A 3D Shape and Textural Classification Tool for Identifying Malignant Breast Cancer

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Introduction: The paucity of non-invasive tools with sufficient specificity to identify aggressive breast tumors has serious downstream effects, contributing to the number of low-risk patients undergoing high-morbidity interventions (eg, radiation or prophylactic mastectomy) [1,2]. While dynamic contrast-enhanced (DCE) MRI has shown potential for characterizing and monitoring tumors, the results of such studies are conventionally reported in terms of basic summary statistics, such as the median or mean transendothelial transfer coefficient (K^{trans}) for an entire tumor [3]. However, many tumors will exhibit discrete areas of high perfusion or capillary permeability, which are thought to signify ongoing angiogenesis [4]. These angiogenic 'hot spots' could potentially yield important diagnostic or prognostic information that will be obscured by simply reporting the average K^{trans} for the whole tumor. Recent evidence suggests that morphological or 'shape' features can also add value, as most benign breast tumors exhibit well-defined margins, whereas malignancies are more likely to appear lobulated with ill-defined margins [5,6]. The purpose of this study was to evaluate the potential of advanced DCE-MRI combined with shape and texture descriptors to identify malignant breast cancer.

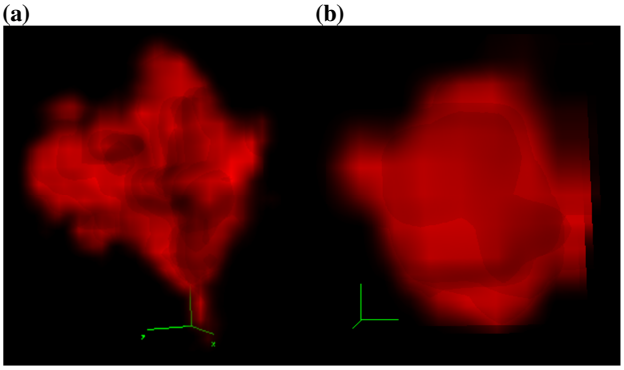
Methods: We retrospectively studied 52 histologically proven cases (35 women), including 26 benign and 26 malignant tumors. All studies were performed at 3T with a dedicated phased-array receive-only coil. DCE-MRI was performed using a 3D gradient echo sequence with fat-saturation and the following parameters: 1 min temporal resolution, 6 measurements (time-points), 330 mm FOV, 448 x 314 matrix, 160 slices, 1.0 mm slice thickness, TR/TE 4.3/1.6 (ms), and 12 º flip angle. Gadolinium-based contrast agent (0.1 mmol/kg) was injected after the first DCE time point. DCE datasets were motion-corrected by an automatic sub-pixel registration algorithm implemented in ImageJ (http://rsbweb.nih.gov) [7]. K^{trans} maps were computed using NordicICE software (NordicNeuroLab, version 2, Bergen, Norway), assuming that the percent increase in signal was proportional to Gadolinium concentration. Tumor volumes of interest (VOIs) were drawn manually on post-contrast DCE images, then applied to the K^{trans} maps. Seventy textural features were initially computed including gray-level co-occurrence and run-length matrix features [8]. Shape descriptors were computed for 3 orthogonal planes and included basic geometric measures including roundness, eccentricity, and features based on lesion topology (eg, number of cavities and branch-points). All textural and shape features were computed using MaZda version 4.6 [8]. For feature selection, we identified the most discriminative shape and textural features on the basis of the Fisher coefficient of each (ie, the ratio of between-class and within-class variance [9]). We generated logistic regression models by combining the shape and textural features with the highest Fisher coefficients and designating 'benign' and 'malignant' as outcomes. We assessed the performance of each model (sensitivity, specificity and accuracy) using ROC analysis and compared areas under the ROC curves using the method of DeLong [10].

Results: Representative tumor VOIs for (a) malignant and (b) benign (fibroadenoma) cancers are depicted in Fig. 1. The diagnostic performance of shape, textural, and combined shape and textural feature models is provided in Table 1. Although the textural model appeared to achieve higher specificity than the shape-only model (and vice-versa), a comparison of areas under the respective ROC curves revealed no significant differences between or among any of the logistic regression models for predicting malignancy (P>0.05 for each comparison).

TABLE 1: Diagnostic accuracy of Textural and Shape features

Logistic Regression Model:	Accuracy	Se	Sp
Textural: top 3 features (Entropy, Gray-level non-uniformity, Short-runs emphasis) [11-12]	78	62	85
Shape: top 3 features (Blair-Bliss ratio[13], Roundness, circularity)	79	92	65
Combined Top 4 Shape (Blair-Bliss, Roundness), and Textural (Entropy, GLNU)	77	73	81
Combined Top 6 Shape and Textural features	80	92	65

FIGURE 1: (a) malignant and (b) benign fibroadenoma tumors



Conclusion: In this preliminary study, we have identified a potential recipe for predicting malignant breast cancer comprising of shape and textural features. While textural features appear to provide good specificity and modest sensitivity, the converse was true for shape-based models. With optimization, and a larger, prospectively designed study, this computer-aided classification approach shows potential to provide improved accuracy compared to conventional MRI criteria.

References: [1]Chan LW, et al. Int J Radiat Oncol Biol Phys 2010; [2] Esserman LJ, et al. JAMA 2009; [3] O'Connor Br J Cancer 2007; [4] Bhujwalla Top MRI 1999; [5] Evans AJR 2006; [6] Yang Comp Biol Med 2009; [7] Thevenaz et al. IEEE Trans Image Process 1998;7:27; [8] Szczypinski et al. Comput Methods Programs Biomed 2009; 94:66; [9] Mayerhoefer et al. JMRI 2005;22(5):674-80; [10] DeLong ER, et al. Biometrics. 1988;44(3):837-45; [11] Haralick 1973; [12] Galloway 1975; [13] Blair & Bliss 1967.