LEARNING-BASED SEGMENTATION OF THE WHOLE BREAST IN CT IMAGE FOR RADIOTHERAPY

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ABSTRACT
Automatic segmentation of the whole breast in CT image is an essential task for treatment planning in breast cancer radiotherapy. Current procedure requires extensive manual contouring of the critical organs like breast, heart etc., which is time-consuming and subjective. Automatic breast segmentation is a hard problem due to the inhomogeneity of the breast tissue, large shape variation, abnormalities due to cancer and subtle differences with surrounding tissues. In this paper, we use learned local image features from training data to guide the contour deformation in a level-set framework. We further constrain the segmentation by detecting the lateral and medial boundary of the breast using HOG based detector. The effectiveness of the proposed method has been demonstrated by the experiments on 30 clinical patient data.

Index Terms— Breast Segmentation, Learning-based, Radiotherapy

1. INTRODUCTION
Accurate and consistent delineation of the targets and organs at risk (OARs) is critical for treatment planning in radiotherapy (RT). For the breast radiotherapy, whole breast is the target volume that need to be delineated before the treatment planning. Currently, this task is manually done by physicians slice by slice. The procedure is not only time-consuming but more importantly not consistent among different physicians. Hurkmans et al. [1] found that there are large variations of the delineated whole breast among intra- and interobserver. With the aim to automate the breast radiotherapy procedure, we have developed methods for automated beam placement for whole breast radiotherapy [2] based on the manual delineated targets and OARs. In this paper, we propose an automated whole breast segmentation method.

For similar problem, Reed et al. [3] used image based deformable registration to map the whole breast from a template to a new image. However, authors did not give examples to demonstrate this method can be successfully applied to images that are significantly different from the template image, especially considering the large variation of the shape of the breast among patients. Godley et al. [4] used a similar method but also applied to chest wall, heart and nodal regions. Ortiz et al. [5] proposed a hybrid method to segment the breast in MRI image. It is based on 3D local edge detection and Poisson surface reconstruction followed by an atlas-based shape refinement. Since MRI has different characteristics compared with CT image, this method cannot be directly applied to our problem. There are works [6, 7] on classifying breast tissue into different categories e.g., fibro-glandular vs. fatty tissue or tumor. Here, we aim to segment the whole breast including fibro-glandular, fatty tissue and tumor.

In this paper, we propose a learning-based segmentation method to automatically segment the whole breast in the CT image in a slice-by-slice manner. As shown in Fig. 1(d), we consider the whole breast contour in each image slice as the region enclosed by the inner contour (between breast and chest wall), the outer contour (between breast and air), and the lateral and medial end points. The outer contour can be easily found by simply thresholding. Determining the inner contour is a hard problem as there is only subtle differences between fibro-glandular tissue and the muscle near the chest wall. We propose to deform an initial contour, the convex hull of the chest wall, to the inner contour position. Probability distributions of local image features of points on the inner contour of the breast are first learned from a set of manually segmented training images. A probability map indicating the probability that a certain pixel belongs to the inner boundary is estimated to guide the contour deformation in the Geodesic Active Contour (GAC) framework. Since there is no clear boundary at the lateral and medial of the breast, we build two detectors to find these two end points based on the local appearance of the image. The final segmentation of the breast is the region enclosed by the inner contour, the outer contour and detected lateral and medial end points. Results of intermediate steps are shown in Fig. (1).

2. PRE-PROCESSING AND INITIALIZATION
The planning CT images are of size $512 \times 512 \times N$, where $N$ is the number of slices, usually around $80 - 120$. The outer contour of the breast that contacts with the air can be easily delineated by simple thresholding. For the inner contour of the breast, chest wall defined by ribs and sternum can be used as good initialization due to their steady shape and high contrast...
where \( \phi \) of the low contrast between the breast tissue and muscles near the chest wall. The weak edge between breast and muscle is overwhelmed by the strong edge between chest wall and lung. The contour would deform towards the lung instead of the desired boundary if we use the \( g(\cdot) \) function defined in (2).

### 3. LOCAL IMAGE FEATURES DRIVEN CONTOUR DEFORMATION

#### 3.1. Geodesic Active Contour

GAC is a boundary-based segmentation method whose basic idea is to find a minimum-length curve measured in a weighted space induced from the image \([9]\). Let \( C(s) \) represents a curve parameterized by the length \( s \) along the curve, so that \( C(s) \) indicates the \((x, y)\) coordinate of a point in the curve at the length \( s \) from the starting point. The functional associated with the curve \( C \) to be minimized is defined as

\[
E(C) = \int_0^{L(C)} g(C(s))ds
\]

where \( g(\cdot) \) is a decreasing function of image gradient. Ideally, the evolving contour should stop at the location where the gradient is large. A common choice of \( g \) is an edge indicator function

\[
g(x) = \frac{1}{1 + |\nabla G_\sigma(x) \ast I(x)|^2}
\]

where \( G_\sigma \) is the Gaussian filter with standard deviation \( \sigma \), \( I \) is the image. The associated curve evolution equation in the level-set formulation \([9]\) is

\[
\phi_t(x) = |\nabla \phi(x)| (\text{div} (g(x) \frac{\phi(x)}{|\nabla \phi(x)|}))
\]

where \( \phi \) is the level-set function of the contour \( C \).

GAC cannot be directly applied in our problem because of the low contrast between the breast tissue and muscles near chest wall. A connected component analysis is applied to remove small structures smaller than 30 pixels. Convex hull \([8]\) of the extracted bone structure is used as the initial contour (green contour in Fig 1(b)). Note that, although this initial contour is closed to the inner contour between breast and the chest wall, muscle attached on the chest wall should be excluded from the breast.

#### 3.2. Contour Deformation Based on Learned Probability distributions of Local Image Features

A boundary indicator map \( h(\cdot) \) is defined over the image which is inversely proportional to the probability of points lying on the boundary between breast and chest wall. We use the learned probability distributions of the local image features from the training images to derive probability of each point belonging to the boundary. In the training phase, a set of points along the manually delineated contour are uniformly sampled. A set of local features was computed at each point using a square local image patch. Given a point \( x = (x, y) \), its intensity \( I \) and the gradient \( g = (g_x, g_y) \), we compute the local mean image intensity \((I_{\text{int}})\), local mean intensity inside \((I_{\text{in}})\) and outside \((I_{\text{out}})\) of the contour, local variance \((\sigma)\), and also the inward contour norm vector \( \vec{N} \). Regions inside and outside of the contour are defined based on the current contour location as shown in Fig. 1(c). The overall feature vector is defined as: \( F = (I_{\text{int}}, I_{\text{out}}, \log(I_{\text{int}}/I_{\text{out}}), I_{\text{in}}, \sigma, g \cdot \vec{N}) \), where \( g \cdot \vec{N} \) is the magnitude of the gradient projected on the inward contour norm vector.

Denote the probability of a point with a feature vector \( F \) to be a boundary point as \( p(F) \) and assume that features are independent so that \( p(F) = \prod_i p_i(F_i) \), where \( n \) is the number of local features \((n = 6 \text{ in our case})\). Kernel density estimation is used to estimate \( p(F_i) \) based on the th feature of training samples. Specifically, we assume \( p(F_i) = \frac{1}{N} \sum_{k=1}^N K_\sigma(F_i - F_i^k) \), \( i = 1 \cdots n \), where \( N \) is the total number of boundary points, \( K_\sigma(\cdot) \) is Gaussian kernel function and the bandwidth \( \sigma_i \) is estimated from the th feature of samples. The boundary indicator map \( h(\cdot) \) is related to the probability map by

\[
h(F(x)) = -\log(p(F(x))) = -\sum_1^n \log p_i(F_i(x))
\]

where \( F(x) \) indicates the feature vector at pixel \( x \).
The energy function to be minimized is defined as

\[ E(C) = \int_0^{L(C)} h(F(C(s)))ds \] (5)

We use the same curve evolution equation given in (3), with \( g(\cdot) \) replaced by \( h(\cdot) \) to iteratively deform an initial contour until it converges. During the deformation, \( h(F(x)) \) is updated after each iteration in a narrow band of the current contour position, as the contour deformation is only affected by \( h(F(x)) \) that is near the current contour.

4. DETECTION OF THE LATERAL AND MEDIAL BOUNDARY OF THE BREAST

The deformed contour from the previous section gives only the boundary between breast and chest wall. The lateral and medial boundary points of the breast need to be determined in order to get a closed contour of the breast. Histogram of Oriented Gradient (HOG) detector [10] is used to detect these two end points. To build HOG detector, image patches surrounding the manually selected points in the training image are used as positive samples, while random picked image patches from the remaining regions of the image are used as negative samples. Calculated HOG descriptors of positive and negative samples are fed into a Support Vector Machine (SVM) to build the detector. Two detectors are trained separately for two boundary points. To detect the lateral point, a test image is scanned using a sliding window from left to right and top to bottom over a defined search range. The location with the largest decision value is considered as the lateral point. We used a multiresolution search over the search region to reduce the complexity. A similar procedure is used to detect the medial boundary point. Let \( \Omega \) be the image domain, \( T \) be the region enclosed by the deformed inner contour, \( B \) be the region enclosed by the outer contour of the body, \( (x_L, y_L) \) and \( (x_M, y_M) \) be the detected lateral and medial end points. The final segmentation of the breast is defined as \( S = (\Omega \setminus T) \cap B \setminus \{(x, y) : y > y_L\} \cap \{(x, y) : x < x_M\} \), where \( \Omega \setminus T \) indicates the complement of \( T \), or the region outside \( T \). In our notation, \( x \) and \( y \) indicate the horizontal and vertical positions of a pixel, with origin at the top left corner of the image, and increasing to the right and below. Fig.1(d) demonstrates contours that enclose the final segmentation \( S \).

5. EXPERIMENTAL RESULTS

30 clinical data are used in this study. 20 are used to learn local image features, while the remaining 10 are used as testing data. For each of the total 952 image slices in the 20 training data that contains the manual breast contour, \( N = 10 \) points are sampled along the inner contour of the manually delineated breast segmentation. The size of the image patch that is used to compute the local image features is chosen as 7 by 7. For the boundary points detection, the same training data is used to build the detectors. A total number of 640 positive samples and 3200 negative samples are used for building the lateral point detector, and 867 positive samples and 4335 negative samples are used for the medial point detection.

To evaluate the proposed automated segmentation method, we compute the average distance from points on the manual contour to the automated segmented boundary on each image slice. More specifically, for each point on the inner boundary of the manual contour, we compute the nearest distance to the automated segmentation, and then take the average as the distance error for that slice. Results are shown as box plot in Fig.2, in which 1-20 are training data, and 21-30 are testing data. The upper and lower edges of the blue box are the 25th and 75th percentiles among all slices in the same dataset. Red line is the median value. The whiskers extend to the maximal and minimal data points. The median distance of all datasets is 2.3mm. Note that, instead of calculating the distance for all points in the entire closed breast contour, we only measure the average distance of points along the inner contour of the breast, since this part is what matters most for the treatment planning. The distance of the whole breast contour would be much smaller, since the delineation of the outer contour is more accurate. From Fig.2, the segmentation results of testing data have similar distance error compared with training data, although data #23 have a large median error around 8mm. By looking into data #23, we found the error mainly occurs in the superior slices of the breast, where our method includes some muscle that was spared by physician. A representative slice is shown in Fig.3(d). Similar case appears in data #22 and #28. This is probably due to the small capture range of the GAC based method. The deformed contour stops at a local minimum instead of moving forward to the location that is far from the initial contour (e.g. Fig.3(d)).

Dice’s coefficient \( s = \frac{2|X \cap Y|}{|X| + |Y|} \) is also computed, where \( X \) is the manual segmented volume and \( Y \) is the automated segmented volume in our case. Overlapping ratios of manual and automated segmentation defined as \( \frac{|X \cap Y|}{|X|} \) and \( \frac{|X \cap Y|}{|Y|} \), respectively, are also measured. Table 1 shows the proposed algorithm has similar performance for training data and testing data, as previously demonstrated using the distance criterion. Segmentation by proposed method covers majority of the manual segmentation and have extra coverage of the lateral and medial part of the breast in most cases (as in Fig.3). By adjusting the training samples of lateral and medial points detectors, we expect higher Dice’s coefficient can be achieved.

| Data     | Dice  | \( \frac{|X \cap Y|}{|X|} \) | \( \frac{|X \cap Y|}{|Y|} \) |
|----------|-------|-----------------------------|-----------------------------|
| Training | 0.87  | 0.94                        | 0.81                        |
| Testing  | 0.87  | 0.92                        | 0.83                        |

6. DISCUSSION AND CONCLUSIONS

With a median distance error of 2.3mm, a Dice’s coefficient of 0.87 and a coverage of 0.92 of the manual segmentation, proposed method mimics the segmentation by physician quite well. For comparison, [5] has a comparable median distance of 2.7mm at the inner contour of the breast and a Dice’s co-
efficient of 0.88 (vs. 2.3 mm and 0.87 in our case) in MRI image. Although the distance error of 1.3 mm and Dice’s coefficient of 0.94 are reported in [3], it need to be pointed out that those numbers are computed using the physician-edited segmentation as the “ground truth”, which is generated using the automated segmentation result as the start. Therefore there is bias towards auto-segmentation result, whereas in our setup, the “ground truth” is pre-defined by physician on the “raw” CT image.

The proposed method for automated whole breast segmentation is an essential component towards fully automated treatment planning for breast radiotherapy. Future work includes improving results for the superior slices of the breast, and applying similar methodology to segmenting other targets and organs at risk (e.g. heart, lung) that are needed in breast radiotherapy.

7. REFERENCES


