

Robustness of Morphologic Features for the Characterization of Mass Lesions in Dynamic, Contrast-Enhanced Breast MR Images

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1. Purpose

Dynamic contrast enhanced breast MRI (DCE BMRI) has emerged as tool for breast cancer diagnosis. While DCE BMRI is known to have a high sensitivity studies show a limited specificity of the method, leading to a large number of benign lesions being biopsied. The present paper is part of an effort to address the clinical demand for computer-aided diagnosis tools to support radiologists in the diagnostic reading process of DCE BMRI studies. The natural pipeline for such an approach consists of (i) segmentation of suspicious breast lesions, (ii) extraction of features from the segmented area, and (iii) classification of the lesion as benign or malignant, or into finer sub-classes. A segmentation method for mass-like breast lesions was presented by the authors at the SPIE Medical Imaging conference 2007 [1].

In an attempt to base the lesion classification on a small set of meaningful features, three morphological features for the characterization of mass lesions are compared. Lesion segmentation results can vary depending of the used algorithm and user input. Since the feature extraction step depends on the results of the segmentation, the robustness of the feature computation with respect to variations in the segmentation results is of utmost importance. In the present paper a novel feature for the characterization of the margin of mass-like breast lesions is presented and compared to two common morphological features. The features are evaluated with respect to 3 different criteria. (1) Robustness against variations in the segmentation of the lesion. (2) Lesion characterization: The potential of the three shape features to characterize the margin of a lesion with respect to the reported margin type according to BI-RADS. (3) Finally the features are compared with respect to the classification of lesions as benign or malignant. Since manually drawn contours vary more than computer segmentations [1] we use manual contours for the analysis in this paper.

2. Materials & Methods

2.1 Data

27 dynamic contrast enhanced breast MR scans containing one or more mass lesions per study were used for the purpose of this paper. One mass lesion per case was used for the analysis and manually contoured by three radiologists. The manual segmentations were used as input for the subsequent feature computations. For 20 of the masses a biopsy proven classification was available (8 benign, 12 malignant). For all of the masses categorization of the lesion margin according to the ACR Breast Imaging and Reporting Data System (BI-RADS) was available (15 smooth, 12 irregular).

The images were acquired on a Philips MR Intera Achieva 1.5 T scanner at the University of Chicago Hospitals. In-plane resolution varied between 0.93 mm and 1.06 mm. Slice thickness was 2 mm. 7 dynamics were acquired in intervals of 57 seconds.

2.2 Shape features

Three morphologic features were investigated and compared in this study.

2.2.1 Irregularity

Irregularity has been proposed by Gilhuijs et al. [2]. It is based on a comparison of the surface of the sphere of the effective lesion radius (S^{eff}) and the actual lesion surface (S) and defined as $1 - (S^{eff}/S)$. The effective lesion radius is the radius of a sphere with the same volume as the lesion.

2.2.2 Compactness

The compactness is defined as volume of the lesion normalized by the volume of a sphere with the same surface area as the surface area of the actual lesion. This is the natural 3D extension of the 2D definition given by Sinha et al. in [3].

2.2.3 Normalized Mean Distance to Surface

As a new feature we propose the Normalized Mean Distance to the lesion surface. For each point in the lesion the distance to the surface is computed. The integral of the distance values is normalized by the lesion volume in order to obtain the mean distance to surface. This value is normalized by the mean surface distance of a sphere with the effective lesion radius.

For the sake of consistency we will compute the "regularity" ($=1 - \text{irregularity}$) instead of the irregularity. Thus, all three features take values ranging from 0 to 1, where 1 is achieved by a perfectly spherical lesion. For more irregular lesions the values decrease with a lower limit of 0.

3. Results

In order to analyze the redundancy of the features the correlation of the obtained feature values were computed. The correlation between *irregularity* and *compactness* was 99.8%, whereas the correlation of the Normalized Mean Distance to Surface to each of the other features was 95%.

3.1 Feature robustness

In order to assess the robustness of the features with respect to the different lesion segmentations provided by the three radiologists, we compute the correlation of the feature values for all pair-wise combinations of segmentations per lesion.

The mean correlation values are 85% for the *irregularity*, 84% for the *compactness*, and 87% for the *Normalized Mean Distance to Surface*.

3.2 Lesion margin characterization

In order to assess the characterization power of each of the three features with respect to the lesion margin type, an optimal threshold was computed from the segmentations provided by the first two readers. This threshold was applied to the feature values of the third reader. According to the threshold each lesion was labeled either *smooth* or *irregular*. A correctly labeled irregular lesion was considered a true positive. A correctly labeled smooth lesion was considered a true negative. The sensitivity for all three features was identically 0.92. The specificity was 0.73 for the *irregularity* and the *compactness* and 0.87 for the *Normalized Mean Distance to Surface*.

3.3 Lesion classification

The above analysis was repeated for the 20 mass lesions for which a biopsy proven classification as *benign* or *malignant* was available. Here the sensitivity for all three features was 0.83. The specificity was 0.63 for the *irregularity* and 0.75 for the *compactness* and the *Normalized Mean Distance to Surface*.

4. Conclusions

The high correlation between the three investigated shape features indicates that in an attempt to carefully select a small number of features for a computer aided diagnosis system at most one of the features should be selected. Instead of using a large set of possible features a small set meaningful features should be used. Since the computation of the feature values depends on a (manual or automatic) segmentation of the lesion, the used features should exhibit the highest possible robustness with respect to the segmentation that is used for the computation.

Comparing the three investigated features *irregularity*, *compactness*, and *Normalized Mean Distance to Surface* with respect to these criteria, our experiments show that the *Normalized Mean Distance to Surface* yields the highest robustness with respect to the segmentation. At the same time the specificity with respect to the characterization of lesion margins is higher than for the other two features.

Acknowledgements: We gratefully acknowledge the help of Drs. G. Newstead, A. Shimauchi, C. Sennett, H. Abe, S. Sung, and S. Makim, University of Chicago Hospitals, as well as Drs. L. Fajardo, and B. Adkins, University of Iowa.

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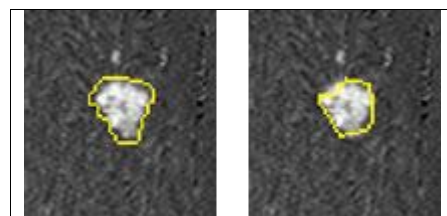


Fig 1. An example of a mass lesion contoured by two different users shows the significant variations of the input to the feature computation step.