Association of Computer-Based Quantitative Diagnostic Features for CAD with Tumor Phenotype Evaluated by BI-RADS Descriptors

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Introduction:

Morphological appearance of enhanced lesions in breast MRI provides important information to differentiate between benign and malignant lesions. This is particularly helpful for diagnosis of malignant lesions that do not present the malignant type enhancement kinetics. The BI-RADS lexicon gives a guideline for radiologists to describe a lesion. The ACS has recommended annual MRI screening to high-risk women. More and more breast MRI examinations are expected to be performed. As such, development of computer-aided diagnosis (CAD) systems is urgently needed. In CAD the morphological features of lesion are analyzed using computer-based algorithms, then a diagnostic classifier is selected based on a combination set of features that can achieve the best performance. Very recently, Behrens et al. [1], published a review paper pointing out that for these computer extracted features to be accepted, the link with BI-RADS lexicon needs to be established. In our previous work we have presented a quantitative morphological and texture feature analysis method for development of CAD [2]. In this study, we tried to explore the association of extracted quantitative features with lesion phenotype appeared on MRI.

Methods:

Seventy-one histological confirmed malignant (N=43) and benign (N=28) lesions were used for initial CAD development. Fuzzy C-means algorithm was utilized to automatically segment lesions. Then 8 morphological, 10 GLCM and 14 LAWS' texture energy features were obtained to describe the morphology properties of each lesion. The artificial neural network (ANN) was used as the classification method and the leave-one-out cross validation was used to evaluate the generated classifier. The selected classifier was consisted of 7 features (Compactness, NRL Entropy, NRL Ratio, Surface Area, Gray Level Entropy, Gray Level Sum Average, LAW_LS), and that reached the area under the ROC curve (AUC) of 0.90. Then the dataset was randomly separated into a training set (14 benign and 22 malignant) and a validation set (14 benign and 21 malignant) to further evaluate the robustness of the selected classifier. A classifier of 5 features (Compactness, NRL Entropy, Gray Level Entropy, Gray Level difference Variance, LAW_LS) was selected in the training set, and that achieved AUC of 0.82 in the validation set. The association of these selected features with lesion phenotype was analyzed. All lesions were combined and sorted based on the ascending order of each index, and lesions with the high vs. low index values were visually compared.

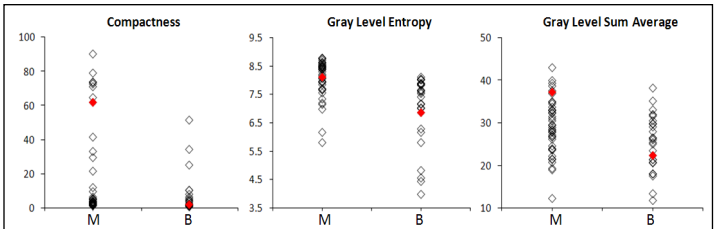

Fig. 1 Distribution of three selected features between malignant (M) and benign (B) groups. The illustration cases are indicated as the red dots.

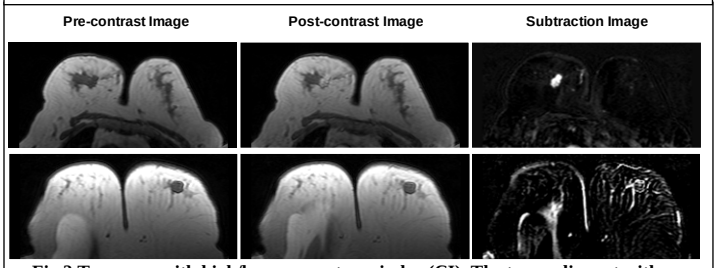

Fig.2 Two cases with high/low compactness index (CI). The top-malignant with CI=63, ranking # 60/71. The bottom-benign case with CI=2, ranking #22/71.

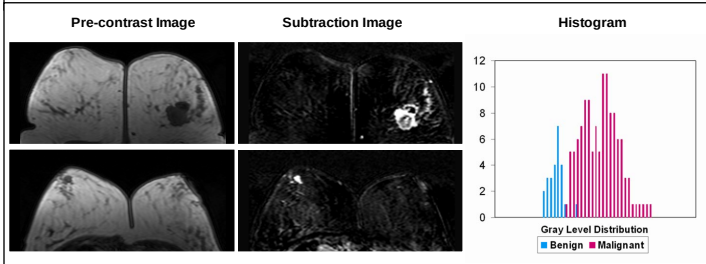

Fig.3 Two cases with high/low gray level entropy index (EI). The top-malignant with EI=8.1, ranking # 41/71. The bottom-benign with EI=6.6, ranking #10/71.

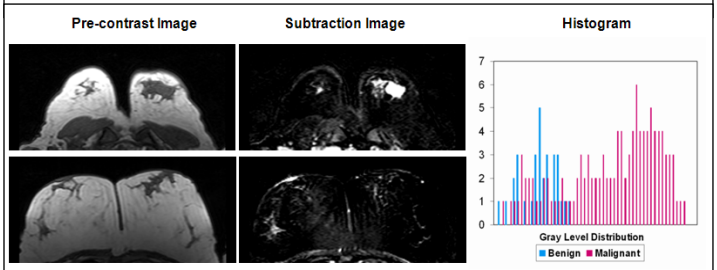

Fig.4 2 cases with low/high gray level sum average index (SAI). The top-malignant with SAI=37, ranking # 66/71. The bottom-benign with SAI=22, ranking #21/71.

Results:

Fig.1 shows the distribution of 3 selected features, Compactness, Gray Level Entropy, and Gray Level Sum Average, separately in the malignant and benign group. For each feature one malignant lesion showing a high index and one benign lesion showing a low index are demonstrated in Figs. 2-4. The compactness is defined as the ratio of the square of surface area to the volume; therefore it is sensitive to shape and margin. As shown in Fig.2, the benign lesion has CI=2 (ranked #22/71), and the malignant lesion has CI=63 (ranked #60/71). The group comparison showed significantly lower CI in the benign (p=0.03). This feature appeared to be associated with shape and margin in BI-RADS lexicon, round shape for the benign and more irregular shape for the malignant lesion. As shown in Fig.3, a homogeneously enhanced lesion has a lower GLCM entropy (benign lesion in Fig.3, EI=6.6, ranked #10/71) compared to the heterogeneously enhanced lesion (malignant lesion in Fig 3, EI=8.1, ranked #41/71). In group analysis, the benign lesions had lower entropy compared to malignant tumors (p=0.002), indicating that they were more likely to show homogeneous enhancements. Another gray level texture feature 'Gray level sum average' was significant higher (p=0.01) in the malignant than in the benign groups. This feature indicated the total gray level enhancement distribution, suggesting a higher enhancement in malignant compared to benign lesions. An example is given in Fig 4. The malignant lesion has SAI=37, ranked #66/71, and the benign lesion has SAI=22, ranked #21/71. Therefore, both the GLCM entropy and sum average appeared to be associated with the internal enhancement patterns defined in the BI-RADS lexicon.

Discussion:

The quantitative analysis to extract morphology and texture features using computer-based algorithms is essential for the development of CAD. While the enhancement pattern can be easily categorized by visual assessment, it represents a great challenge to link such features to computational numbers. As can be seen in Fig.1, for each individual parameter there is a great overlap between the malignant and benign lesions. Furthermore, each index may be associated with different descriptors defined in BI-RADS lexicon. For example, shape and margin can both contribute to the compactness index. The other two features presented here, GLCM entropy is associated with homogeneous/heterogeneous enhancements, and gray level sum average is associated with the degree of enhancements; both are also related. This is a complex problem, and there will not be a simple one-to-one correspondence relationship. The study presented here may provide the initial step towards establishing this link between computer-based quantitative features and BI-RADS visual descriptors.

Reference: [1] Behrens et al. Comp Med Imag and Graph. 2007(31):236-247. [2] Nie et al. 2007 ISMRM abstract # 134.

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