An Automatic Template-based Breast Segmentation Method for Fat-suppressed MRI

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Background and purpose:

Breast segmentation in MRI is a required step for developing automatic computer-aided diagnosis (CAD) systems for detection of suspicious lesions; also it is needed for quantitative measurement of breast density by differentiating between fibroglandular tissue and fatty tissue within the breast. Manual segmentation can be easily implemented, but it is time consuming thus impractical; also the results may be operator-dependent and inconsistent. Two types of breast MR images are commonly acquired: fat-suppressed (fat-sat) and non-fat-suppressed (non-fat-sat). The non-fat-sat image shows a greater tissue contrast between dense(dark) and fatty(bright) tissues, thus it is easier for density segmentation. However, fat-sat images are commonly used for cancer detection, and they can also be used for density measurement by using properly optimized segmentation algorithms. Template-based registration provides a feasible means for automatic breast segmentation. This can be done using the breast as the template, but due to the high variations of body and breast shapes, usually several different templates are needed for choosing the most appropriate one to achieve satisfactory results. Another strategy is to use the chest region (including the lung and the heart) as the template. Most women have similar chest regions that can be detected at similar locations in breast MR scans. In this study we report an automatic chest template-based breast segmentation method for segmentation of the breast and fibroglandular tissue on breast MRI. A rigorous evaluation of segmentation accuracy was also performed.

Methods:

Breast MRI from 20 healthy volunteers from 45 to 63 years old were analyzed. **Fig.1** shows the generation of the chest-template. By using a randomly selected subject, the chest region template was manually outlined along the posterior chest wall muscle and the outer boundary of the lung. In order to make the registration focus within the chest region, a cropped bounding box covering the thoracic region is applied as the input for registration. Three body landmarks, the thoracic spine and the lateral margin of the bilateral pectoralis muscles (the highlighted points in **Fig.1**) are manually identified on the template. **Fig.2** shows the procedures to identify the chest region in a subject based on registration. After the chest template is deformed to match the subject, the deformed location of the three landmarks are used to perform the V-shape cut, which is a necessary step to determine the posterior lateral boundary of the bilateral breasts [1]. The procedures include: 1) A bias field correction algorithm, N3+FCM [2], is employed to remove intensity inhomogeneity. 2) A fuzzy c-means (FCM) clustering algorithm is used to detect the lung region based on its low intensity and central location. 3) The subject's chest region image is smoothed using a Caussian kernel followed by the FCM clustering algorithm to ensure the robustness of non-rigid registration. 4) The demons algorithm [3] is applied to register the template chest region image with the subject's chest region image, and then the deformed chest template (the green contour in **Fig.2a**) is excluded to obtain the segmented breast (**Fig.2b**). 5) The chest wall muscle and breast skin (the greening points in **Fig.2b**) is extracted based on Canny edge detection algorithm and Bezier curve fitting. 6) The final breast area on this image is obtained after the exclusion of chest wall muscle and skin. The segmentation will start from one middle slice. After it is done the deformed chest model for the nth slice is then served as the chest template for the n-1th slice and n+1th slice, and the process continues to all neighboring slices in the superior and inferior direction. After the breast segmentation is completed on all imaging slices, N3+FCM is used for bias field correction and FCM is used to segment fibroglandular tissue within the breast, by using a total of 6 clusters, 3 for dense and 3 for fatty tissues.

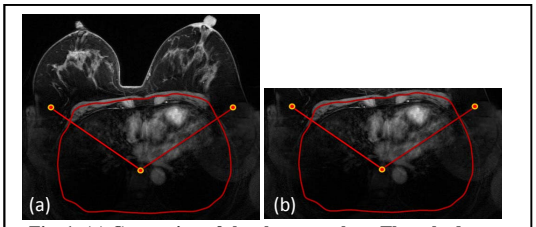

Fig. 1: (a) Generation of the chest template. Three body landmarks are used to perform the V-shape cut to define the posterior-lateral boundary of the breast. (b) The cropped bounding box to focus the registration on the chest region.

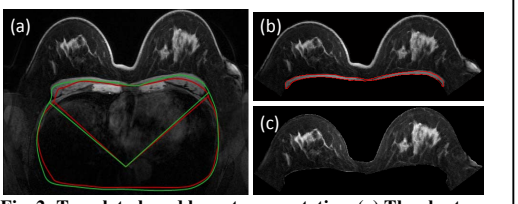

Fig. 2: Template-based breast segmentation. (a) The chest template (red) is deformed to match the subject's chest (green). Based on the deformed 3 landmarks, the v-shape cut is done. (b) The chest wall muscle is extracted using model fitting. (c) Final segmented breast after muscle exclusion.

Fig. 3: Three examples of breast and fibroglandular tissue segmentation, (a) low; (b) moderate; (c) extreme dense breasts. The green color shows the breast; red color for dense tissue.

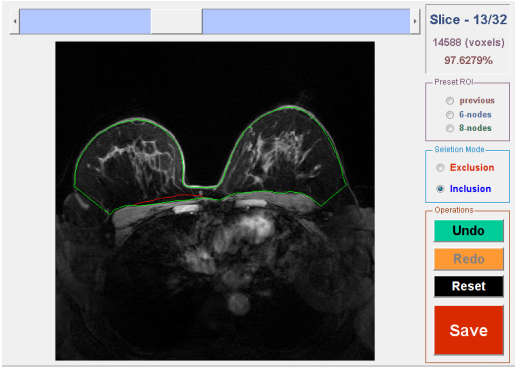

Fig. 4: The GUI program for evaluating segmentation accuracy. The operator can mark areas that need to be included or excluded. Red is the original contour that wrongly excludes some fat near the chest all, and green is the modified contour.

Results:

Figure 3 shows the segmentation results of 3 different cases with fatty breast (very low density), moderate dense breast, and extreme dense breast. It can be seen that the V-shape cut can be successfully performed to define the posterior-lateral boundary of the breast without excluding any fibroglandular tissue. The muscle detection method based on curve fitting is able to produce a smooth contour of breast, and to exclude all chest wall muscle satisfactorily while preserving the fibroglandular tissues near the chest wall (in **Fig.3b** and **Fig.3c**). A correction program using graphical user interface was developed for evaluation of segmentation accuracy, shown in **Fig.4**. For tissues that should be included but are wrongly excluded, it is assigned as exclusion error. For tissues that should be excluded but are wrongly included, it is categorized as inclusion error. Table 1 shows the mean volume from the 20 healthy volunteers and the error analysis results. One major breast segmentation error is associated with wrong inclusion of chest wall muscle, and one major fibroglandular tissue segmentation error is the wrong tissue exclusion near the chest wall.

Table 1: Evaluation of the Segmentation Accuracy and Source of Error

	Total Volume(cc)	Exclusion error volume(cc)	Inclusion error volume(cc)	Total Error %
Breast	954 ± 409	11.3 ± 10.5	42.2 ± 23.2	5.4% ± 1.4%
Fibro Tissue	137.9 ± 68.5	2.94 ± 2.68	1.13 ± 1.24	2.7% ± 1.9%

Discussion:

In this work we presented an automatic template-based breast segmentation method for fat-sat MR images. The program is robust with a mean error of 5.4% for breast segmentation, and 2.7% error for fibroglandular tissue segmentation. The program is very easy to use and requires minimal operator training. A robust, automatic, and reliable breast segmentation tool would contribute in the development of CAD for cancer diagnosis, as well as for analysis of breast density in large multi-center studies to build risk prediction models for personalized risk management.

References: [1] Nie et al. Med Phys 2008; 35:5253-62. [2] Lin et al. Med Phys 2011; 38:5-14. [3] Thirion Med Imag Anal 1998; 2:243-60.