A LESION SHAPE AND MARGIN CHARACTERIZATION METHOD IN DYNAMIC CONTRAST ENHANCED MAGNETIC RESONANCE IMAGING OF BREAST

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ABSTRACT

This study presents a shape and margin characterization method of breast mass lesions in dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI). The overlap between a mass lesion and its minimum volume enclosing ellipsoid (MVEE) is used to capture the overall shape of a lesion. Various statistical measurements on distance from the lesion surface to its MVEE surface are computed to characterize margin (boundary) features of a lesion. In the evaluation study using 28 benign and 20 malignant manually segmented lesions, MVEE-based features are demonstrated to be significant ($p < 0.05$). Our study shows that MVEE based features provide higher sensitivity and specificity in SVM and ANN classifications of benign and malignant lesions.

***Index Terms*—** Mass lesion, Shape, DCE-MRI, classification.

1. INTRODUCTION

In Breast Imaging-Reporting Data System (BI-RADS) of Magnetic Resonance Imaging published by the American College of Radiology (ACR) in 2003, a tumor mass is represented by morphological (shape, margin, internal enhancement) and kinetic (dynamic enhancement) characteristics. Morphological features extracted by radiologists are reported to significantly influence the diagnostic accuracy of tumor classification [1, 2, 3]. Goto *et al.* [1] reported that the analysis of morphological features of breast lesions showed higher diagnostic accuracy than using kinetic features. However, the morphological characterization is subject to the experiences of radiologists. Therefore, it is desirable to develop an automatic shape and margin (boundary) analysis system to allow consistent evaluation in follow-up studies and provide a computer diagnosis report as a reference for radiologists.

Shape analysis in medical imaging processing domain is commonly used in feature extraction of region of interests (ROIs) for classification [4] or retrieval [5] purpose or evaluate the status or development of ROIs [6].

There are two main categories in the breast lesion shape and margin (boundary) characterizations. One is based on normalized radial length (NRL) where the radial length is defined as the distance from the center of a lesion to the lesion surface [7]. The other shape features are various versions of weighted average of information obtained in 2D slices along the third spatial dimension or projected slices [8, 9].

This study presents a minimum volume enclosing ellipsoid (MVEE) based method to characterize shape and margin features of mass lesions. The assumption is benign lesions usually present a regular (round or oval) shape with a smooth margin, while malignant lesions have a lobulated or irregular shape and irregular or spiculate margin. We compare the performance of two classifiers using the proposed features and existing NRL based features on manually segmented lesions. The proposed features are demonstrated to be able to differentiate malignant from benign lesions accurately by having a higher sensitivity and specificity in both artificial neural network and support vector machine classifiers.

2. SHAPE AND MARGIN ANALYSIS METHOD

In Fisher's scoring system [10] for breast lesion analysis, a lesion with round, oval and lobulated shape and well-defined margin (boundary) are given lower scores than a lesion with irregular shape and ill-defined margin, which implying malignancy.

Similar to this system, we assume a benign lesion have a regular shape and well overlapped with its minimum volume enclosing ellipsoid (MVEE). MVEE of a lesion is the ellipsoid with the smallest volume that encloses the lesion. The overlap of a lesion with its MVEE can indicate how regular the lesion shape is. The smoothness of the boundary or margin can be measured by the distribution of the distance between the lesion surface and the corresponding ellipsoid surface.

2.1. Minimum volume enclosing ellipsoid (MVEE)

The MVEE problem can be formulated as an optimization problem [11, 12]. To obtain MVEE of a lesion is to fit the lesion with an ellipsoid with minimum volume that encloses all the voxels of the lesion. An ellipsoid $\mathcal{E}$ of dimension n in center from is written as:

$$\mathcal{E} = \{x \in \mathbb{R}^n | (x-c)^T E(x-c) \leq 1\} \quad (1)$$

where $c \in \mathbb{R}^n$ is the center of the ellipsoid and E is an $n \times n$ positive definite symmetric matrix which determines the shape and orientation of the ellipsoid. The eigenvectors of E represents the direction of axes of the ellipsoid $\mathcal{E}$ and the eigenvalues determine the length of each axis.

The volume of an ellipsoid $\mathcal{E}$ is given by:

$$V(\mathcal{E}) = \eta \det((E^{-1}))^{\frac{1}{2}} \quad (2)$$

where η is the volume of an n-dimensional unit hypersphere. Therefore obtaining the MVEE is an optimization problem that finding the matrix E and ellipsoid center c that minimize the volume in equation (2) subject to the ellipsoid definition in equation (1). Let S be a lesion that $\{x_i \in S | x_i \in \mathbb{R}^n\}$, MVEE problem can be formulated as:

$$\begin{aligned} \text{minimize}_{E,c} \quad & \det(E^{-1}) \\ \text{subject to} \quad & (x_i - c)^T E(x_i - c) \leq 1 \quad \forall x_i \in S \end{aligned} \quad (3)$$

In this study, the equation (3) is solved using algorithm implemented by Moshtagh [12].

2.2. Shape and margin features

In breast lesion classification of DCE-MRI, volume, surface, compactness and fractal dimensions are widely used as gross shape features [8, 7]. In our study, we further include the volume overlap ratio (VOR) of a lesion to its MVEE as another overall shape feature:

$$\text{VOR} = \frac{V_m}{V_\mathcal{E}} \quad (4)$$

where V_m and $V_\mathcal{E}$ are the volume of a mass lesion and its MVEE correspondingly. The value is between $[0, 1]$ where a larger value suggests the lesion is more similar to an ellipsoid and thus the shape is more regular.

In our study, the margin features are represented by measurements of normalized surface distance (NSD), meaning the distance from a lesion surface to its MVEE surface. The closest work is from Nie *et al.*[7] who measured normalized radius length (NRL) defined as the normalized distance from the centroid of a lesion to its surface. Fig 1 shows NRL and the distance from a lesion surface to its MVEE surface.

Let x_i be the location of i-th voxel on the surface of a lesion and c be the center of the MVEE of the lesion, the projection of x_i on the MVEE surface is obtained by finding the intersection of the ray that starts from c heading for the direction of x_i and intersects with the surface of MVEE at location p_i. The lesion surface is determined as the voxels that at least one of their 18-connection neighbor is 0 in the lesion mask. The NSD is then defined as:

$$d_i = \frac{||x_i - p_i||}{||p_i - c||} \quad \forall x_i \in S \quad (5)$$

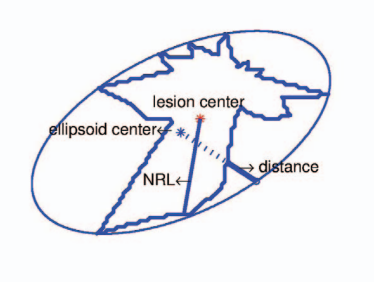


Fig. 1: The dotted line shows the ray passes though the ellipse center and the connected solid line is the distance of the lesion surface to the ellipsoid surface. NRL is computed from the lesion center to the lesion surface.

Various statistical measurements of NSD can be used as margin features, such as mean, standard deviation, entropy, skewness and kurtosis. In addition to those standard measurement we also include smoothness and clumpness measurements.

Roughness of the lesion surface and is defined as

$$\text{Smoothness} = \frac{\mu}{\sigma} \quad (6)$$

where μ is the mean value of all d_i and σ is the standard deviation. The larger smoothness value suggests a smoother surface.

The clumpness is defined as

$$\text{clumpness} = \frac{1}{M} \sum_{i \in 1..M} (d_i - \mu) : d_i > \mu \quad (7)$$

where M is the surface voxel number. The lesions with lobulated shape and irregular margin should have higher clumpness value.

3. EVALUATION

The study includes 28 benign and 20 malignant biopsy-proven mass lesions from breast DCE-MRI database collected from 2006 to 2011 in St. Vincent's Hospital, Australia. All DCE-MR breast images were acquired with a Siemens Avanto 1.5T MR system. There were two protocols. The first protocol used $T_R = 4.19$ ms, $T_E = 1.22$ms, field of view $= 320$ mm and flip angle = 10°. The voxel dimensions were

Feature	p-value	
	NRL	NSD
Mean	0.0112	< 0.001
Clumpness	0.0091	0.0012
Entropy	0.1229	0.0025
STD	0.3476	< 0.001
Skewness	0.4967	< 0.001
Roughness	0.9362	< 0.001
kurtosis	0.1675	0.1521

Table 1: t-test result for margin features computed by NRL and NSD measurements.

approximately $0.76 \times 0.76 \times 1\text{mm}^3$. The temporal resolution was 1.02 minutes. The second protocol had $T_R = 4.82$ms, $T_E = 1.79$ms, field of view $= 380$mm and flip angle = 10°. The voxel dimensions were around $0.72 \times 0.72 \times 1\text{mm}^3$. The temporal resolution was 1.01 minutes.

The contour of each lesion was manually extracted from the second post-contrast image in the Axial direction and then corrected from Sagittal and Coronal direction. This initial lesion segmentation was then reviewed and corrected by a radiologist. The volume of the benign lesions ranges from 33.40 to 2009.6 mm^3 with the median of 161.27 mm^3 and mean the of 391.04 mm^3. Malignant lesions volume ranges from 82.94 to 5934.2 mm^3 with the median is 642.78 mm^3 and the mean is 1149.7 mm^3.

There are 36% benign and 50% of malignant lesions present washin and washout kinetic patterns. The average washin rate, washout rate and time-to-peak obtained on lesion regions are shown to be not significant in t-test ($p > 0.05$). Since the focus of this paper is on shape analysis, only general kinetic analysis result is reported and voxel based kineic analysis is not performed.

The MVEE based shape and margin features are compared with the NRL method in differentiating benign from malignant lesions. t-test is used for individual feature analysis. Artificial neural network (ANN) and support vector machine (SVM) classifier are used to evaluate a group of features in classifications of .

3.1. t-test results

The overall shape features of volume, surface, compactness and VOR are shown to be significant in t-test with $p < 0.05$ on the benign and malignant lesion groups.

The t-test result of the margin features computed using NSD and NRL based methods are shown in Table 1. The mean and clumpness computed using both methods are shown to be significant but NSD method is more significant. NRL based entropy, standard deviation, skewness and roughness features are not significant while using NSD is more appropriate. Kurtosis is not significant using NRL or NSD. Overall, the t-test results suggest NSD are more suitable to compute margin features.

		MVEE	NRL
SVM	Sensitivity	82.1%	77.2%
	Specificity	79.3%	57.1%
ANN	Sensitivity	90.0%	71.3%
	Specificity	99.8%	99.7%

Table 2: ANN and SVM classification results using MVEE and NRL based features.

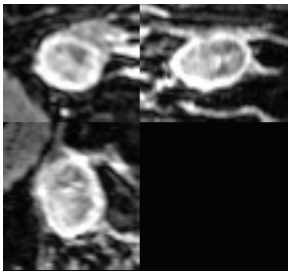


Fig. 2: Three views of a malignant tumor that is very close to its MVEE.

3.2. Artificial neural network (ANN) classification results

ANN is used to classify the mass lesions into malignant and benign class. One ANN trains overall shape features of volume, surface, compactness, fractal dimension and NRL based margin features. The other ANN trains MVEE based features. It includes VOR as another gross shape feature and applies NSD based margin features.

A four-layer feed-forward ANN is implemented using Matlab. Sigmoid transformation function is used in three hidden layers and linear transformation functions are used in an output layer. Levenburg-Marguqrdt algorithm is used to train the classifier. We randomly select out of 28 benign lesions (71%) and 14 out of 20 malignant lesions (70%) in training set, and randomly select 4 benign and 3 malignant lesions to tune the classifier parameters. The rest 4 benign and 3 maligant lesions are used in testing. The performance of the two classifiers are obtained in 200 trails. In Table 2 ANN classifier using MVEE based features shows a better sensitivity of 90% than NRL of 71.3% and they have a similar high specificity.

In classier using MVEE based features, there are four misclassified malignant lesions. Three of them are of small volumes: 82.94 mm^3, 136.51 mm^3 and 203 mm^3. This could be due to the small lesions lacking in morphological features that can be captured at certain spatial image resolution. The other misclassified malignant lesion has the largest volume (5934.2 mm^3) and its shape is very close to an ellipsoid shown in Figure 2. The proposed features cannot distinguish a malignant

tumor that is close to an ellipsoid from the benign. Since we assume only benign lesions have round or oval shapes. For this kind of malignant tumors, using the texture and kinetic features are essential.

3.3. SVM classification results

SVM classifiers are implemented in Matlab to build a classifier. Polynomial kernel of order 3 is used in the training. Unlike the test setting in ANN classification, this evaluation does not explicitly make the benign and malignant lesion number proportional in training or testing set. The SVM classifiers using MVEE and NRL based features have a sensitivity of 82.1% and 79.3%, specificity of 79.3% and 57.1% respectively.

4. DISCUSSION AND CONCLUSION

In this study, we quantitatively analyzed the shape and margin features of mass lesions using measurements based on their minimum volume enclosing ellipsoid. The t-test and classification results (ANN and SVM) suggest the proposed MVEE based features can better differentiate benign and malignant lesions than the NRL method.

This study can be extended to include texture and kinetic features to characterize mass lesions. A future work could be is to link the proposed shape characterization with the BI-RADS lexicons to build an automatic diagnosis reporting system as a reference for radiologists. Another future work is to compare the shape measurement of lesions by using manual and automatic segmentations.

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