et al., 2015) where the aim of the authors was to extract an endocardial border encompassing only the blood pool, we try here to follow the

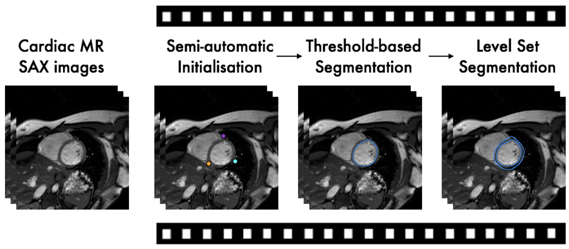

Figure 1: Overview of the proposed framework.

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classical guidelines of the clinicians. Therefore, we integrate as much as possible the trabeculations inside the region enclosed by the endocardial border. Our framework mixes a threshold-based algorithm to produce an estimation of the shape of the cardiac wall and a level set method to refine it. This framework is very fast in terms of computation time. The figure 1 illustrates this pipeline. We have assessed our strategy on two databases published at the MICCAI 09 and 11 challenges.

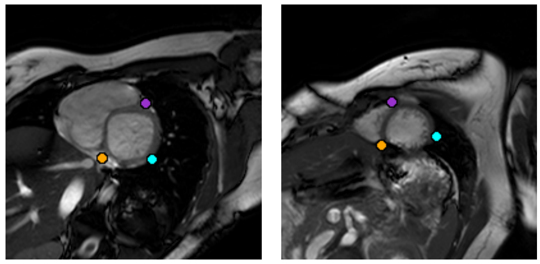


Figure 3: Manual initialization on the basal slice (left) and propagation on the apical slice (right).

2 PROPOSED FRAMEWORK

Our aim is to retrieve a shape homeomorphic to a ring: the wall of the left ventricle. For that we combine two different approaches. First a threshold-based segmentation builds a first shape close to the solution. Then, a level set segmentation refines it and produces the final result.

After analysing several manual segmentations, we have extracted some criteria which characterize the expectations of the experts. The contour produced by the algorithm must be relatively smooth. The endocardial contour must integrate the blood pool, the pillars and all the trabeculations along the edge. Building up an algorithm able to satisfy those constraints requires an analysis of the impulse responses of the tissues. The figure 2(a) presents the distributions of the blood pool, the cardiac muscle and the environment of the heart. This histogram is based on the labels produced by an expert.

It shows that the parts corresponding to the blood pool and to the muscle share a small range of values on the histogram. This is a direct consequence of the integration into the blood pool of the pillars and the trabeculations. This last integration raises some difficulties. The gray levels of the trabeculations correspond to a transition between two modes in the histogram and it is also a spatial transition between two regions. Our aim is to integrate as much trabeculations as possible in the blood pool, in order to produce a contour close to what the experts expect. As we use a threshold-based method, we have to find an algorithm that determines a reliable threshold.

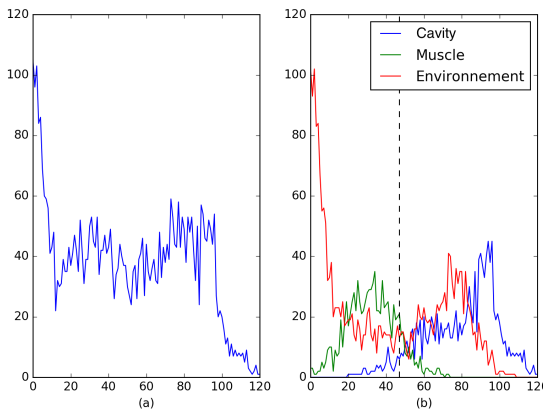


Figure 2: The histogram of the different tissues is based on expert segmentation.

2.1 Semi Automatic ROI Detection

To initialize our method the expert, have to select three points on the basal slice. Two of these points are on each side of the shared border between the ventricles. More precisely, these locations correspond to the intersection between the anteroseptal and anterior regions and between the inferoseptal and inferior regions. The last point is located on the free wall of the mycoardium at the intersection between the anterolateral and the inferoseptal region. These points are then automatically propagated from the base to the apex using a block matching algorithm. The result of our initialization procedure is illustrated on the figure 3.

2.2 Threshold-based Segmentation

Our approach is a specialization of the optimal algorithm proposed by Otsu (Otsu, 1975). This method computes the optimal threshold T_{Otsu} which splits an histogram in two modes. Unfortunately, our histograms are not exactly bimodal: they are biased by the distribution of the pixel associated to the environment. Hence, the threshold given by Otsu is shifted from the optimal position for our problem. For example, on the figure 2(b) the Otsu threshold (black line) is closer to the green mode than to the blue one. This bias might have a significant impact on the quality of the segmentation. In extreme situations, like the one presented on the figure 5(c), it can lead to the creation of a connection between the two ventricles.

We look for a factor f_{ref} as $f_{ref} \times T_{Otsu}$ gives a segmentation that contains only the blood pool and little or no trabeculations. We call this surface S_{ref}.

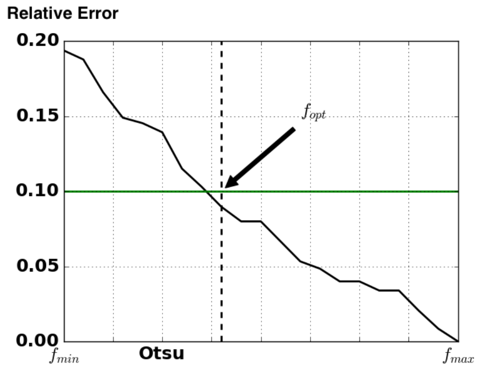


Figure 4: Example of relative error to the surface of S_{ref}. The line in green is the desired error corresponding to a relative difference of 10%. The vertical line in dashed black is the optimal threshold selected by our method.

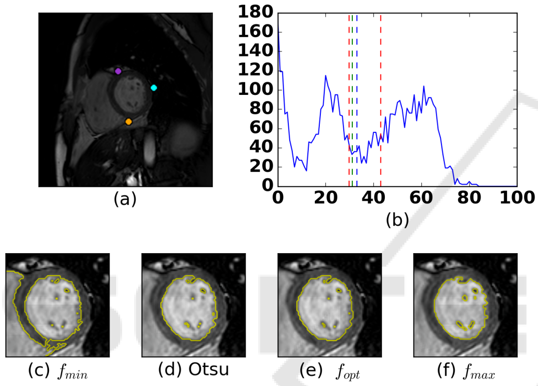


Figure 5: Illustration of the threshold-based segmentation. (a) The original image. (b) The histogram associated to the ROI in (a). (c-f) The results of the segmentation obtained by applying factors to the Otsu threshold T_{Otsu}.

Then, we iteratively compute the relative errors between S_{ref} and the surfaces of the segmentations obtained by applying factors inferior to f_{ref} to the value T_{otsu}. Using these errors values, we compute a curve similar to the one presented on the figure 4. According to the expert segmentation, the trabeculations occupy 10 percent of the surface of the endocardium. We used this value to set our stopping criterion.

Experimentally, we have found that setting f_{ref} to 1.3 gives reliable results. The figures 5 and 6 show that the selected $T_{opt} = f_{opt} \times T_{Otsu}$ leading to S_{opt} may be on the left or on the right of the value T_{Otsu} depending on the dynamic range of the images.

Finally, we compute the convex hull of S_{opt} to include the pillars. We obtained our first representation of the wall S_w by computing the external morphological gradient of S_{opt} with a dilation equal to 7.5mm. This value corresponds to the lower boundary of the average thickness of the cardiac wall. We also store a thicker gradient image S_{tw} with a thickness of 8.5mm.

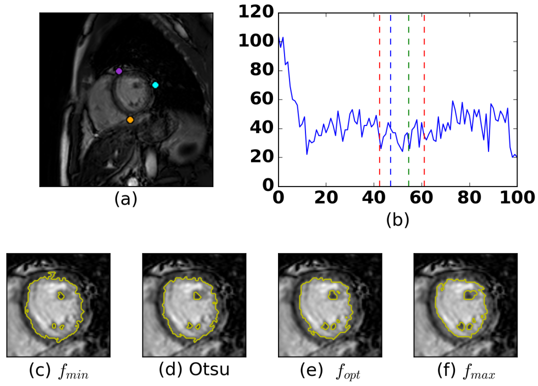


Figure 6: Illustration of the threshold-based segmentation. (a) The original image. (b) The histogram associated to the ROI in (a). (c-f) The results of the segmentation obtained by applying factors to the Otsu threshold T_{Otsu}.

This image is used as a shape reference in our level set model.

2.3 Level Set-based Segmentation

2.3.1 Deformable Model Framework

The variational formulation of the segmentation problem by means of a deformable model is stated as:

$$\mathcal{S} = \arg\min_{\mathcal{S}^* \in \mathcal{F}_\mathcal{S}} E(\mathcal{S}^*) \Leftrightarrow \frac{\delta E(\mathcal{S})}{\delta \mathcal{S}} = 0 \quad (1)$$

In our case $\mathcal{S}$ corresponds to the final shape of our model. This shape is taken from a family of solutions $\mathcal{F}_\mathcal{S}$, by minimizing the energetic functional E. This optimization problem is solved by means of a descent method on an artificial temporal parameter t. The model is put into motion, it is a deformable model:

$$\frac{\partial \mathcal{S}}{\partial t} = -\frac{\delta E}{\delta \mathcal{S}} = V\mathbf{n} \quad (2)$$

This problem is equivalent to a front propagation where the variation is homogeneous to a speed V onto the normal $\mathbf{n}$. The calculus of variations on E can be computed using shape derivative tools (Aubert et al., 2003). In the level set framework, Sethian (Sethian, 1999) showed that this problem can be stated as:

$$\frac{\partial \phi}{\partial t} = V|\nabla \phi|, \quad (3)$$

where ϕ, the level representation, is a higher order function and $\phi^{-1}(0) = \mathcal{S}$.

2.3.2 Proposed Model

As our threshold-based method produces an initial shape very close to the solution, the level set is used to fine-tune the final contour. Our model combines three terms as:

$$E = \alpha E_{LCV} + (1-\alpha)E_{LM} + \beta E_{RC} \quad (4)$$

where the term E_{LCV} is the local version (Foulonneau et al., 2003) of the well known Chan & Vese functional (Chan and Vese, 2001). Global methods provide more energy but are meaningful only if the distribution over the considered object follows a stationary process. As our images present some non-stationarity over the myocardium and over its neighbourhood, the local evaluation of the averages ensures that the mislabelling along the perimeter is fixed. This term is stated as:

$$E_{LCV}(\phi) = \int_{\Omega_{\mathbf{x}}} \delta\phi \int_{\Omega_{\mathbf{y}}} \mathcal{B}(\mathbf{x},\mathbf{y}) \cdot F\left(I(\mathbf{y}),\phi(\mathbf{y})\right) d\mathbf{y}d\mathbf{x} \quad (5)$$

where I is the current cardiac image and $\mathcal{B}$ is the ball used to extract the local neighborhood along the current contour at each location $\boldsymbol{x}$. Here, F stands for the Chan & Vese model.

The term E_{LM} is the shape constraint applied to the segmentation. This functional relies on the Legendre moments as it was introduced by Lankton (Lankton and Tannenbaum, 2008). It ensures that the global shape is correct and homeomorphic to a ring. The shape reference is set to S_{tw}. This term is stated as:

$$E_{LM}(\mathcal{S},\mathcal{S}_{ref}) = \sum_{i=0}^{N-1}\left(\lambda_i - \lambda_i^{ref}\right)^2 \quad (6)$$

where the Legendre moments λ_i are the results of the decomposition of the shapes $\mathcal{S}$ and $\mathcal{S}_{ref}$ over a basis of Legendre polynomials. The order of the decomposition is linked to the quality of the description. This decomposition is invariant to the scale and the translation.

Finally the regularization term E_{RC} ensures that the contour remains relatively smooth and is based on the length of the contour. Our model is initialized with S_w.

3 RESULTS

In order to quantitatively evaluate the detected endocardial and epicardial contours we used a local and a global measure. The global measure is the Dice metric which evaluates the overlap between the expert surface and the computed one. The local measure is the average perpendicular distance from the automatically segmented contour to the corresponding manually drawn expert contour, averaged over all contour points.

3.1 Evaluation on the Database MICCAI09

The database built for the MICCAI 09 challenge for the segmentation of the left ventricle contains 45 patients. For each patient a SSFP sequence in short axis acquired on a 1.5T GE Signa is given along with a segmentation of the cardiac wall done by an expert. All the images have been acquired in apnoea (10 to 15 seconds) with a temporal resolution of 20 images per cycle. Between 6 to 12 SAX slices are given to cover the myocardium from the base to the apex. Each slice has a thickness of 8mm and the distance between two slices is 8mm. The spatial resolution is 1.25mm in the short axis plan.

This database is split in three parts: Online, Training and Validation. We get respectively an average value for the Dice metric of $0.89(\pm 0.04)$, $0.91(\pm 0.04)$ and $0.90(\pm 0.04)$. For the average perpendicular distance between the manual segmentation and our contour, we get an average equal to $2.39(\pm 1.64)$, $2.31(\pm 1.78)$ and $2.24(\pm 1.51)$mm. These results position us virtually at the third place of the challenge.

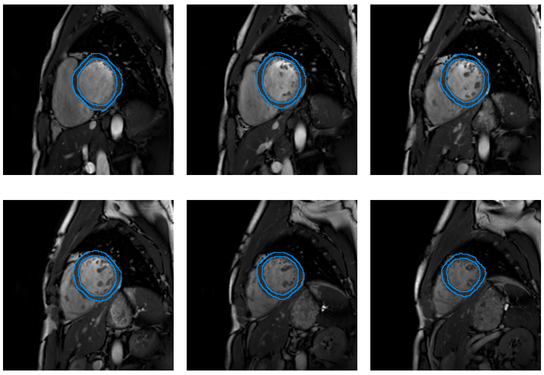
3.2 Evaluation on the Database MICCAI11

We have also used the multimodal database built for the MICCAI 2011 challenge: Motion Tracking Challenge (MTCdb). This database contains the exams of 15 patients. The SSFP images were acquired on a 3T Philips Achieva System with a temporal resolution of 30 images in short axis per cycle. The spatial resolution is between 1.15 and 1.25mm for each slice and the space between two slices is equal to 8mm. About 9 to 14 slices are necessary to capture the heart from the base to the apex.

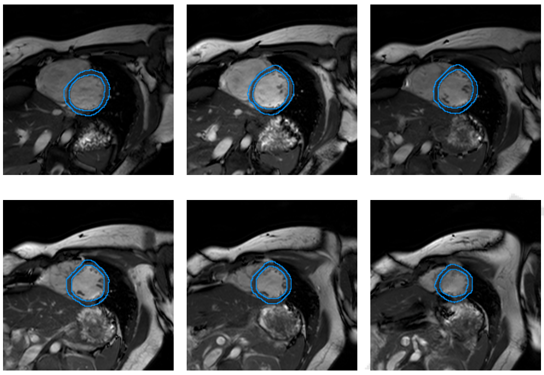
On that database, we get an average Dice metric of $0.94(\pm 0.04)$ and an average perpendicular distance equal to $1.46(\pm 1.54)$mm. The figure 7 illustrates the quality of the contours we obtained. As expected the endocardial border encompass the trabeculations and the contours are smooth.

4 CONCLUSION

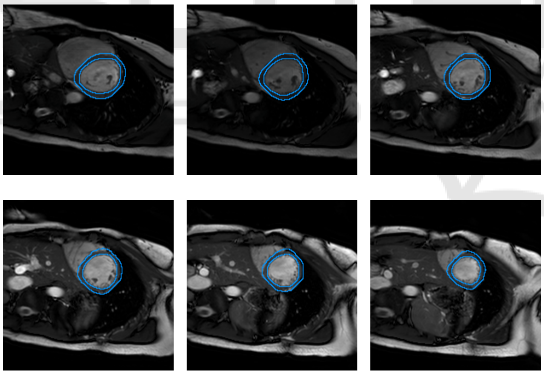
We have presented a segmentation framework to efficiently and reliably segment the endocardial and the epicardial borders in MR images. Our aim was to encompass as much as possible the trabeculations inside the endocardial border to follow the guidelines



(a) Patient 1



(b) Patient 2



(c) Patient 3

Figure 7: Illustration of the segmentation results for some patients. Slices from the base to apex.

of the experts. We have evaluated our approach on two databases and have obtained results that virtually positioned us at the third place of a challenge. Our results are similar to those obtained with a deep learning algorithm. Nevertheless, we obtain them in a fraction of the computational time required by this approach.

REFERENCES

Aubert, G., Barlaud, M., Faugeras, O., and Jehan-Besson, S. (2003). Image segmentation using active contours: Calculus of variations or shape gradients? *SIAM Journal on Applied Mathematics*, 63(6):2128–2154.

Beitone, C., Tilmant, C., and Chausse, F. (2015). Fully automatic deformable model integrating edge, texture and shape-application to cardiac images segmentation. In *VISAPP (1)*, pages 517–522.

Chan, T. F. and Vese, L. A. (2001). Active contours without edges. *IEEE Transactions on image processing*, 10(2):266–277.

Feng, C., Li, C., Zhao, D., Davatzikos, C., and Litt, H. (2013). Segmentation of the left ventricle using distance regularized two-layer level set approach. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 477–484. Springer.

Foulonneau, A., Charbonnier, P., and Heitz, F. (2003). Geometric shape priors for region-based active contours. In *Image Processing, 2003. ICIP 2003. Proceedings. 2003 International Conference on*, volume 3, pages III–413. IEEE.

Jolly, M. (2009). Fully automatic left ventricle segmentation in cardiac cine mr images using registration and minimum surfaces. *The MIDAS Journal-Cardiac MR Left Ventricle Segmentation Challenge*, 4.

Lankton, S. and Tannenbaum, A. (2008). Localizing region-based active contours. *IEEE transactions on image processing*, 17(11):2029–2039.

Ngo, T. A., Lu, Z., and Carneiro, G. (2016). Combining deep learning and level set for the automated segmentation of the left ventricle of the heart from cardiac cine magnetic resonance. *Medical Image Analysis*.

Otsu, N. (1975). A threshold selection method from gray-level histograms. *Automatica*, 11(285-296):23–27.

Petitjean, C. and Dacher, J.-N. (2011). A review of segmentation methods in short axis cardiac mr images. *Medical image analysis*, 15(2):169–184.

Sethian, J. A. (1999). *Level set methods and fast marching methods: evolving interfaces in computational geometry, fluid mechanics, computer vision, and materials science*, volume 3. Cambridge university press.