

# **A robust breast segmentation method to support computer aided evaluation and breast density assessment**

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## **Introduction**

Advanced computer assisted image evaluation of breast cancer requires separation of breast tissues from other tissues and regions of the body, such as chest muscle, lungs, heart and ribs, that may confound image analysis. In addition, MR breast images generally have inhomogeneous signal intensities, together with partial volume effects at tissue or skin interfaces, that can compromise the performance of automated image processing methods used for tissue classification, patient motion correction or lesion localization. In this study, we aimed to develop a robust semi-automated algorithm for the segmentation of breast tissues.

## **Materials and Methods**

We have employed an algorithm based on bias corrected fuzzy c-mean clustering (BC-FCM) [1] is proposed. It performs morphological operations on the T1 weighted pre-contrast non-fat suppressed images slice-by-slice in consecutive stages: BC-FCM based thresholding, biggest object selection and hole filling. Results for each slice are stored to form a 3D object. This object is further processed by applying 3D morphological image opening followed by closing to determine the full breast extent. Finally, using the segmentation result for the slice in which the breast occupies the largest area is used to extract air-breast boundary curve. On this curve, the location of the local minimum between the two maximums (usually these are nipples locations) is computed and used to localize left and right breasts, separately.

To determine the performance of the automated segmentation, true positive volume fraction (TPVF) and false positive volume fraction (FPVF) are calculated based on the set of voxels within the breast region estimated by the automated segmentation and the set of voxels delineated by manual correction of the segmentation [2]. The value of TPVF ranges from 0 (no overlap) to 1 (complete overlap) while the value of FPVF is also bounded between 0 (no misclassified voxels) and 1 (total misclassification).

## **Results**

4351 pre-contrast images from 50 patients scanned in 13 clinics as a part of MARIBS study were used [3]. These images were acquired in the coronal plane with 1.33×1.33 mm<sup>2</sup> resolution in the x and y directions and 2.5 mm slice thickness with no gap. Patients were positioned prone with the breast to be imaged in gentle compression within dedicated breast coils.

The segmentation algorithm was implemented using IDL 7.0 (ITT Visual Information Solutions, USA). An example analysis for a patient is illustrated in Figs. 1a-e. The algorithm performed well with high average TPVF, and low FPVF with an overall performance of 0.97, and 0.04, respectively. At a TPVF threshold of 0.89, 94% of the breasts were segmented correctly. On the other hand, 6% of the breasts were misclassified at a FPVF threshold of 0.17 (Figs. 2a-b).

## **Discussion and Conclusion**

Breast anatomy on MR images is affected by intensity inhomogeneity and partial volume effects. In images acquired from different centres and scanners, there is considerable variation in the extent of these effects. Recent reported breast segmentation algorithms are designed to work on images acquired using a particular MR scanner [4-9] and are able to generate satisfactory results for certain patients (if the patient's chest is flat [4] and the axilla, midsternum and breast nipples are localized [7]) and for certain degrees of intensity inhomogeneity and partial volume artifacts [5, 6, 8, 9].

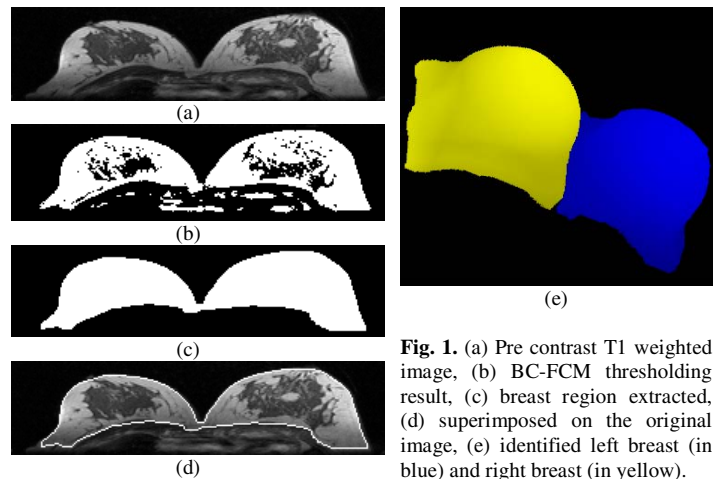
In this study, we introduce a segmentation approach that requires no prior information concerning breast anatomy and may minimize the impact of inhomogeneity, partial volume and scanner manufacturer. Statistical analysis on a large dataset shows that the segmentation technique is robust and performs very well on multi-centre data.

## **References**

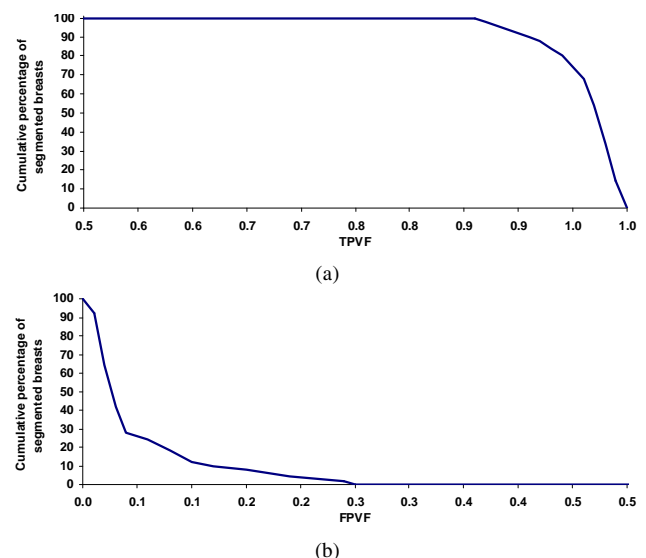
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**Fig. 1.** (a) Pre contrast T1 weighted image, (b) BC-FCM thresholding result, (c) breast region extracted, (d) superimposed on the original image, (e) identified left breast (in blue) and right breast (in yellow).



**Fig. 2.** Plots for cumulative percentage of the segmented breasts versus (a) TPVF and (b) FPVF