Automatic Segmentation of the Dense Tissue in Digital Mammograms for BIRADS Density Categorization

Delgermaa Demchig MD, Ziba Gandomkar MS, Patrick C. Brennan PhD

Medical Image Perception and Optimization Group (MIOPeG), Faculty of Health Sciences, University of Sydney, Sydney, NSW, Australia

Rationale

Currently, the Breast Imaging Reporting and Data System (BIRADS) density categorization is the most popular tool for density assessment among radiologists. However, it is subject to inter-observer variabilities. Therefore, different automated methods have been proposed for dense tissue segmentation. In [1], a technique based on modeling of breast tissue using a Gaussian mixture model was proposed to segment the fibroglandular tissue in digitized mammograms. We modified and extended this method to segment the dense tissue in digital mammograms and then classified them to different BIRADS density categories.

Methods

Three readers were asked to evaluate 150 craniocaudal (CC) digital mammograms and assign a BIRADS density score to each mammogram. The majority voting was used to determine the label of each image. Half of the cases were cancer-containing while rest of them were normal. The images were collected from nine different machines from seven manufacturers. The steps of the dense tissue segmentation are shown in Figure 1. Briefly, mammograms were filtered using a median filter and then the breast mask was found by thresholding. The mixture of Gaussian distributions was fitted to the grey-level histogram of breast tissue. The appropriate value for the number of components in the model was found iteratively. Finally, based on the fitted model, a threshold was selected to segment the dense area.

In order to find whether the percentage of dense tissue differed significantly among different BIRADS categories, the Kruskal-Wallis H-test was utilized. Pairwise comparisons between different categories were done using the rank-based Tukey-Kramer test.

We compared two different methods for classification of mammograms into four BIRADS categories. First, we thresholded the percentage density into four levels. The cut-off values for thresholding was found by grid search method. Second, we extracted 21 textural feature [2-4] and three first order statistical features (mean, standard deviation, skewness) from both fatty and dense tissues and fed these features, along with area of dense tissue, total breast area, and percentage density into an ensemble of decision trees for classification. The leave-one-out cross-validation was used to evaluate the method. The statistical analysis and implementation of the algorithm was performed in MATLAB environment.

Results

The percentage density differed significantly among different BIRADS categories ($\chi^2(3)$ =89.9, $p<0.0001$) and differences between all pairs were significant. The first method resulted in a correct classification rate (CCR) of 66.7% for predicting consensus of three radiologists' BI-RADS categories (BIRADS-I: 79.2%, BIRADS-II: 83.1%, BRADS-III: 31.3%, BRADS-IV: 52.2%) while the second method's CCR was 82.7% (BIRADS-I: 79.2%, BIRADS-II: 90.1%, BRADS-III: 75.0%, BRADS-IV: 73.9%). For two-category classification, where BIRADS-I was combined with BIRADS-II (low density) and BIRADS-III with BIRADS-IV (high density), CCRs were 90.0% (high: 95.8%, low: 80.0%) and 90.7% (high: 93.7%, low: 85.5%) respectively for method 1 and 2.

Conclusions

The proposed automatic method was able to predict radiologist-based BIRADS density categories by using both the percentage density with textural and intensity-based features. It can be hypothesized that radiologists consider both amount of dense tissue and tissue texture in density assessment.

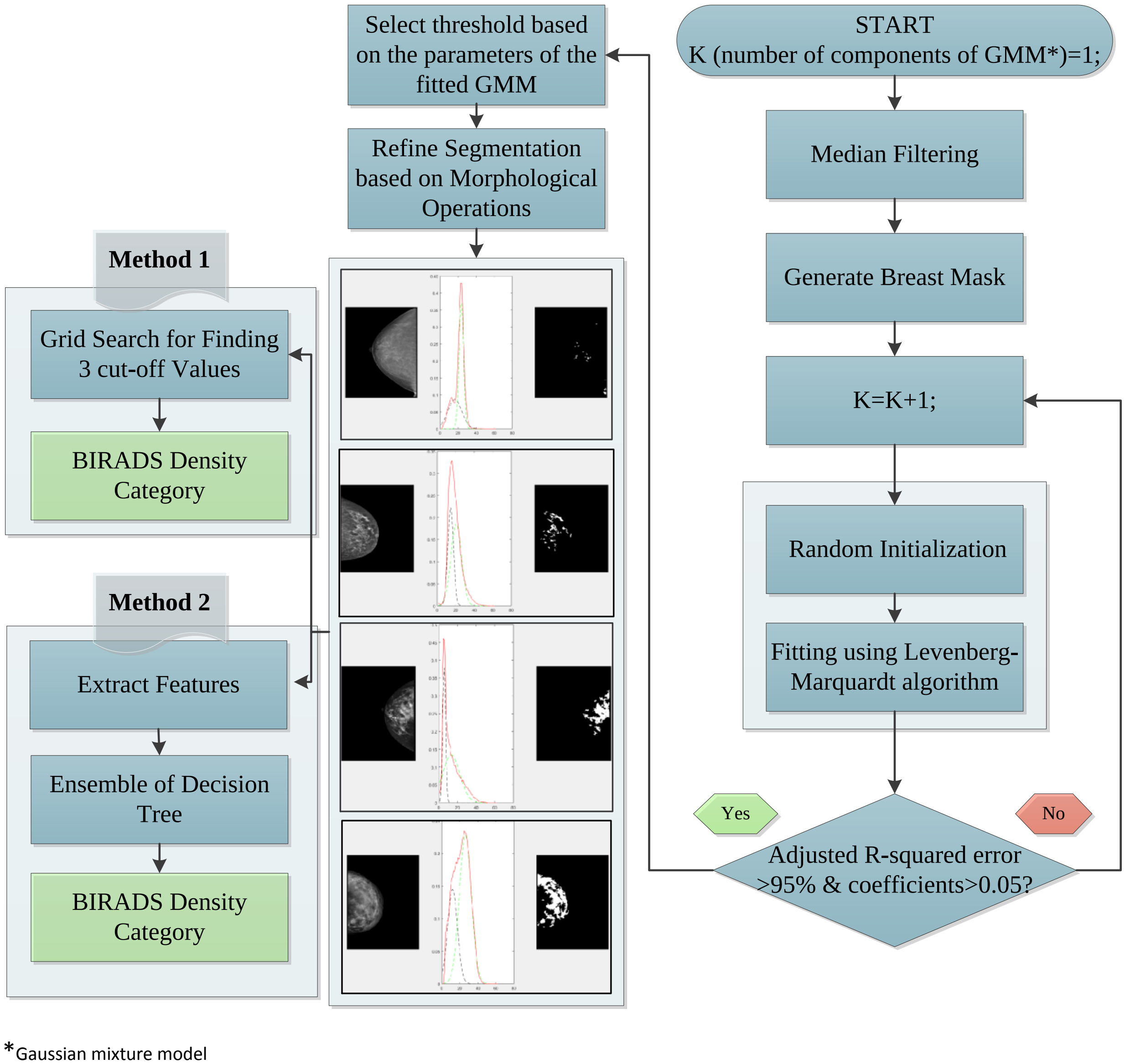

Figure 1- Steps of the proposed algorithm

References

[1] Ferrari, R. J., Rangayyan, R. M., Borges, R. A., & Frere, A. F. (2004). Segmentation of the fibro-glandular disc in mammograms using Gaussian mixture modeling. Medical and Biological Engineering and Computing, 42(3), 378-387.

[2] Haralick, R. M., & Shanmugam, K. (1973). Textural features for image classification. IEEE Transactions on systems, man, and cybernetics, 3(6), 610-621.

[3] Soh, L. K., & Tsatsoulis, C. (1999). Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices. IEEE Transactions on geoscience and remote sensing, 37(2), 780-795.

[4] Clausi, D. A. (2002). An analysis of co-occurrence texture statistics as a function of gray level quantization. Canadian Journal of remote sensing, 28(1), 45-62.