Differentiation between Intermingled and Central Type Breast Parenchymal Patterns Using Quantitative 3D Morphology and Texture Analysis on Segmented Dense Tissue

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Background and purpose:

Breast density is an established risk factor for developing breast cancer, yet it is still not clear about which parameter measured on which images have the highest predicting value. A recent study demonstrated that the fibroglandular tissue volume is a better predictor than the percent density that is normalized by the breast volume [1]. Also evidence suggests that the relative distribution of adipose and fibroglandular tissue (referred as breast parenchymal pattern in this work) is involved in cancer development [2-3]. The adipose tissue that is abundantly present around the ductal epithelium of the mammary gland may function as a slow-release depot for lipid-soluble carcinogenic agents. However, the link between parenchymal pattern and cancer risk has never been reported. It can be due to the fact that there is no appropriate method to analyze the distribution pattern. MRI provides 3D images of the breast, and that allows for the slice-by-slice segmentation of the fibroglandular tissue to facilitate the evaluation of breast parenchymal pattern. We have previously develop a quantitative analysis method to characterize the morphological distribution pattern of fibroglandular tissue segmented on MRI [4]. In this work, we further incorporated the texture parameters based on the internal distribution of the signal intensities to differentiate between two parenchymal patterns that were visually distinguishable.

Methods:

58 normal volunteers without any symptoms were included in this study. Each case was visually inspected by a radiologist to assign into Type-I: the intermingled pattern with mixed fatty and fibroglandular tissue, or Type-C: the central pattern with confined fibroglandular tissue surrounded by fat. This yields a total of 30 Type-C and 28 Type-I patients. The fibroglandular tissue was segmented on all images slices [5], and reconstructed as a 3D object. Then, three morphological parameters were computed as followed: **1) Circularity**, the ratio of the dense tissue inside a case-dependent sphere to the total dense tissue volume. The sphere position and size is determined and identical to the centroid and total volume of the dense tissue. **2) Convexity**, the volume ratio of the total dense tissue to the its minimum convex hull. **3) Irregularity**, the index which compares surface area ratio the total dense tissue to the effective sphere where the sphere volume is identical to the dense tissue (Fig. 1).

Texture analysis consisted of the coefficient variance (CV) of image intensity, and the gray-level co-occurrence matrix (GLCM) texture evaluation based on the segmented fibroglandular tissue. Intensity CV and ten GLCM texture parameters were calculated on every slice, and then the pixel-weighted average from all slices was calculated. The three most distinguishable texture parameters were determined by student t-test, based on the smallest p values. These three texture parameters were then combined with the three morphological parameters to differentiate between Type-I and Type-C.

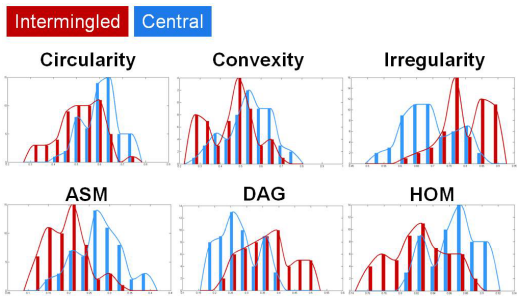

Figure 2: The histogram of the selected 6 quantitative 3D morphology (top row), and texture (bottom row) parameters between Type-I and Type-C cases.

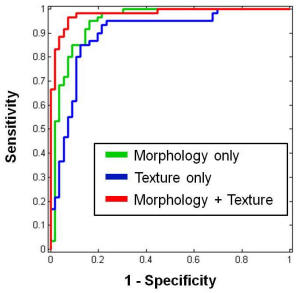

Fig. 3: ROC curves differentiating between Type-I and Type-C.

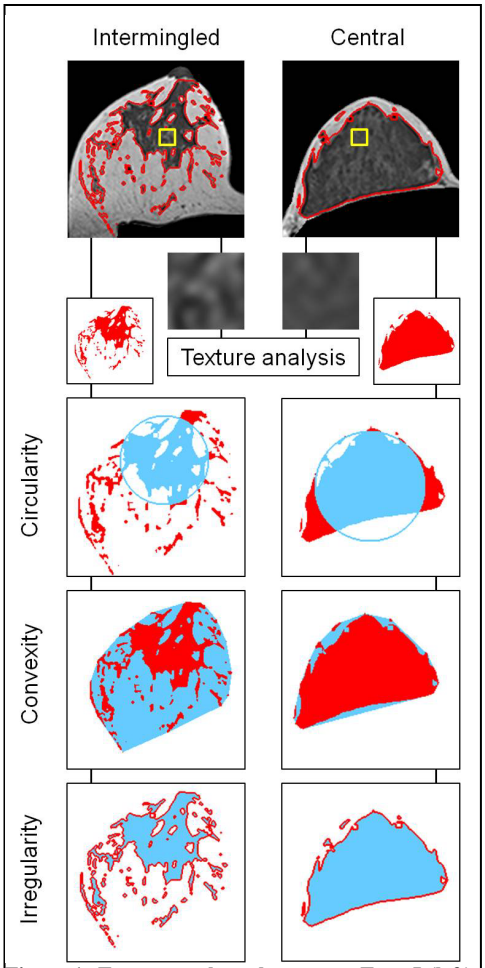

Figure 1: Two parenchymal patterns, Type-I (left): intermingled dense and fatty tissue, Type-C (right): confined fibroglandular tissue surrounded by fat.

Results:

The three selected texture parameters were energy (ASM), difference average (DAG), and homogeneity (HOM) representing the orderliness, descriptive contrast, and statistics property of GLCM, respectively. Fig. 2 shows the histogram of all 6 parameters in Type-C and Type-I. Fig. 3 shows the ROC analysis results by using the 3 morphology parameters, 3 texture parameters, and all 6 parameters combined. The area under the ROC curves of each individual parameter and combined parameter sets are summarized in Table 1. The combined parameters have a higher AUC than using the morphology or texture alone.

Table 1: The area under ROC curve (AUC) in differentiation between Type-I and Type-C.

Morphology	Circularity (CIRC)	0.75
	Convexity (COVX)	0.71
	Irregularity (IRGT)	0.87
	CIRC + COVX + IRGT	0.95
Texture	Homogeneity (HOM)	0.82
	Energy (ASM)	0.88
	Difference Average(DAG)	0.81
	HOM + ASM + DAG	0.90
Morphology + Texture		0.98

Discussion:

We present an improved quantitative analysis method by adding the texture to the morphological analysis to characterize the breast parenchymal patterns based on MRI. This method is constituted by three morphological parameters to depict the peripheral shape and roughness property, and three texture parameters to characterize the internal distribution of signal intensities by calculating the homogeneity and contrast within the image of the segmented fibroglandular tissue. The ability in differentiating Type-I and Type-C were evaluated using the ROC analysis, and the results showed that the addition of texture parameters could better distinguish these two parenchymal patterns. With this method available, we may investigate the role of the morphological distribution and the texture of fibroglandular tissue analyzed on MRI in prediction of the risk in developing breast cancer.

References: [1] Shepherd et al. Cancer Epidemiol Biomarkers Prev. 2011; 20(7):1473-82. [2] Schäffler et al. Nat Clin Pract Endocrinol Metab. 2007; 3(4):345-354. [3] Boyd et al. N Engl J Med. 2007; 356(3):227-236. [4] Nie et al. Med. Phys. 2010; 37(1):217-226. [5] Lin et al. Med. Phys. 2011; 38(1): 5-14.