Abstract

This work presents a technique to perform segmentation of the left ventricle in images of the human myocardium. Segmentation is one of the first steps of the image analysis. Edge-based segmentation provides the detection of region boundaries, but the contours are only based on local computations, and is often sensitive to local variations in intensity, noise and physical artifacts. In interactive methods, problems like these fatigue the user and require many interventions at the contour delineation process. To reduce these problems, we propose the addition of two new features in the Live-Wire method: a region intensity and a proximity feature. Experimental results show that this alternative approach can achieve accurate edge localization and improved efficiency.

1. Introduction

The segmentation of the left ventricle (LV) of the heart is an important step in methods for visualization, tracking and estimation of the temporal evolution of the ventricular wall. In general, the myocardium is segmented manually on a single reference frame and the same mask is used on all time frames in the image sequence. Manual segmentation requires expert knowledge and suffers from variability across observers.

Current techniques for MR image segmentation include edge-detection [1,2,3], region-based [4,5,34], statistical [6,7] fuzzy [8,9,14], level sets [10, 30], and neural network approaches.

Segmentation methods can be classified into two categories: semi-automatic [11,12] and fully automatic segmentation [13,14]. Interactive image segmentation methods provide efficient control to user on the segmentation process and have received much attention in recent years.

Snakes and Balloons [15, 16, 17, 28] have been widely used. The basic principle underlying deformable models was introduced by Kass et al. [15]. The user specifies an initial contour, which is subsequently deformed based on image-derived criteria (such as energy), assuming that the contour at a minimum global energy should match with the desired boundary. However, active contours have three major difficulties: initialization, parameterization and topological flexibility. Topology Adaptive Snakes – T-snakes – [29] adapt the initial active contour to the object topology and allow the simultaneous detection of multiple objects. Although T-snakes deal with the initialization and topology problems, the internal parameters have to be defined a priori by trial-and-error for specific shapes. To determine suitable parameters, most works use local geometry [26, 27], initial constraints, deformable templates, statistical estimations and multi-resolution approaches. The main limitation of the former approach is the quality of the edge detection. The technique presented at [26] does not work in the presence of gaps.

Active Appearance Models introduced by Cootes et al. [7, 31, 32] are statistical models describing an object’s shape and image texture. For both shape and gray values, an average and a series of eigenvectors is computed, from which the modes of variation of the model are determined. When matching the model to an unseen image, the object contours are localized by minimizing the error between the model and the image, within the boundaries of statistically plausible deformations of the model.

McDonald and Sheehan [33] introduced a method using boosted decision trees for pixel classification based on feature images, containing geometry features and gray-level statistics of a sequence of images.

Methods based on dynamic programming (DP) use graph searching strategy to find object boundary. A new paradigm named Live-Wire (LW) for boundary segmentation was presented at [18, 19, 20]. Several methods have been proposed to improve the Live-Wire segmentation. Udupa et al. [8] reduced the user interaction time through two-dimensional dynamic programming. Ying et al. [21] combined region-growing with live-wire to acquire a better performance in very noise images. Falcão et al. [22] used the previously published live-wire framework with a substantially faster shortest-path algorithm for improve the speed. Mortensen et al. [19] extended the live-wire method and introduced the intelligent scissors. The technique is intuitive and can be applied to black-and-white or color images of arbitrary
complexity. These algorithms attempt to overcome the problems associated with using only local information for edge segmentation.

Edge-based segmentations provide the localization of the region boundaries, but the contours are only based on local computations, and are very often sensitive to local variations in intensity, noise and physical artifacts. In interactive methods, problems like these fatigue the user and require many interventions at the contour delineation process. To reduce these problems, we propose the addition of two new features in the LW method. The first feature is based on region information. The second one is based on distance information [23, 24, 25].

We have developed an interactive segmentation method with two specific aims: 1) to detect the left ventricle edges with minimal user assistance, and with precision and accuracy; 2) to reduce the direct influence of artifacts and noise on the segmentation results.

The paper is organized as follows. In Section II, we review the live-wire method. Section III describes our approach. Section IV presents the experimental results. Finally, we present the conclusions in Section V.

We follow the steps outlined below when submitting your manuscript to the IEEE Computer Society Press. This style guide now has several important modifications (for example, you are no longer warned against the use of sellotape to attach your artwork to the paper), so all authors should read this new version.

2. Live-Wire paradigm

Live-Wire algorithms belong to a well known class of user-steered image segmentation methods. These algorithms require manual initialization and depend on the specification of characteristic points by the user. A typical LW algorithm contains three parts: user interaction, cost map calculation and graph searching. The user initially picks a point on the boundary and all possible minimum-cost paths from this point to all other points in the image are computed. A “live” contour is shown in real time to the user through the cursor movement and it is fixed when another point is selected. From this last one, a new minimum-cost way to another point is calculated again. This process is repeated until the object contour has been obtained.

2.1. Cost map

The cost map is a matrix with image size dimensions, which assesses the degree of membership of the pixels to the edges in image. In traditional live-wire method, the cost map has features such as spatial operators, frequency operators, template operators, multi-scaled functions, and so on. Some of these features are used in the proposed approach: maximum intensity \( f_1(p,q) \), minimal intensity \( f_2(p,q) \) and the difference between intensities \( f_3(p,q) \) (gradient’s magnitude), where \( p \) is any pixel of the image and \( q \) is one of the 4-neighborhood pixels from \( p \).

The features \( f_1 \), \( f_2 \) and \( f_3 \) are normalized in the interval between 0 and 1, through the Gaussian function \( g(f_i) \). The final cost function is calculated by:

\[
c(p, q) = w_1 g(f_1) + w_2 g(f_2) + w_3 g(f_3),
\]

where the weights \( w_1, w_2, w_3 \) can be selected empirically under the condition that \( w_1 + w_2 + w_3 = 1 \) be satisfied for the final cost function to remain normalized. The value of \( w_i, i= 0,1,2,3,...n \), is the importance level of the \( f_i \) feature for the cost function. The Figure 1 shows the region of interest (ROI), i.e., the LV from a MR image and the cost images obtained with \( f_1, f_2, f_3 \) and \( c(p,q) \).
3. Region-based live-wire

The purpose of the present approach is to bring in region and distance information into live-wire paradigm. Cardiac images have complex background, diversity, noise and physical artifacts (papillary muscles), so it is often that pieces of the contour present blurring and be poorly and weakly defined. To deal with this problem, we introduce two new features into LW: region intensity and proximity information. Region-based segmentation is less susceptible to noise, and if the high frequency information is either missing, or unreliable, the segmentation remains relatively unaffected.

3.1. Region information

Region-based methods partition an image in homogeneous regions for a given set of properties. We choose to use an intensity measure to characterize the myocardium’s region. The intensity measure repels the attraction to noise pixels during the graph searching. It will favor pixels in regions that have a homogeneous intensity across them similar to myocardium one.

Initially, a template \( T \), representing the approximated LV contour, is obtained to be used for the cost map calculation. The template can be generated by manual tracing or some automatic method. The intensity region-based cost for each pixel \( p \) in the whole image is defined as:

\[
f_4(p) = |m - r(p)|
\]

where \( r(p) \) is the average over the 8-neighborhood from \( p \), and \( m \) is the average intensity over all pixels inside \( T \). This is an useful measure, since it assigns low values for pixels located in regions with similar intensity to myocardium region. The Figure 2 shows the cost image for this feature.

![Figure 2: Cost image of the region-based feature.](image)

3.2. Proximity information

The distance transform computes the distance from a point to an object, i.e., to a set of pixels [23, 24, 25]. The distance from a point to the object contour is the smallest distance from the point to any point of the object contour. The advantages of this feature are twofold: First, it improves the final cost function, and second, it defines a region search for the LW algorithm.

The algorithm for the distance transform calculation works on the binary input image from the template \( T \) and creates an output gray-level image \( DM \) (distance map) as follows:

a) the distances between all points inside a digital ball of radius \( R \) centered at a given contour point on \( T \) are calculated:

\[
DM(p) = \sqrt{x^2 + y^2} \leq R
\]

where \( x \) and \( y \) are the pixel coordinates on the Cartesian plane. It was used the Euclidean metric.

b) the calculated distances are sorted in increasing order, the repeated distances are eliminated, and the respective relative positions of the points for each specific distance are recorded.

The distance map has low cost values next to the boundary and high cost values as it moves away from the object contour, attracting the “live” contour as much as possible to the object’s contour. The cost function based on the distance transform is defined as:

\[
f_5(p) = \frac{(DM + 1)}{D_{max}},
\]

where \( D_{max} \) is the major value of the \( DM \).

It is important to point out that as we perform the segmentation of the image sequence, \( T \) becomes each time more inefficient. Thus, we need to re-create another \( T \) at each 5 images and redo the process to obtain a new distance map. This is important because the LV is a non-rigid structure and its contour deforms in time. This would not be necessary for rigid structures. The number of images after which it must redo the template \( T \) depends on the deformation level. The Figure 3 shows the distance map for a template image and Figure 4 presents the region of search extracted from the distance map, i.e., the distance cost map. Dark pixels have low cost values. The two new features are added in Equation 1 as:

\[
c(p, q) = W_1 g_1(f_1) + W_2 g_2(f_2) + W_3 g_3(f_3) + W_4 g_4(f_4) + W_5 g_5(f_5)
\]

The ideal cost function, i.e., the ideal \( c(p, q) \) should have low values at the pixels on the desired contour, and high values elsewhere (inside and outside the contour). This is accomplished by the two new features, since the region feature provides low values inside the contour, and high values outside. The distance feature provides low values.
only for pixels nearest the contour, and gradually higher values as the distance from the contour becomes higher in both direction: from the contour to inside the object, and from the contour to the object outside. In addition, the distance transform in our approach defines the search region, since it is possible to set a high cost value for all pixels with distance larger than an assigned threshold. The Figure 5 shows the final cost image \( c(p,q) \). As can be observed, after the introduction of the proximity feature, the cost values inside the contour were increase and the cost values on the contour remain reduced, approaching the ideal case.

Figure 3: Distance map of a contour template.

Figure 4: Region of search and cost image extracted from the distance map.

4. Experimental results

In this Section, we present the experimental results on real images of the LV to demonstrate the proposed method. An initial point must be specified by the user and, in addition, values of the parameters used in the algorithm are defined on empirical observations, which seems to be a widely used strategy [16,17,18].

The Figure 6 depicts representative results for the myocardial boundaries onto short-axis images. A total of 254 images from end-dyastole and end-systole were analyzed.

Figure 5: Cost image representing the union of the region-based feature with the distance feature.

The estimated boundaries in myocardium images were consistent with that reported in the literature. In particular, for very noise images, where contours are hard to detect, the proposed method performed consistently and the interaction process was made more agile.

We have used as our efficiency measure the segmentation speed and the number of interventions that the user needs to do to produce the correct contour. To validate the effectiveness of the proposed approach, the method was compared with the traditional live-wire. The segmentation speed \( VS \) is the number of images segmented per minute
\[
VS = \frac{1}{t},
\]
where \( t \) is the time spent to segment one image. The segmentation repeatability \( RS \) indicates how many times the user in average had to intervene during the delineation process. The Table 1 shows the user intervention reduction rate for the segmentation using the proposed approach related to the traditional live-wire method.

The traditional LW described in Section 2 presents a major drawback when dealing with poorly defined boundaries: it is sensitive to the blurry region. Our approach, however, do work at this situation, as shown in Figure 7.

<table>
<thead>
<tr>
<th></th>
<th>Traditional live-wire</th>
<th>Proposed approach</th>
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<tbody>
<tr>
<td>velocity</td>
<td>4.34</td>
<td>5.12</td>
</tr>
<tr>
<td>repeatability</td>
<td>10.51</td>
<td>7.6</td>
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Table 1: Results for the segmentation using the traditional live-wire and the proposed approach.
5. Conclusions

In this paper we have introduced an approach to the problem of the segmentation of the left ventricular wall of the heart. The method uses the previously published live-wire framework, and extends it introducing two new features to improve and to turn the process more agile, requiring less user interaction. We made use of the distance transformation and the effectiveness of the region approach in images characterized by noise and artifacts.

References


