

Quantitative Morphology and Texture Analysis of Breast Parenchymal Pattern

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Purpose

Mammographic density is a well-established risk factor for breast cancer [1]. The density refers to the extent of fibroglandular tissue, the higher the percentage, the higher the cancer risk. A large cohort longitudinal study has demonstrated that women with increase density over time were associated with a higher cancer incidence [2]. The parenchymal patterns on mammogram were qualitatively characterized by Wolfe patterns or BI-RADS category of 1-4. However, these categories mainly reflected the extent of fibroglandular tissue, not the respective distribution of fat and fibroglandular tissue. Compared to the 2D projection view provided by mammogram, breast MRI acquires a 3D volume of uncompressed breasts, which may provide a more accurate information about parenchymal patterns. MRI has evolved from a research imaging tool to an established clinical modality for breast imaging. The American Cancer Society has issued a guideline recommending annual breast MRI screening for woman who has greater than 20-25% lifetime risk developing breast cancer. More and more women are expected to have MRI. As such, an analysis method that will be able to obtain reading of “percent fibroglandular density” and “fibroglandular/fat tissue composition texture” may provide very useful information for evaluating breast density. In this study we investigated the feasibility of using quantitative morphology/texture features analysis in differentiating three different breast fibroglandular or parenchymal patterns on MRI.

Methods

43 breast MRI studies acquired using a Phillips Eclipse 1.5T scanner were included in this study (Age 33-79 yo). Only the normal breast that did not harbor any abnormal findings was analyzed. Breast parenchymal patterns were visually categorized into three types by an experienced radiologist. Type-I: the breast is primarily composed of fat (N=10); Type II: the fat and fibroglandular tissues are intermixture together (N=15); and Type-III: fibroglandular tissue is inside surrounded by fat outside (N=18). Examples from these 3 categories are demonstrated in Fig. 1. These three cases did not have any abnormal findings. For analysis, the breast was first segmented using body landmarks as the initial step, followed by applying fuzzy C-means, dynamic searching algorithms and b-spline fitting. All imaging slices containing the fibroglandular tissue were identified, and only the middle 5 slices were selected for analysis. The fat/glandular composition texture was analyzed using 10 GLCM (energy, maximum probability, contrast, homogeneity, entropy, correlation, sum average, sum variance, difference average, and difference variance) and 14 LAWS' texture energy features. The texture parameters were compared among three groups with Typ1-I, II, and III patterns. Then the fibroglandular tissues were segmented using fuzzy C-means algorithm for analysis of 8 morphology parameters, including area, perimeter, NRL (Normalized Radial Length) Mean, NRL Entropy, NRL Ratio, Sphericity, Compactness, and Roughness. The detailed breast and fibroglandular tissue segmentation procedures are described in another abstract.

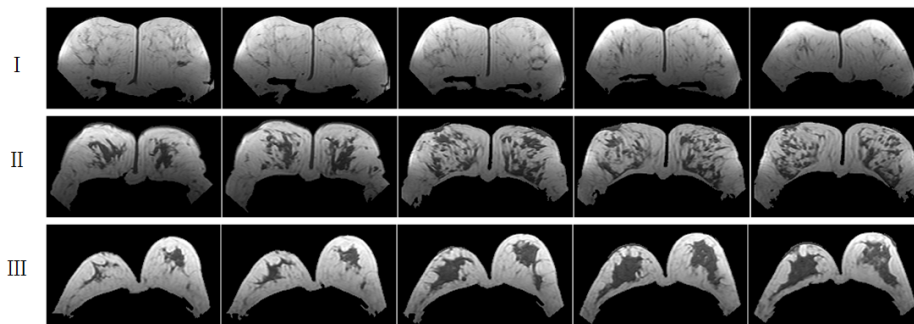


Figure 1: Three parenchymal patterns, I: mostly fat, II: intermingled, III: fibroglandular surrounded by fat.

Table 1: Comparison between Type-II & III patterns

Parameter	Mean ± Stand Deviation		% difference
	II	III	
Percentage	0.17±0.01	0.16±0.06	3.0%
Area	6.56±0.50	4.12±1.54	37.1%
Perimeter	3.30±0.72	1.45±0.36	56.0%
NRL_mean	0.47±0.10	0.34±0.03	27.9%
NRL_entropy	0.10±0.02	0.20±0.04	50.5%
NRL_ratio	0.19±0.03	0.25±0.05	22.6%
Circularity	2.17±0.32	1.55±0.26	28.4%
Compactness	36.4±10.4	9.94±1.31	72.7%
Entropy	7.2±0.07	7.72±0.11	7.1%
Energy	0.10±0.02	0.08±0.01	18.6%

Results

The texture properties including 10 GLCM and 14 LAWS' texture energy features were obtained for all 43 cases, and the difference between Type-I vs. II, I vs. III, and II v. III were analyzed. Except for the gray level sum mean and variance, all other GLCM and LAWS' features showed a significant difference ($p=0.03\sim 8E-6$) between Type-I vs. II or III, indicating that the extremely fatty Type-I could be easily identified using GLCM features. For differentiating between Type-II and III, only GLCM entropy and energy showed marginal significance ($p=0.02$), suggesting that texture features were not sensitive to differentiate between them. The morphology features calculated from the segmented tissues for Type II and III breast shown in Figure 1 are summarized in Table 1. The percentage density is 17% for Type II and 16% for Type III case examples (also listed in Table 1), very close only showing 3% difference. All 8 morphological features showed a greater difference, up to 72.7% difference for the compactness. The compactness was defined as the perimeter over the surface area, and that was the most sensitive parameter to differentiate between these two parenchymal patterns. For the extremely fatty Type-I, the segmentation of fibroglandular tissue is not reliable, not suitable for morphology feature analysis.

Discussion

In this study, we applied two sets of commonly analyzed texture features, GLCM and LAWS, to quantitatively characterize breast parenchymal patterns on MRI. In addition, morphological features from segmented fibroglandular tissues were also studied. One potential application of this study is to identify the association of computer extracted breast parenchymal patterns with breast cancer risk. The percent density shown on mammogram is a well-established risk factor; but the role of parenchymal pattern has not been reported, possibly due to the limitation of projection mammogram, not reliable for texture analysis. MRI provides tomographic images with tissue contrast for analyzing the parenchymal pattern. Our study demonstrated that women with a similar percent density may show distinctly different patterns, and the morphology of the segmented fibroglandular tissue may be used to quantitatively characterize the pattern. This provides the first step to evaluate the role of pattern parameters, and possibly to be built into a risk model in the future to better predict cancer risk. In turn, it may alert a woman and her physician to devise an individualized surveillance plan for early detection of breast cancer. The long-term goal of this research is to develop computerized radiographic markers for assessing breast density and parenchymal patterns, for determining the risk of breast cancer, also for assessing the efficacy of chemoprevention for risk reduction.

References: [1] Santen et al. *Endocr Relat Cancer*. 2007;14(2):169-87. [2] Boyd et al. *N Engl J Med*. 2007;356(3):227-36.

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