Fully Automated Segmentation of the Pectoralis Muscle Boundary in Breast MR Images

Lei Wang\textsuperscript{a}, Konstantinos Filippatos\textsuperscript{b}, Ola Friman\textsuperscript{a}, Horst K. Hahn\textsuperscript{a}

\textsuperscript{a}Fraunhofer MEVIS - Institute for Medical Image Computing, Bremen, Germany; \textsuperscript{b}MeVis Medical Solutions AG, Bremen, Germany

ABSTRACT

Dynamic Contrast Enhanced MRI (DCE-MRI) of the breast is emerging as a novel tool for early tumor detection and diagnosis. The segmentation of the structures in breast DCE-MR images, such as the nipple, the breast-air boundary and the pectoralis muscle, serves as a fundamental step for further computer assisted diagnosis (CAD) applications, e.g. breast density analysis. Moreover, the previous clinical studies show that the distance between the posterior breast lesions and the pectoralis muscle can be used to assess the extent of the disease. To enable automatic quantification of the distance from a breast tumor to the pectoralis muscle, a precise delineation of the pectoralis muscle boundary is required. We present a fully automatic segmentation method based on the second derivative information represented by the Hessian matrix. The voxels proximal to the pectoralis muscle boundary exhibit roughly the same Eigen value patterns as a sheet-like object in 3D, which can be enhanced and segmented by a Hessian-based sheetness filter. A vector-based connected component filter is then utilized such that only the pectoralis muscle is preserved by extracting the largest connected component. The proposed method was evaluated quantitatively with a test data set which includes 30 breast MR images by measuring the average distances between the segmented boundary and the annotated surfaces in two ground truth sets, and the statistics showed that the mean distance was 1.434 mm with the standard deviation of 0.4661 mm, which shows great potential for integration of the approach in the clinical routine.

Keywords: pectoralis muscle segmentation, breast-chest boundary segmentation, breast MR imaging

1. INTRODUCTION

Breast cancer is the most commonly diagnosed cancer disease among women and a major cause of death. X-ray mammography is conventionally used for screening and diagnosis of breast cancer. However, due to its well-known limitations in the cases of imaging dense or postoperative breasts, Dynamic Contrast Enhanced breast MRI (DCE-MRI or breast MRI more generally) is regarded as an invaluable complementary tool because of its high sensitivity in detecting and characterizing breast tumors.\textsuperscript{1} The Breast Imaging Reporting and Data System (Bi-RADS) was developed by the American College of Radiologists as a standard to rate the level of suspicion of breast MR findings.\textsuperscript{2} In this reporting system, not only the characterization of lesions is included, but also their position and distance to other relevant anatomical structures such as the nipples, the skin and the pectoralis muscle. The distance between posterior breast masses and pectoralis muscle can be used to assess the extent of the disease in patients suspected to have tumor invasion into the underlying muscle.\textsuperscript{3} To automatically report this distance, a precise delineation of the boundary surface of the pectoralis muscle is required. However, the large variation of anatomical detail and different imaging protocols, such as axial, sagittal or coronal acquisition, make the segmentation problem challenging.

Several methods have been proposed for segmenting breast MR images, where the identification of breast-chest boundary serves as a subtask. Nie et al. suggested a B-spline curve fitting method to exclude the chest wall muscle from breast region.\textsuperscript{4} Wang et al. proposed a threshold-based level set algorithm to determine the initial contour between chest and breast.\textsuperscript{5} Lu et al. located breast-chest walls with a dynamic search process.\textsuperscript{6} Ertas et al. introduced a segmentation approach to extract the breast region from pre-contrast MR images by applying cellular neural networks.\textsuperscript{7} However, these methods are not dedicated to segment the pectoralis muscle.
and precisely identify its surface. Besides, the quantitative evaluation of the segmented surface of the pectoralis muscle is not presented in these works.

In this work, we propose a practical and general-purpose approach for detecting and segmenting the pectoralis muscle boundary on the basis of the Hessian matrix. The approach is partially inspired by the work of Sato et al., Frangi et al., and Descoteaux et al., who used Hessian-based filter for segmenting tube-like structures.

2. METHODS

Hessian-based filters have been widely employed to analyze the local structures of 3D images. The relation between the Eigen values of the Hessian matrix helps to differentiate several specific geometrical structures of a 3D image, such as blob-like, tube-like or sheet-like objects. In this work, the pectoralis muscle boundary to be segmented in the 3D breast MR images is a dark step-edge structure (see Fig. 1(a)) rather than a pure manifold plane. Applying a second derivative Hessian-based sheetness filter results in a zero-crossing at exactly the boundary edge, meanwhile negative (on breast) and positive (on pectoralis) side-lobes on each side of the boundary, where the Eigen values with maximal magnitudes possess opposite signs and roughly equal quantity (see Fig. 1(b)). However, considering the fact that the voxels in the positive side-lobe, which can be adequately close to the boundary by carefully setting the scale of the filter, exhibit roughly the same Eigen value patterns as the ones in a sheet-like object, these boundary-proximal voxels can still be enhanced and segmented by defining a sheetness filter like what people did to segment sheet-like structures.

2.1 Hessian-based Sheetness Filter

Descoteaux et al. proposed a sheetness measure used for enhancing bone structures. Each voxel was given a score ranging from 0 to 1, representing the likelihood that it is located in a sheet-like surrounding neighborhood. Three ratios, $R_{\text{sheet}}$, $R_{\text{blob}}$, $R_{\text{noise}}$ were designed in their work to highlight sheet-like structures, eliminate blob-like and noisy structures and slightly preserve the tube-like structures. In this work, we focus on enhancing sheet-like structures and eliminating all other structures. Hence, we choose a somewhat different and simplified measure constructed by two ratios, whose behavior is investigated as in Table 1.

Table 1. Theoretical properties of the ratios defined for the sheetness measure assuming the Eigenvalues sorted in $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|

<table>
<thead>
<tr>
<th>Defined ratios</th>
<th>sheet-like</th>
<th>tube-like</th>
<th>blob-like</th>
<th>noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{\text{sheet}} =</td>
<td>\lambda_2</td>
<td>/</td>
<td>\lambda_1</td>
<td>$</td>
</tr>
<tr>
<td>$R_{\text{noise}} = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}$</td>
<td>$\lambda_1$</td>
<td>$\sqrt{2}\lambda_1$</td>
<td>$\sqrt{3}\lambda_1$</td>
<td>0</td>
</tr>
</tbody>
</table>

Ultimately, with the help of these two ratios, we define the sheetness measure:

$$S = \left\{ \begin{array}{ll} 0, & \text{if } \lambda_1 = 0, \\
\exp\left(-\frac{R_{\text{sheet}}^2}{2\alpha^2}\right) \left(1 - \exp\left(-\frac{R_{\text{noise}}^2}{2\beta^2}\right)\right), & \text{otherwise}, \end{array} \right. \quad (1)$$

where the parameters $\alpha$ and $\beta$ control the sensitivity of each ratio to the measure. As suggested, in this work, $\alpha$ and $\beta$ are set to 0.5 and half of the maximum $R_{\text{noise}}$ respectively. The sheetness measure $S$ is scaled from 0 to 1. More specifically, its maximum will theoretically be assigned to the sheet-like local structures and all other structures will be scored with low scores.

2.2 Segmentation Work Flow

The segmentation work flow comprises four key steps, preprocessing, detecting the region of interest (ROI) of the pectoralis muscle, enhancing and segmenting the pectoralis muscle, and extracting and refining the pectoralis muscle boundary. The parameters of all used filters were tested to be robust and fixed.
Figure 1. The segmentation work flow. (a) A representative image slice indicating the breast-air boundary and the pectoralis muscle boundary (by white arrows), and the gradient directions of their example voxels labeled by red and green arrows respectively. (b) Response of the sheetness filter with positive and negative side lobes on each side of boundary edge. (c) Erase the negative side-lobe. (d) Threshold the sheetness score. (e) Remove the breast-air boundary. (f) Extract the main part of pectoralis muscle using connected component filter. (g) Generate a mask (ROI) through the main part of pectoralis muscle. (h) Apply the sheetness filter within ROI and threshold the scores followed by a vector-based connected component filter. (i) Extract the boundary contour of the pectoralis muscle and stretch it to the corners (in red) overlaid with input image.
2.2.1 Preprocessing
To reduce the computational efforts and compute the Hessian matrix in a fixed scale for all input images, the input images are resampled subject to an isotropic voxel spacing $2.5\text{mm} \times 2.5\text{mm} \times 2.5\text{mm}$. The scale of the second order derivative of a Gaussian kernel, which is used for computing the Hessian matrix, is set to be $2.5\text{mm}$ such that after applying the sheetness filter, the positive side-lobe lying on the pectoralis would adequately close to the boundary. The negative side-lobe generated by the sheetness filter can be easily erased by explicitly constraining the sign of the Eigen values with maximal magnitude to be positive (see Fig. 1(c)).

2.2.2 Detecting the region of interest (ROI)
After assigning and thresholding the sheetness scores with a threshold value 0.6, only the highly enhanced structures, such as breast-air and pectoralis muscle boundaries, are left (see Fig. 1(d)). The exclusion of the breast-air boundary is essential, because it will be enhanced by the sheetness even stronger than the pectoralis muscle boundary, which confounds the connected component filter to select the breast-air boundary as the largest component (see Fig. 1(d)). Notice that most voxels proximal to the breast-air boundary and the pectoralis muscle boundary possess roughly opposite gradient directions (see Fig. 1(a)). Hence, we conduct a gradient direction filtering process by selecting the voxels whose gradient directions point roughly from image top to bottom (indicated by green arrows in Fig. 1(a)). Here, the scale parameter of the first derivative Gaussian kernel used to compute gradient vector is set to be $2.5\text{mm}$. Consequently, most parts of the breast-air boundary are eliminated, whereas a few parts of pectoralis muscle are also jeopardized (see Fig. 1(e)). Afterwards, a 3D connected component filter is applied, and the main parts of the pectoralis muscle are extracted by selecting the largest component (see Fig. 1(f)). Even though the extracted main parts are incomplete due to the filtering process of gradient directions, they reveal the coarse location of the pectoralis muscle and can be used to generate a mask image that labels the ROI of the pectoralis muscle (see Fig. 1(g)).

2.2.3 Enhancing and segmenting the pectoralis muscle
Once the ROI of the pectoralis muscle is identified, the designed sheetness filter scores each voxel again inside the ROI with a value scaling from 0 to 1. A sheetness-score-threshold is set to be 0.5 in this step, which has been tested to be robust through a large number of experiments. Usually, some unwanted sheet-like anatomical structures, such as the boundaries of the lung in thorax and the splitting planes between the arm and body, are enclosed in the ROI and thus enhanced by the Hessian-based filter as well. To eliminate them, a 3D vector-based connected component filter is exploited to investigate both the geometrical connectivity and the consistency of the Eigen-directions of the segmented objects. Voxels with acute alteration of the vector direction are regarded as isolated and excluded. Here, the uniformed Eigen vector associated with the largest Eigen value is examined in the filter, and the distance threshold is set to be 0.1, which means the two neighbor voxels will be determined to be connected if the dot production of their Eigen vectors is larger than 0.9. Finally, the largest connected component with maximal number of voxels is selected as shown in Fig. 1(h).

2.2.4 Extracting and refining the pectoralis muscle boundary
Firstly, the holes or gaps of the segmented object are filled and bridged by a connection cost filter followed by a morphological closing filter with scale of $3 \times 3 \times 3$ both for dilation and erosion. To fetch a neat and complete pectoralis muscle boundary, we employ a surrounding filter to obtain the outer contours of the segmented object. To extend the resulted outer contour to the image corners, two nearest points on the contour to the bottom-left and bottom-right corners are searched out respectively (see Fig. 1(h)), and they are linked to the corresponding corners by drawing two line segments. Finally, the segmented boundary contour overlaid with the original image is demonstrated in Fig. 1(i).

3. RESULTS AND EVALUATIONS
The breast DCE-MR images were acquired in three acquisition protocols, T1-weighted coronal, T1-weighted axial, and T2-weighted axial. The test data set includes 30 independent non-fat suppressed MR images (none were used during algorithm development) acquired from 30 different female patients, 10 from each imaging protocol. The method operated on pre-contrast breast DCE-MR images, and the processing time for the image
with maximum resolution ($512 \times 512 \times 70$) was about 12 seconds using a 3.07 GHz Intel CPU and a GeForce gtx285 graphics card.

To evaluate the method quantitatively, two ground truth sets were built for the test set as shown in Fig. 2(a)(c). The pectoralis muscle boundaries were manually annotated by two independent radiologists, such that the inter-observer variation could be maximally decreased. The radiologists annotated every 2 to 8 slices depending on the available slice number to make sure that at least 15 equally distributed slices were annotated for each image as shown in Fig. 2(b)(d). To precisely evaluate how well the segmented boundary surface (see Fig. 2(f)) matched the ground truth contours, especially in the parts of the pectoralis muscle, the distance between the points on the ground truth contours and their corresponding paired points on the segmented pectoralis contours (Fig. 2(e)) was measured. For each point on the ground truth contour, its paired point on the segmented pectoralis contour was defined as the one with the least distance to it. The sum distance was computed over all these point pairs for all slices that have been annotated in the ground truth. Ultimately, the average distance was calculated by dividing the sum distance with the count of the point pairs.

Table 2 lists the sum distances, the counts of the point pairs, the average distances, and the imaging protocols for all 30 images in the test data set. Considering the voxel space, all the distances were given in millimeter and measured twice for both databases of the ground truth. From the table, it can be observed that the maximal average distance between the ground truth contours and the segmented surfaces was 2.471 mm, whereas the minimum was 0.546 mm. The mean value of all average distances measured for both ground truth datasets was
1.434 mm, and the standard deviation was 0.4661 mm. The aberration has no clinical significance when measuring the distance from the posterior breast lesions to the pectoralis muscle. The segmentation task becomes more challenging for the extreme dense breasts, because the large amounts of breast parenchymas can be very close to the pectoralis muscle and exhibit approximately the same intensity level. The vector-based connected component filter can prevent the segmented pectoralis muscle boundary from passing the boundary of the breast parenchymas by constraining the acute variations of the vector directions. Figure 3 gives some successful segmentations for extreme dense breasts in different imaging protocols. To further demonstrate the performance of our approach in clinical application, two more boundary surfaces of the segmented pectoralis muscles selected from the test data set are visualized in 3D as shown in Fig. 4, where the silhouettes of the breast tissues and the lesion masses are rendered, and the distances from the lesion masses to the pectoralis muscle surfaces are measured and presented as well.

Figure 4. Two example visualizations of the segmented surfaces of the pectoralis muscle (red plane) and the lesion masses (yellow entities) overlaid with the silhouettes of the breast tissues. The distances from the lesion masses to the pectoralis muscle surfaces are measured and presented with yellow line segments.
4. CONCLUSIONS AND DISCUSSIONS

In this work a novel step-wise method to segment the pectoral muscle boundary is presented. The method is fully automatic without the requirements of the prior information and tuning parameters. The proposed method is based on exploring the second derivative information of the 3D image interpreted by the Hessian matrix. The voxels proximal to the pectoralis muscle boundary exhibit roughly the same Eigen value patterns as a sheet-like object in 3D, which can be enhanced and segmented by a specially designed Hessian-based sheetness filter. By applying the filter within a detected ROI which excludes the breast-air boundary and thresholding the filter response, the most significant sheet-like structures, e.g., the pectoralis muscle boundaries, are preserved. To erase some unwanted enhanced structures inside the thoracic cavity, a vector-based connected component filter is applied. In the refinement stage, the completely connected contours of the pectoralis muscle boundary are identified. The proposed method was tested with a test set including 30 breast DCE-MR images with variant degrees of difficulties and alterations acquired in three imaging protocols. Two radiologists manually annotated the test images independently and built two data sets of the ground truth. The method was quantitatively evaluated by measuring the average distances between the segmented boundary surface and the annotated surfaces in each ground truth, and the statistics showed that its mean value was 1.434 mm with the standard deviation of 0.4661 mm. The quantitative validation shows a great potential for integration of the approach in the clinical routine, and is to be integrated in a commercial product.
REFERENCES


