Development of Breast MRI Computer-Aided Diagnosis System:Automated Segmentation and Selection of Unspecific Morphology and Texture Features

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Purpose:

Dynamic contrast enhanced MRI (DCE-MRI) has evolved into an established alternative for detection and diagnosis of breast lesions. It has demonstrated a high sensitivity, however, the specificity is varied, which may lead to unnecessary biopsies or over treatment. As the use of breast MRI increases, the accuracy and efficiency in interpretation of breast MR becomes a challenging issue. Computer-aided diagnosis (CAD) system has been demonstrated as a useful tool to assist the radiologists' interpretation of mammogram as "a second reader". Very little work was done for breast MRI. The currently commercial system such as CADstream only provides a display platform. We have started to develop a fully automated CAD system which can provide "an intelligent thinking and final impression" based on all morphological and kinetic information to aid in detection and diagnosis of breast cancer on MRI. In this pilot study we applied clustering based algorithm to automatically segment lesions, and performed quantitative analysis to obtain morphological and texture descriptors. An artificial neural network (ANN) was employed to select features for classifying benign vs. malignant lesions. This work will be incorporated into our future CAD system design.

Methods:

For our CAD design, we will use computer algorithms to follow radiologists' interpretation steps: automatically searching suspicious area and using quantitative feature descriptors to classify it as malignant or benign. The steps and procedures can be summarized in the flow chart shown in Figure 1. For this pilot study, we implemented the lesion segmentation, characterization and classification parts as outlined in the red box. Randomly chosen 26 benign/35 malignant cases were used to test the diagnostic capability of morphology/texture features. In each patient, the cancer ROI on each imaging slice was automatically outlined using fuzzy c-means clustering based algorithm, and all ROI's were combined to obtain a 3D representation of the lesion. Figure 2 shows the results from step-by-step procedures. After lesion is delineated, eight morphological features including volume, surface, NRL (Normalized Radial Length) Mean, NRL Entropy, NRL Ratio, Sphericity, Compactness, and Roughness were calculated to describe the morphological properties for each case. Ten GLCM texture features (energy, maximum probability, contrast, homogeneity, entropy, correlation, sum average, sum variance, difference average, and difference variance) and 14 LAWS' texture energy features were obtained to describe the texture properties for each case, all together 32 morphological/texture features. The multi layer perceptron artificial neural network was used as classification method and due to the limited sample size the leave-one-out cross validation was used to evaluate the generated classifier. The best structure was determined experimentally. Each parameter set was normalized to have the zero mean and unit variance before training. Forward search strategy was applied to find the optimal feature subset, which was obtained when the MLP classifier produced the least error rate. The ANN analysis was performed using morphology/texture features, and the classification accuracy was compared using the ROC analysis.

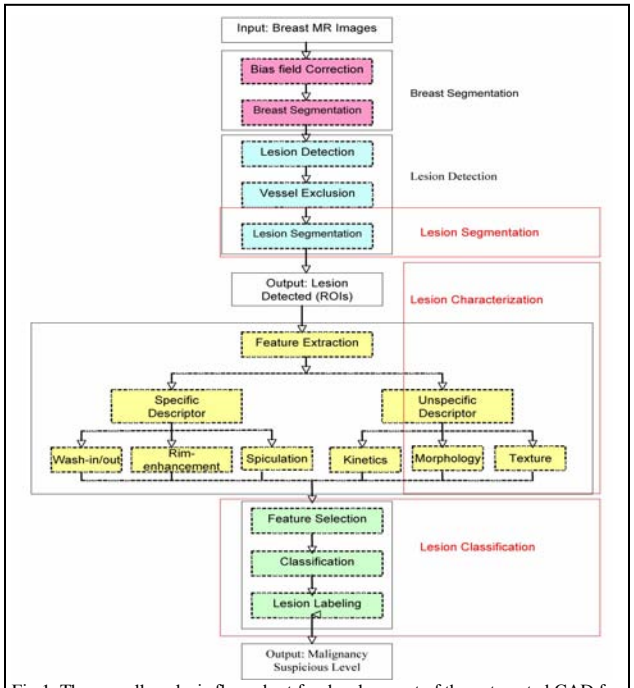

Fig 1. The overall analysis flow-chart for development of the automated CAD for diagnosis of breast cancer, starting from data input, then following these steps: 1) image homogeneity correction and breast segmentation, 2) lesion detection, 3) lesion segmentation, 3) lesion characterization using specific and unspecific morphological, texture and kinetic parameters, 4) lesion classification to find one set of optimized malignant features, and lastly 5) lesion labeling and output of impression. The contents shown in red are illustrated in this study.

Results:

The ANN classification based on 32 morphology/texture features can achieve AUC (area under ROC curve, as shown in Figure 3) of 0.95. When the sensitivity is set at 95%, the specificity is 85%, still pretty high. The selected features including 3 morphological (compactness, NRL Entropy, NRL Ratio), 1 GLCM (difference variance), and 1 Laws' (LAW_LR) features. Besides the combination feature set, the diagnostic performance of each individual predictor was also analyzed. The area under ROC curve based only on the "Compactness" feature can achieve the highest AUC, 78%, which suggests that it could be very useful for diagnosis. The morphological feature "Compactness" (p=3E-06), "NRL Ratio" (p=0.0002), "NRL Entropy" (p=0.009) and LAW's texture feature "LAW_LR" (p=0.0007) were significantly lower in the malignant cases compared to the benign group. The GLCM feature "gray level difference variance", by itself did not show significant differences (p=0.29) between these two groups, but it could be combined with other features to achieve the optimal diagnostic accuracy.

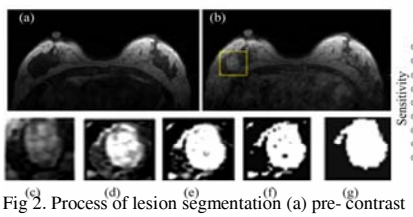

Fig 2. Process of lesion segmentation (a) pre- contrast image, (b) post-contrast image, (c) selected square ROI, (d) Unsharp filtered image, (e) Membership map from FCM, (f) Binarized membership, (g) 2-D connected component and hole filling.

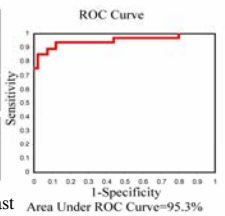

Fig 3. The ROC curve for ANN analysis

Discussion:

In this study, we used clustering method to automatically segment breast lesions. The segmentation accuracy was verified by an experienced radiologist (the accuracy for volume overlap was 91%). We showed that the accuracy of diagnosis (the area under ROC curve) based on 5 selected features from 32 morphology and texture features can reach to 95%, which is very promising. In this pilot study, we have demonstrated that quantitative analysis of morphology and texture are feasible, and these unspecific features can be selected by an artificial neural network for differential diagnosis to distinguish between benign and malignant lesions. There are some known malignant features of breast cancer on MRI, including spiculation, rim enhancement, and hot-spot enhancement kinetics showing rapid wash-in and wash-out. In our future work these 3 well-established malignant features will directly enter into the final set of malignant features as specific descriptors, and together with the unspecific descriptors as selected in this work can be combined to select a final set of features which can achieve the highest accuracy. The goal of this on-going project is to develop a fully automated breast MRI CAD system to aid in detection and diagnosis of benign and malignant diseases. Automatic breast segmentation and lesion detection will be implemented in the future, and together with the work shown here can be integrated to develop a complete CAD system.

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