Comparative Analysis of Texture Characteristics of Malignant and Benign Tumors in Breast Ultrasonograms

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We evaluated various texture features and region of interest (ROI) types of breast ultrasonograms in order to determine the best-performing combinations for differentiating between benign and malignant solid breast nodules. A total of 21 breast ultrasonograms (12 benign, nine malignant) containing solid breast nodules were evaluated. Eight ROI types were defined around the nodules. The texture feature of each ROI was measured and the ratios of texture features were calculated for each pair of ROIs. This procedure was repeated for five different feature types, thus yielding texture feature ratios for 140 different combinations of ROIs and texture features. We evaluated the performance of the texture feature ratio in differentiating between benign and malignant nodules using *t* test analysis. Evaluating the top ranked texture and ROI combinations, we found edge density and mutual information were the best two texture features, and that the ROI types of outside lesion and lesion margin had good performance.

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BREAST CANCER is one of the most common cancers in women and the incidence continues to increase. Mammography associated with clinical breast examination is the most efficient method for early detection of breast cancer. Recently, breast ultrasonograms have become increasingly used to differentiate between benign and malignant palpated or mammographic nodules. Studies have been performed to find a computerized scheme for texture classification of ultrasonograms that may help reduce the number of biopsies performed on benign lesions. However, the reported accuracy varied significantly according to the texture feature types and regions of interest (ROI) types employed.¹⁻⁴

In this study, we evaluate various texture feature types and ROI types of breast ultrasonograms to determine the best-performing combinations in dif-

ferentiating between benign and malignant solid breast nodules.

MATERIALS AND METHOD

Twenty-one ultrasonograms were selected for the patients who had either a palpable or mammographically visible breast mass, and also had a pathology examination. Among the 21 ultrasonograms, nine were malignant and 12 were benign.

At the time of examination, the images were captured with a video frame grabber (Meteor-II, Montreal, Canada) with a matrix of 640×480 and then transferred to a personal computer (PC) for subsequent processing.

ROI Selection

Eight different rectangular ROIs were defined as shown in Fig 1. ROI₁ was the largest rectangular region that would fit inside the lesion. ROI₂ was the region that extended beyond the lesion margins in all directions by 2 to 3 mm. ROI₃, ROI₄, and ROI₅ were upper, lateral, and lower rectangles beyond the lesion margin, respectively.

ROI₆, ROI₇, and ROI₈ were upper, lateral, and lower rectangles including nodule margin, respectively. The sizes of rectangles in ROI₃ through ROI₈ were about the same as that of the lesion.

Texture Feature Calculation

Five texture features were employed to analyze textual properties of given ROIs: edge density (ED), autocorrelation (AC), inertia of co-occurrence matrix (ICM), correlation coefficient of co-occurrence matrix (CCCM), and mutual information (MI).

Edge density. A pixel location (m, n) was declared as an edge location if its sobel gradient $g(m, n)$ exceeded some threshold t . The location of edge points constituted an edge map $\epsilon(m, n)$, which was defined as

$$\epsilon(k, l) = \begin{cases} 1, & (k, l) \in I_g \\ 0, & \text{Otherwise} \end{cases} \quad (1.1)$$

where

$$I_g @ \{(m, n); g(m, n) > t\} \quad (1.2)$$

Given an edge map, the edge density was measured by the average number of edge pixel per unit area.⁵

Autocorrelation. Autocorrelation was defined as:

$$A(\Delta m, \Delta n) = \frac{1}{(m - \Delta m)(n - \Delta n)} \quad (1.3)$$

$$\times \sum_{x=0}^{m-1-\Delta m} \sum_{y=0}^{n-1-\Delta n} f'(x, y)$$

$$\times f'(x + \Delta m, y + \Delta n)$$

$$f'(x, y) = f(x, y) - \bar{f}$$

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Fig 1. ROI₁ was the largest rectangular region that would fit inside the lesion. ROI₂ was the region that extended beyond the lesion margins in all directions by 2 to 3 mm. ROI₃, ROI₄, and ROI₅ were upper, lateral, and lower rectangles beyond the lesion margin, respectively. ROI₆, ROI₇, and ROI₈ were upper, lateral, and lower rectangles including nodule margin, respectively.

where $\bar{f}$ was the mean value of $f(x, y)$. Mean value was subtracted from the ROI image before autocorrelation in order to exclude the effect of base intensity. We set 4 pixels for distance $\Delta m, \Delta n^3$ in this study.

Inertia of co-occurrence matrix. Let n be the total number of any possible joint pairs and n_{kl} be the occurrences of the pixel values lying at distance d in the image. The cooccurrence matrix elements c_{kl} were given by⁶:

$$c_{kl} = \frac{n_{kl}}{n} \quad (1.4)$$

$$ICM = \sum_k \sum_l (k - l)^2 c_{kl} \quad (1.5)$$

Table 1. List of Top 10 Combination of ROIs and Texture Features

	P Value	Nominator ROI	Denominator ROI	Texture Feature
1	.0005	ROI ₈	ROI ₄	ED
2	.0010	ROI ₃	ROI ₇	MI
3	.0030	ROI ₁	ROI ₃	MI
4	.0030	ROI ₁	ROI ₇	MI
5	.0040	ROI ₁	ROI ₄	ED
6	.0070	ROI ₃	ROI ₈	AC
7	.0080	ROI ₃	ROI ₈	ED
8	.0100	ROI ₅	ROI ₄	ED
9	.0110	ROI ₄	ROI ₈	AC
10	.0130	ROI ₃	ROI ₄	ED

(a)

(b)

(c)

Fig 2. Distribution of texture feature ratios for the top three good-performing types of ROIs and texture features.

Correlation coefficient of co-occurrence matrix. CCCM was defined as:

$$CCCM = \frac{\sum klp(k, l) - m_x m_y}{\sqrt{S_x^2 S_y^2}} \quad (1.6)$$

$$m_x = \sum_l l \sum_k c(k, l) \quad m_y = \sum_k k \sum_l c(k, l)$$

$$S_x^2 = \sum_l l^2 \sum_k c(k, l) - m_x^2 \quad S_y^2 = \sum_k k^2 \sum_l c(k, l) - m_y^2$$

In this expressions, $m(x, y)$ and $S(x, y)$ were the mean and standard deviation, respectively.²

Mutual information. Mutual information was a measure for image similarity that has been used for image registration. We employed MI as a texture feature in this study, because it showed good performance in the preliminary study.⁶

Given two image A and B with pixel value probability distributions, $P_A(a)$ and $P_B(b)$, and joint probability distribution, $P_{AB}(a, b)$, mutual information was defined as:

$$I(A, B) = \sum_{a,b} P_{AB}(a, b) \log \frac{P_{AB}}{P_A(a) \cdot P_B(b)} \quad (1.7)$$

In this study, image A was the sub-image of ROI and B was the 4 pixel shifted version of A.⁷

Texture Feature Ratio and Statistical Analysis

Texture feature values measured from ultrasonograms tend to vary depending on the machine types and control gain settings employed. In this study, we used the ratio of texture feature values in order to compensate the variation.

Once the texture features for eight ROIs of given image set were computed, the ratios of texture feature values were calculated for possible 28 ROI combinations. This procedure was repeated for five different texture feature types, thus yielding 140 different types of texture value ratios. We used independent

two-population (benign and malignant) *t* test to evaluate the performance of 140 types of texture feature ratios in classifying benign and malignant groups.

RESULTS

P values of 140 types of feature value ratios ranged from .0005 to .9995. The top 10 good-performing types are listed in Table 1. The best-performing type was combination of ROI₈ (lateral outside) and ROI₄ (lateral margin) with edge density as feature. Most of the top 10 types had ROI combination of lesion outside and lesion margin.

The sensitivities of the top three types were 100%, 88.8%, and 88.8%, and their specificities were 83%, 83%, and 75%. Figure 2 shows the distribution of texture feature ratios of the top three good-performing types for the 21 lesions.

SUMMARY AND CONCLUSIONS

This study revealed that the selection of ROI types was very important for the texture classification of breast ultrasonograms. While previous studies have used ROI types of inside lesion and extended lesion, our study showed that the ROI types of outside lesion and lesion margin had better performance with edge density or mutual information texture features.

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