BREAST DELINEATION USING ACTIVE CONTOURS TO FACILITATE COREGISTRATION OF SERIAL MRI STUDIES FOR THERAPY RESPONSE EVALUATION

Rupa Chittineni, Min-Ying Su, Orhan Nalcioglu

Department of Electrical Engineering and Computer Science and Tu and Yuen Center for Functional Onco-Imaging, University of California, Irvine, 92697

ABSTRACT

MRI is the most accurate imaging modality to monitor response of breast cancer undergoing neoadjuvant chemotherapy, by comparing the tumor volume measured in follow up MRI, taken during the course of therapy, to its baseline value. Due to the deformable nature of the breast, its' shape in MR acquisitions taken in different studies varies significantly. If these images can be co-registered, the location of lesion in each study can be matched. Breast MR images collected often include large areas outside the breast, such as the thoracic region and surrounding air, which may pose a hindrance to registration algorithms. In this paper, we describe a segmentation algorithm to delineate the breast region from the chest by using the invariant, rigid structure such as the chest, as opposed to the use of varying breast outlines employed in currently available solutions. This ensures robustness and reproducibility of our algorithm.

Index Terms— Segmentation, contour, registration, biomedical, MRI

1. INTRODUCTION

MRI is now recognized as the most sensitive imaging modality for breast cancer and in many cases has been shown to provide more clarity in clinical situations where dense breasts are not imaged well with routine mammography or ultrasounds [1, 2, 3, 4]. Another use of MR imaging techniques is as a monitoring device. Neoadjuvant chemotherapy is fast gaining popularity as an important part of breast-cancer treatment and management [5, 6, 7, 8, 9]. The goal of neoadjuvant chemotherapy is to down-stage cancers to render them operable and/or to facilitate breast conservation surgery. If therapy failure can be predicted early, it can be aborted to spare the patient from ineffective treatment and the associated morbidity, and also to allow an earlier switch to the next effective regimen. MRI has been proven as the most accurate imaging modality to predict residual tumor size [8, 9]. When residual diseases were still visible, they may be easily detected by visual examination. Comparing the volume of tumor measured in follow up MRI taken during the course of therapy to its baseline may provide the most accurate assessment for determining response. However, when the tumor starts to disappear, it may be difficult to establish its previous location and hence enhanced tissues due to treatment induced mastitis developed at the adjacent normal breast tissues may be mis-diagnosed as residual cancer. Co-registration of the baseline images to the follow-up study would allow the location of the previous tumor site to be correctly identified, and that would allow accurate evaluation of response, either by visual assessment or by computer-aided analysis. Due to the highly deformable nature of the breast, the shape of breasts may change a lot between different studies. These deformations or changes may also be attributed to different positioning of the patient (e.g. different body or arm position, or different padding) or natural aesthetic changes that occur over a period of time. Figure 1 shows the baseline MR images of two patients and their corresponding follow-up images each taken approximately 2-4 weeks apart. As is obvious, the shapes of the breast in each follow up image is quite different from the baseline. Dedicated breast coils are used in the scanning. However, as seen in the figure 1, extraneous regions such as the thoracic region are also captured. This unnecessary information poses a problem to the alignment routine. Besides the additional overhead in terms of computation cost, the registration itself may be compromised due to the need for alignment along all possible outlines on the image. Surrounding air captured during acquisition may also contribute to low visual clarity or low contrast around breast boundary. Hence, before embarking on alignment and registration of the various images, it would be wiser to eliminate or segregate the breast region from the thorax to aid the efficiency of registration algorithms. This paper describes an algorithm to segment the breast region from the chest, thus ensuring that registration algorithms are not working overtime to accommodate both the rigid and non-rigid structures in breast MR images thereby inducing large volume changes that are unacceptable. Section 2 describes the breast extraction algorithm. Section 3 discusses the results obtained, their quantitative analysis and application in registration algorithms for evaluating neoadjuvant chemotherapy response. Section 4 summarizes our findings and opens avenues for future directions in this field.

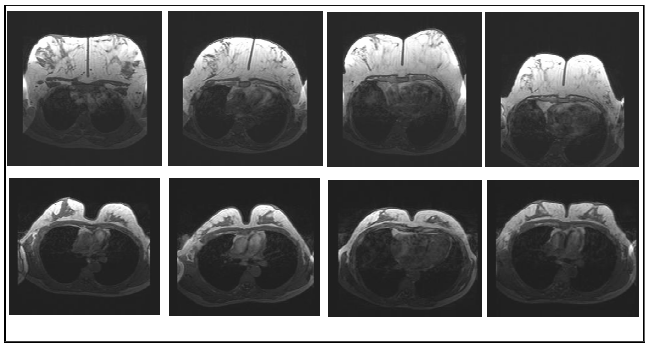

Fig 1: Baseline (column 1) and 3 follow-up MR images (column 2, 3, 4) of two patients undergoing neoadjuvant chemotherapy, depicting variations in breast shape, between studies.

2. BREAST DELINEATION FOR REGISTRATION ACCURACY

There are numerous algorithms that address the issue of segmenting breast-air and breast-chest [10, 11, 12, 13] boundary. Breast-air segmentation is trivial as there is sharp rise in MR signal intensity when traversing the images from the air region to the breast. A simple high-pass filter could highlight this boundary (figure 3b), thus segmenting the breast from the air region.

Breast-chest segmentation is a challenging problem. Literature suggests some solutions to address this problem, but each relies on providing an initial estimate of the boundaries through user interaction along the breast-chest edge, and then applying algorithms to refine them by eliminating discontinuities and ensuring smoothness. This method may not always be effective, especially when there is fat-suppression and intensity representations of breast parenchyma almost merge with intensity representations of the thoracic region, especially the heart. In [11], the author uses morphological tools to trace an initial boundary. By extracting the curvature extrema (left axilla, mid-sternum and right axilla) from each slice and joining them by straight lines, he obtains his first initial estimate. As is obvious, this technique may fail to locate the mid-sternum in our test case, i.e. row 1 of figure 1. A search for a more robust method for breast-chest segmentation led us to explore techniques that allow us to crop out the heart and chest region instead. The chest region is a rigid structure and it is safe to assume that its location and shape would remain consistent in each breast MR acquisition.

In our implementation, we apply a discrete dynamic contour model [14] to the high-pass filtered image generated after applying the breast-air segmentation step. An initial contour is provided by the user. This contour need not trace out the boundaries of chest wall. A simple closed curve in the center of the thoracic cavity would suffice. Our algorithm pulls the contour towards the highest gradient points along the outward radial direction (figure 3c). These points are fitted with a b-splines representation to ensure smoothness and continuity. To address the problem of the contour terminating at false boundaries, due to the presence of noise, we enforce a constant pressure on the spline. This force, called the balloon force ensures that when contour progression encounters an independent gradient pixel, it surpasses it to stop only at strong edges. The smoothness constraint inherent in the B-splines ensures a smooth boundary. Finally all regions that lie within this contour are removed by applying a point-in-polygon test. The resultant image boundary is back-projected onto the source image. At this step, our source image is transformed to a form shown in figure 3 (d). To further separate the breast from the hollow chest, we obtain an estimate of the breast width and height from the breast-air boundary and use it to compute the final image. This is essentially the bounding box of the breast. Figures 3 and 4 depict the steps involved in our implementation, pictorially.

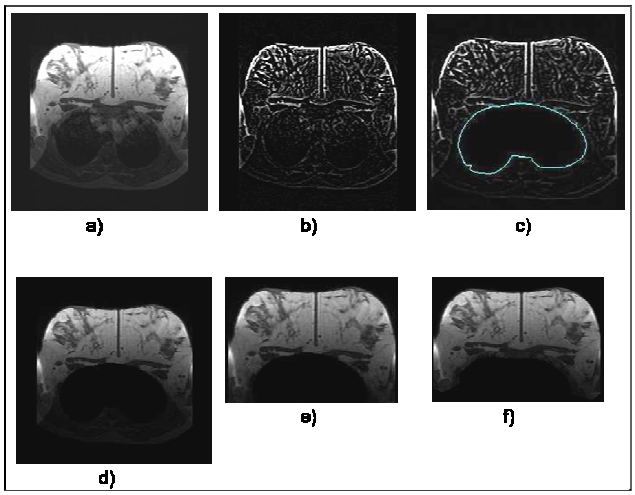

Fig 3: Breast delineation process, test_case_1: a)source image, b)gradient image, c)discrete dynamic contour encapsulating the heart, d) back-projection of subtraction image onto source image, e) breast ROI using our algorithm, f) breast ROI using manual method.

Having thus obtained the breast region-of-interest (ROI), we use it as input to our registration algorithm. The algorithm described above is applied to 2D slices. For extracting breast ROI from 3D data, the above process may be applied repetitively over each slice. A segmentation of the images into left and right breast may be done to further aid the registration process as explained in the next section.

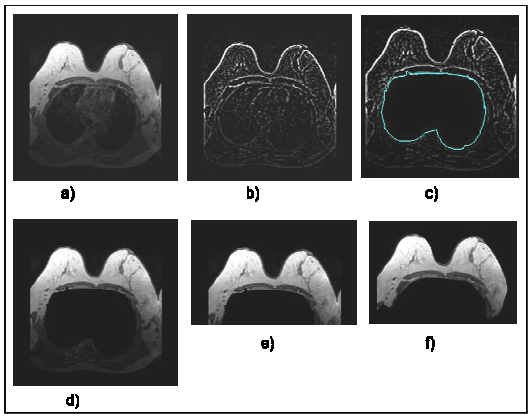

Fig 4: Breast delineation process, test_case_2: Breast delineation process, test_case_1: a)source image, b)gradient image, c)discrete dynamic contour encapsulating the heart, d) back-projection of subtraction image onto source image, e) breast ROI using our algorithm, f) breast ROI using manual method.

3. RESULTS, ANALYSIS AND VALIDATION

Figures 3e and 4e show the results obtained from our algorithm for two test cases. The source images were acquired on a 1.5 tesla MR system. Our algorithm was tested against 10 breast MR images, each varying in size and shape. To explain the relevance of our region delineation routine, a sample registration of baseline and follow-up MR images using segmented breast images is shown in figure 5. The segmented breast images from B/L and F/U were registered using our non-rigid registration algorithm [15]. A description of the registration algorithm is beyond the scope of this paper, but a brief explanation of the results is provided to understand the importance of the breast extraction algorithm.

Figure 5, first row shows the subtraction of pre-contrast and post-contrast MR images for capturing the tumor location (tumor visible as a bright spot). The first column corresponds to the baseline (B/L) MR image. The second column refers to the first follow up (F/U) MR images conducted 35 days later. The third column corresponds to third follow-up MR image taken 6 months from the baseline acquisition. There are no visible malignant regions in the 3rd follow-up image. A comparison of the images in the first row shows that the patient is responding very well to the particular chemotherapy drugs. Tumors marked with crosshairs are corresponding ones. But this is not evident in the superimposed images shown in row 3. The enhanced regions in the follow-up images of first row could be due to mastitis. To prove otherwise and/or provide an accurate analysis of the follow-up images, it is necessary to establish the exact location of baseline tumors within F/U MR images. A one-one correspondence is established using our registration algorithm [15]. The warped follow-up images are shown in row 2. A superimposition of follow-up with the B/L image is shown in row 4. It may be noted that the crosshairs are now exactly overlapping, indicating that the tumor visible in F/U-1 is indeed the same as seen in B/L image. Comparing the tumor volumes in B/L and F/U volumes show that the patient is responding to chemotherapy. F/U-3 shows no sign of malignant tumors at the location seen in B/L. This confirms the success of neoadjuvant chemotherapy.

The outlines of the breast overlap or lie very close to each other as is seen the magnified image of the highlighted region. If we attempted to apply our registration algorithm directly to the source breast MR images without prior segmentation, then the registration accuracy would be compromised. Significant volume changes would be induced to accommodate for greater correlation of the image features. This would result in an inaccurate estimation of tumor volume, which is the basis for assessing chemotherapy response.

To validate the results from our breast delineation algorithm we used qualitative and quantitative means. Qualitative validation was achieved by visually comparing the results with images from manual segmentation. For quantitative analysis, we compute the number of pixels in the breast ROI obtained from manual and our automated algorithm. A plot of the percentage error for 10 test cases is shown in figure 6. As can be seen, in most cases the error is less than 0.3%. The few variations that occur may be attributed to the fact that our algorithm takes into account the highest intensity gradient alone. This may sometimes lead the contour into false boundaries as is the case in figure 4.

4. CONCLUSION

We have developed an automated breast segmentation algorithm by employing an indirect analogy. By using non-deformable structures as the foundation of our algorithm, we developed a robust algorithm for segmenting and extracting breast ROI from breast MR images for varying shapes and sizes. The percentage error in all cases tested is less than 0.5%. We are currently improving our algorithm to address the segmentation issues relating to peripheral slices of the breast volume. These slices are characterized by lack of chest region and/or indistinct chest boundaries.

5. REFERENCES

[1] Esserman L et al, *"Utility of magnetic resonance imaging in the management of breast cancer: evidence for improved preoperative staging"*, Journal of Clinical Oncology, Vol 17, pp. 110-119, 1999.

[2] Boetes C et al, *"Breast tumors: comparative accuracy of MR imaging relative to mammography and US for demonstrating extent"*, Journal of Radiology, Vol 197, 197, 743-747, 1995.

[3] Kriege M. et al., *"Magnetic Resonance Imaging Screening Study Group. Efficacy of MRI and mammography for breast-cancer screening in women with a familial or genetic predisposition"*, New England Journal of Medicine, Vol. 351, pp. 427-437, 2004.

[4] Gilles R., et al, *"Locally advanced breast cancer: contrast-enhanced subtraction MR imaging of response to preoperative chemotherapy"*, Journal of Radiology, Vol. 191, pp. 633-638, 1994.

[5] Abraham D.C., et al., *"Evaluation of neoadjuvant chemotherapeutic response of locally advanced breast cancer by magnetic resonance imaging"*, Journal of Cancer, Vol. 78, pp. 91-100, 1996.

[6] Trecate G.et al., *"Locally advanced breast cancer treated with primary chemotherapy: comparison between magnetic imaging and pathologic evaluation of residual disease"*, Tumori: Journal of Experimental and Clinocal Oncology, Vol.85, pp. 220-228, 1999.

[7] Balu-Maestro C. et al, *"Imaging in evaluation of response to neoadjuvant breast cancer treatment benefits of MRI"*, Journal of Breast Cancer Research and Treatment, Vol. 72, pp.145-152, 2002.

[8] Rieber A. et al, *"Breast MRI for monitoring response of primary breast cancer to neo-adjuvant chemotherapy"*, European Journal of Radiology, Vol. 12, pp. 1711-1719, 2002.

[9] Martincich L. et al, *"Monitoring response to primary chemotherapy in breast cancer using dynamic contrast-enhanced magnetic resonance imaging"*, Journal of Breast Cancer Research and Treatment, Vol. 83, pp. 67-76, 2004.

[10] Li L. et al, *"Image Segmentation and 3D Visualization for MRI Mammography"*, Proceedings of SPIE, Medical Imaging, Vol. 4684, pp. 1780-1789, 2002.

[11] Yao J. et al, *"Classification and Calculation of Breast Fibroglandular Tissue Volume on SPGR Fat Suppressed MRI"*, Proceedings of SPIE, Medical Imaging, Vol 5747, pp. 1942-1949, 2005.

[12] Hayton P., M. Brady, L. Tarassenko and N. Moore, *"Analysis of dynamic MR Breast images using a model of contrast enhancement"*, Medical Image Analysis, Vol. 1(3), pp. 207-224, 1996/7.

[13] Wirth, M., A., R. Wang and A. Stapinski, *"An algorithm for extracting the skin surface in MR breast images"*, International Society of Magnetic Resonance in Medicine, 2003.

[14] Lobregt, S. and M.A. Viergever, "*A Discrete Dynamic Contour Model*," IEEE Transactions on Medical Imaging, Vol. 14(1), pp. 12-24, 1995.

[15] Chittineni R., M. Su, J. Chen and O. Nalcioglu, "*Volume-preserving co-registration of time-varying breast MR images for accurate tumor localization*", International Society of Magnetic Resonance in Medicine, 2007.

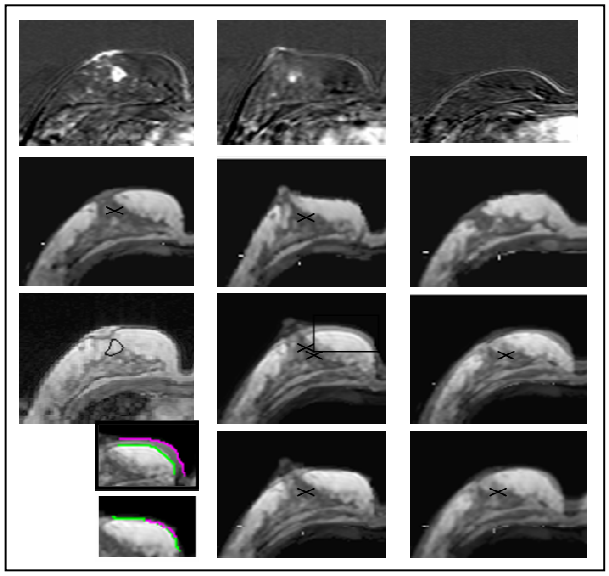

Fig 5: Registration of segmented breast MR images for assessing chemotherapy response

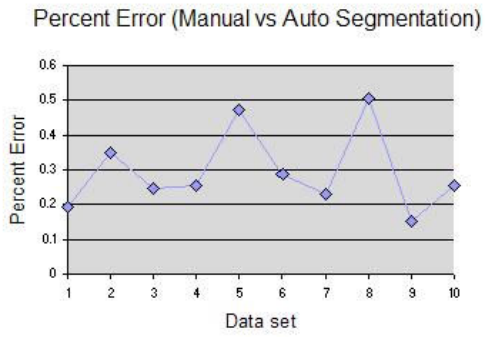

Fig 6: Percentage Error in Manual vs. Automated breast ROI extraction algorithms