Classification of Benign and Malignant Breast Tumors in Ultrasound Images Based on Multiple Sonographic and Textural Features

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***Abstract*—We establish a new set of features for differentiating benign from malignant breast lesions using ultrasound (US) images. Two types of features (sonographic and textural features) are considered. Among them, three sonographic features are novel. Sonograms of 321 pathologically proven breast cases are analyzed and classified into benign and malignant categories. The discrimination capability of the extracted features are evaluated using the support vector machines (SVM) in comparison with the results obtained from artificial neural networks (ANN) and K-nearest neighbor (KNN) classifier. The simulations demonstrate that the proposed algorithm can be an integral part to US computer-aided diagnosis (CAD) systems for breast cancer or an independent program to help accurately distinguish benign solid breast nodules from malignant nodules.**

***Keywords*-breast tumor; feature extraction; computer-aided diagnosis; breast sonography.**

I. Introduction

Computer-aided diagnosis (CAD) systems, which utilize ultrasound (US) imaging to help radiologists in breast cancer detection and classification, are becoming a cutting-edge research field in medical image processing. Recently, several CAD approaches based on linear discriminant analysis [1], support vector machines (SVM) [2], artificial neural network (ANN) [3] and so on have been proposed. Most of these CAD systems require a large number of image samples to train the models or construct the rules for classification. However, a large amount of ultrasound images are not easy to be collected in the real-world. How to build a high-performance CAD system with limited image resources is therefore a crucial task. In [4], the authors applied textural, fractal and histogram-based features to a Fuzzy-SVM classifier using only 87 US images. The purpose of this study is to discover and analyze a new suit of sonography and textural features with high discrimination capacity in order to reduce the training samples in the classification stage.

In this paper, two types of features are chosen to characterize a breast tumor. The sonographic features represent the sonographic characteristics appearing in the US images. A new set of moment and angle chain features are investigated and specifically adapted for US images to capture the contour characteristics of tumors. The ratio features have been well-established in conventional CAD systems and approved to be effective [5]. Therefore, three ratios are considered here to incorporate three clinically useful indicators. In addition, the improved depression features based on the substantial depressions [3] are defined by the representative convex and concave points. The co-occurrence matrix based local features [6] are integrated into the feature set as textural features. Three classification methods are employed to evaluate the discrimination performance of the features. The experimental results indicate that the extracted features have a superior capability of distinguishing benign and malignant nodules.

The paper is organized as follows: In Section II, the image database acquisition and feature extraction methods are described. Section III presents the experimental results using three classifiers. Finally, conclusions and future work are summarized in Section IV.

II. Materials and Methods

A. Data Acquisition

The digital ultrasound image database was provided by the Harbin Institute of Technology and the Second Affiliated Hospital of Harbin Medical University. Ultrasound images were performed using a high-resolution Vivid7 sonography system (GE Healthcare, Milwaukee, WI) and 7.5 $\sim$ 14 MHz liner transducer. The tumor boundaries were marked by five radiologists with more than 10 years experience. There are 321 pathologically proven benign and malignant cases in the database. They are categorized into four classes. The training datasets contain 92 benign cases and 172 malignant cases, and the test datasets have 21 benign cases and 36 malignant cases. An example of supplied image and its marked result are shown in Fig. 1.

B. Feature Extraction

We aim to automatically discriminate and classify breast lesions into benign and malignant classes through multiple sonographic features and local texture analysis. Based on a classification scheme proposed in [5], the features of breast US images are divided into four categories: texture,

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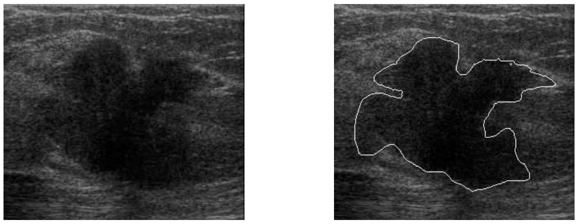

(a) (b)

Figure 1. (a) The original US image. (b) The marked US image.

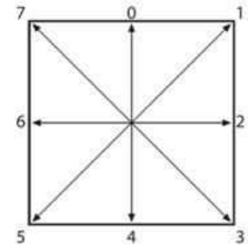

Figure 2. The code of direction.

Table I
THE WEIGHTED VALUE OF EDGE IN FOUR DIRECTIONS

The acute turning angle between two nodes in the chain code	weighted value
$0°$	0
$45°$	1
$90°$	2
$135°$	3

morphologic, model-based and descriptor features. Model-based features are complex and involve a complicated estimation of the model parameters. However, descriptor features are generally the empirical classification criteria of the radiologists and have no numeric expressions. Thereby, we focus on the texture and morphological features. Since most of the morphological features are calculated from the local characteristics of the lesion, such as the shape and margin. We adopt the name of sonographic features for preciseness.

1) Sonographic Features: With widespread use of sonography, the American College of Radiology recently developed a BI-RADS lexicon for breast sonography to standardize the characterization of sonographic lesions. Based on the description of these BI-RADS features, we compute the contour moment, chain code, substantial depression, and three mathematic ratios to determine whether a breast nodule is malignant or benign. The details of these features are described as followings:

Moment

A moment is a quantitative measure of the shape of a set of points, therefore it is used to characterize a contour by summing over all the pixels in the contour. In general, the moment of order $(p+q)$ is defined as [7]:

$$M_{pq} = \sum_{i=1}^{N} I_i\left(x, y\right) x^p y^q \tag{1}$$

where $I_i(x, y)$ is the intensity of the i^{th} pixel at location (x, y), and N is the total number of pixels in the contour. A central moment can be calculated by [7]:

$$\mu_{pq} = \sum_{i=1}^{N} I_i\left(x, y\right) (x-\bar{x})^p (y-\bar{y})^q \tag{2}$$

where $\{\bar{x}, \bar{y}\} = \{M_{10}/M_{00}, M_{01}/M_{00}\}$. In practice, normalized moments are often used and can be written as [7]:

$$\eta_{pq} = \frac{\mu_{pq}}{M_{00}^{(p+q)/2+1}} \tag{3}$$

In [8], Hu proposed a method to compute invariant moments. The essential idea is that by linearly combining the different normalized central moments, it is possible to create invariant functions representing different aspects of the image in a way that is invariant to scale, rotation, and reflection. We choose the 7 Hu's moments defined in [8] as the descriptors to characterize the solid breast nodules.

Improved Chain Code

Chain code is also a popular way to describe the contour. Freeman chain code [9] is one of the most effective chain code representations. Here, we introduce a new chain code as a descriptor of breast tumor. Basically, a polygon is defined as a sequence of code in one of eight directions and each direction is designated by an integer from 0 to 7, as shown in Fig. 2. In order to capture the unevenness of the contour, we design an angle chain. For example, we have a normal chain code "0-1-1-4-5-6-3-2-2-3-2". We then yield a new sequence "3-0-1-3-3-1-3-0-3-3" via Table I by weighting the edge between any two nodes in the original chain code. Based on the angle chain, five features can be defined as:

- Normalized sum angle (F_1):

$$F_1 = \frac{1}{3R} \sum_{i=1}^{R} V_i$$

  where V_i is the value of i^{th} node in the angle chain and R is the number of the nodes.
- Maximum length of consecutive subsequence (F_2):

$$F_2 = \max\left(L_j\right)$$

  where L_j is the length of the j^{th} consecutive subsequence. The consecutive subsequence is the longest subsequence in the angle chain containing none zero value. For instance, "1-3-3-1-3" is a consecutive subsequence of the angle chain "3-0-1-3-3-1-3-0-3-3".
- Average length of consecutive subsequence (F_3):

$$F_3 = \frac{1}{S} \sum_{j=1}^{S} L_j$$

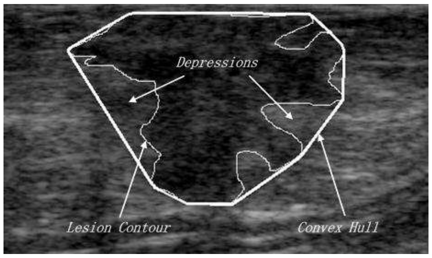

Figure 3. Depressions and convex hull of a lesion.

where S is the total number of consecutive subsequences.

- Most frequent length of consecutive subsequence (F_4):

$$F_4 = \arg\max_{L_j} P(L_j)$$

where $P(\cdot)$ is the discrete probability distribution of the length of consecutive subsequences.

- Normalized number of most frequent length (F_5):

$$F_5 = \frac{1}{T}\ count(F_4)$$

where $count(\cdot)$ is to count the number of subsequences with the most frequent length, and T is the total number of subsequences.

Substantial Depression Values

The spiculation, irregular shape and abnormal contour of a lesion are important sonographic features that characterize a malignant breast lesion. The depression values are effective properties to quantify these two sonographic features. Rather than consideration of both protuberance and depression as proposed in [3], we only compute substantial depression based features since protuberance and depression normally appear concurrently. The depressions of a lesion are shown in Fig. 3. The depression features can be calculated through the following steps:

- Step 1: draw the convex hull enclosing the lesion;
- Step 2: subtract the lesion from the convex hull to obtain the initial depressions;
- Step 3: threshold the initial depressions via a specified value of the area of depressions;
- Step 4: compute the depression values listed as follows:
  (1) the number of the depressions;
  (2) the normalized area of the first, second and third greatest depression;
  (3) the normalized average area of all the depressions.

The normalization is computed by using the area of the entire lesion divided by the area of depression.

Ratios In this work, three mathematic features of different ratios are considered which are used as three clinical indicators to describe the shape characteristics of breast tumors. They are defined as:

- *D:W ratio* — is the ratio of the depth to the width of a lesion, which is derived from the minimal circumscribed rectangle of the lesion. The larger the D:W ratio, the more likely the lesion is malignant.
- *L:S ratio* — is the length ratio of the major (long) axis to the minor (short) axis of the equivalent ellipse of the lesion. Clearly, the L:S ratio is independent of the scanning angle but may be affected by the compressing pressure.
- *C:O ratio* — is the ratio of the convex hull area to the original area of a lesion. Obviously, the greater the degree of depression of a lesion contour, the bigger the ratio value is.

2) Texture Features: An ultrasound image consists of many pixels with different values of gray level intensity. Different tissues have significantly different textures. The textural variation between benign and malignant is an effective feature for classifying breast tumors. The proposed method exploits the distribution of co-occurring values at given offset over an image as features to distinguish benign solid nodules from malignant nodules. The textural features are derived from the spatial gray-level dependence (SGLD) matrices.

SGLD matrix based features are well defined and widely used in measuring texture in images. SGLD matrices are two-dimensional histograms. An element of the SGLD_θ matrix $P(i, j, d, \theta)$ is defined as the joint probability of the gray levels i and j separated by distance d and along direction θ. In order to simplify the computational complexity, the value of θ are often given as $0°$, $45°$, $90°$, and $135°$, and the distance is often defined as the Manhattan distance.

Texture features can be extracted from SGLD matrices with different distances d and directions θ. In practice, given a distance d, four SGLD matrices can be calculated corresponding to $0°$, $45°$, $90°$, and $135°$, respectively, and produce a set of four values for each 14 measures referred in [10]. For each measurement, we can compute the mean and range of the four values. Therefore, a set of 28 textural features is extracted from these four matrices for a given distance d. There are five d values ($d = 1, 2, 4, 8, 16$) [4], hence, totally 140-dimentional texture features are used to identify breast tumor.

C. Breast Tumor Classification

Three well-known classifiers (SVM, ANN, KNN) are employed to evaluate the performance of the extracted features. For the SVM, we utilize linear kernel, polynomial kernel, Gaussian radial-basis function kernel and sigmoid function kernel. We tune the parameters for each kernel to yield the best classification results. In ANN, a general three layer perceptron neural network and the back propagation learning rule are used. We change the neural network's topological structure and learning parameters to improve the performance. The final results are obtained by averaging the outputs from all the artificial neural networks. In the KNN, we adjust K values from a range of $[5, 15]$. The final outcome are the average over the different K values.

III. Experimental Results and Discussions

In the experiments, 321 clinically diagnosed benign and malignant cases are used to train and test the performance of the proposed method. Table II and Table III list the obtained classification results. In Table II, we can see that SVM produces the highest true positive rate, and ANN has the highest true negative rate among these three classifiers, while KNN obtains the worst results compared to the other two methods in terms of false positive rate. Table III indicates that the SVM achieves the highest accuracy, specificity and PPV, meanwhile the ANN yields the best sensitivity and NPV. The performances of all three classifiers achieve over 80% accuracy by combining the sonographic and textural features. The ROC curves of the SVM, ANN and KNN are plotted in Fig.4 which shows that the SVM gains the best performance consistently with the previous results.

Table II
Results of three classifiers

$Algorithms$	TP*	FP*	TN*	FN*
SVM	106	7	173	35
ANN	104	9	174	34
KNN	100	13	169	39

* TP: True Positive; FP: False Positive;
TN: True Negative; FN: False Negative.

Table III
Performances of three classifiers

	SVM	ANN	KNN
$Accuracy(\%^*)$	86.92%	86.60%	83.80%
$Sensitivity(\%^*)$	75.18%	75.36%	71.94%
$Specificity(\%^*)$	96.11%	95.08%	90.37%
$PPV(\%^*)$	93.81%	92.04%	88.50%
$NPV(\%^*)$	83.17%	83.65%	81.25%

* $Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100$;
$Sensitivity = \frac{TP}{TP+FN} \times 100$;
$Specificity = \frac{TN}{TN+FP} \times 100$;
Positive predictive value $(PPV) = \frac{TP}{TP+FP} \times 100$;
Negative predictive value $(NPV) = \frac{TN}{TN+FN} \times 100$;

IV. Conclusions and Future Work

We studied a new integrated set of sonographic and textural features and investigated their use in the breast tumor classification for differentiating the malignant and benign lesions. The moment features are newly introduced to describe the contour of the breast lesions in sonography. The angle chain code is devised to capture the unevenness of lesion contours. The discrimination capability of these extracted features are evaluated via three popular classifiers. The experiments show that the combination of sonographic and textural features achieves good classification results to discriminate benign to malignant nodules. The future work will concentrate on building a fully automated CAD system for breast ultrasound based on the developed feature set.

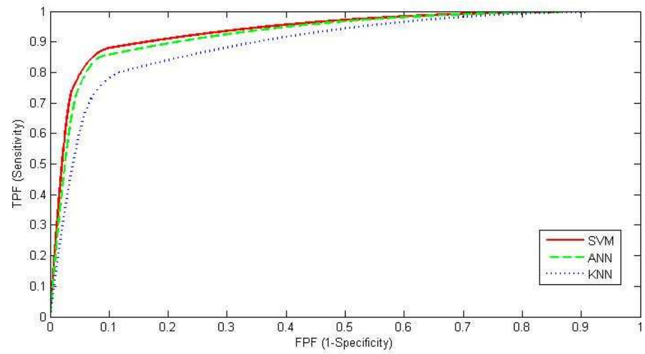

Figure 4. ROC Curves of three classifiers.

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