Segmentation And Classification Of Breast Lesions In Ultrasound Images

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Abstract: This paper proposes a new approach for computer-aided diagnosis (CAD) system with automatic contouring and texture analysis to aid in the classification of breast lesions using ultrasound. First, the goal is to remove the speckle noise while preserving important information from the lesion boundaries, anisotropic diffusion filtering is applied to the ultrasonic image. A morphological watershed transform is used for BUS image segmentation, automatically extracts the precise contour of breast lesions. 32 GLCM features are extracted from the segmented lesion. Support vector machine (SVM) classifier utilizes the selected feature vectors to identify the breast lesion as benign or malignant. Database consists of 50 images (38 Benign and 12 Malignant) and the computer-delineated margins were compared against manual outlines drawn by radiologist. The area under receive operating Characteristic (ROC) curve for proposed CAD systems using all textural features is 0.89. The classifier performance is evaluated by 4 parameters, Accuracy = 92.00, Sensitivity = 94.73, Specificity = 83.34, Matthew's correlation coefficient (MCC) = 0.78.

Index Terms: Breast Ultrasound (BUS), Segmentation, Marker Function, Watershed, Support vector machine (SVM), Receive Operating Characteristic (ROC), Matthew's correlation coefficient (MCC).

1 INTRODUCTION

BREAST cancer is the second leading cause of death for women worldwide. According to cancer statistics 2013, it is estimated that 1.2 million cases of breast cancer will be diagnosed in the year 2013 [1]. Early detection plays a significant role in the fatality of breast cancer. Technologies that aid in the early detection of cancers have therefore attracted much attention from the research community. Mammography is accepted as the “gold standard” for breast imaging. It is widely used as the primary tool for cancer screening. Ultrasonography has been one of the most powerful techniques for imaging organs and soft tissue structures in human body. The advantages of US imaging are no-radiation, sensitive to dense breast, low false positive rate, portable and cheap cost. Therefore, breast US is accepted as the most important adjunct to mammography. Also, it is useful in distinguishing cystic from non-cystic (solid) breast lesions. However, due to the nature of US imaging, the images always suffer from the poor quality caused by speckle noise, low contrast, blurred edge and shadow effect. It takes considerable effort for radiologists to extract the contours of lesions and the manual extraction is not reproducible. Therefore, a CAD technique for segmentation is needed. To improve diagnosis, several research works have been developed quantitative methods to build CAD systems. The goal of breast cancer CAD systems is to distinguish benign and malignant lesions. The computerized segmentation techniques [3] could be classified in two categories: edge-based techniques, which look for edges between regions with different characteristics, and region-based techniques, that cluster image regions that satisfy a given homogeneity criterion. Edge-based segmentation methods do not achieve a good performance when the US image presents weak defined edges or large amount of speckle that produces spurious edges. On the other hand, region-based segmentation methods, such as region-growing [2], snake-deformation [12], level set [10], and morphological watershed transformation [5] have been widely explored for segmenting breast US images. Classifier is used to categorize the images into lesion/non-lesion or benign/malignant classes. Many techniques such as K-Nearest Neighbour (KNN), Support Vector Machine (SVM) and artificial neural network (ANN) [6] have been studied for classification. In this work, we used an anisotropic diffusion filter to reduce speckle without losing important information about lesions boundaries and detailed structures. A region-based watershed transformation is used for segmentation of lesions in BUS images. The marker function is used as the set of minima to impose to the segmentation function to control the flooding of Watershed transformation, in order to obtain accurate potential lesion margins. SVM is used to classify the images as cancerous from non-cancerous lesions. Several approaches have been proposed in the literature to limit the over-segmentation. One can identify shallow basins, likely due to noise, and merge them with some suitably chosen neighbour [15]. Also, inconsistent region separations can be singled out and removed by analyzing the image at a larger scale of interaction. Better yet, one can intervene before running the watershed by introducing some “markers”.

2 IMAGE DATABASE

The database is composed of 50 BUS images: 38 cases are benign, 12 cases are malignant as confirmed by pathology. The images were collected by the doctors of the JSS Hospital (Karnataka, India), using a HD11XE (PHILIPS, Global Information Centre) with a 3-12 MHz linear probe. Every lesion is manually outlined by an experienced radiologist. The manual delineations serve as the reference standard.

3 METHODS

3.1 Speckle Filtering

There are several fundamental requirements for medical image filtering. First, it should preserve the important information from lesion boundaries and detailed structures; second, it should efficiently suppress the noise in homogenous regions; and third, it should enhance the edge information [7]. Speckle, a form of multiplicative, locally correlated noise and is occurring when two or more US waves interfere with each other, constructively or destructively, producing bright and dark spots. It reduces both spatial and contrast resolutions in US images, and contributes to a lower signal-to-noise ratio (SNR), reducing the ability to resolve details and to detect objects of size comparable to its own size. Therefore, filtering techniques for speckle noise are of particular interest for medical US imaging. With conventional spatial filters applied to remove speckle in BUS, such as median, Adaptive weighted median, Wiener filters are the price paid for removing the noise is the blurring of lesion edges. Anisotropic diffusion is a non-linear filtering method, which tries to reduce the speckle of the image whereas preserving the contrast of the lesion edges [4], is the edge sensitive extension of conventional adaptive speckle filter, in the same manner that the original Perona and Malik anisotropic diffusion [11]. Anisotropic diffusion works properly in many kinds of images, mainly when the objects have uniform intensity regions. The nonlinear partial differential equation (PDE) for smoothing image on a continuous domain:

$$\begin{cases} \partial I(x,y;t)/\partial t = div[c(q)\nabla I(x,y;t)] \\ I(x,y;0) = I_0(x,y), (\partial I(x,y;t)/\partial \vec{n})|_{\partial\Omega} = 0 \end{cases} \quad (1)$$

Where is the gradient operator, div the divergence operator, c (q) is the diffusion coefficient, and I0 is the initial image and ∂Ω denotes the border of Ω, is the outer normal to the ∂Ω.

The diffusion coefficient is given by

$$c(q) = \frac{1}{1+[q^2(x,y;t)-q_0^2(t)]/[q_0^2(t)(1+q_0^2(t))]} \quad (2)$$

Where q(x,y;t) is the instantaneous coefficient of variation determined by

$$q(x,y;t) = \sqrt{\frac{(1/2)(|\nabla I|/I)^2 - (1/4^2)(\nabla^2 I/I)^2}{[1+(1/4)(\nabla^2 I/I)]^2}} \quad (3)$$

and q0(t) is the speckle scale function. Here, the instantaneous coefficient of variation q(x,y;t) serves as the edge detector in speckled imagery. The function exhibits high values at edges or on high-contrast features and produces low values in homogeneous regions. The speckle scale function $q_0(t)$ effectively controls the amount of smoothing applied to the image.

$$q_0(t) = \frac{\sqrt{\text{var}[z(t)]}}{\overline{z(t)}} \quad (4)$$

Where var[z(t)] and $\overline{z(t)}$ are the intensity variance and mean over a homogeneous area at , respectively. We examine the mean preservation error, Pixel Signal to Noise Ratio (PSNR) and the standard deviation to quantify the performance of anisotropic diffusion method with the other conventional spatial filters.

3.2 Watershed Transform

The Watershed transform is a mathematical morphology based on visualizing an image in three dimensions: two spatial coordinates versus gray levels. The Watershed transform, which combines aspects of both edge-based and region-based segmentation approaches. The principal objective of watershed transform is finding the watershed lines. Its principle can be understood from an intuitive idea coming from Geography. Let's imagine a landscape or topographic relief is flooded from below by letting water rise through the holes at a uniform rate. Catchment basins will fill up with water beginning from the regional minima. When the rising water in distinct catchment basins is about to merge, a dam is built to prevent the merging. When the water level has reached the highest peak in the landscape, the process is halted. As a result, the landscape is divided into regions or basins separated by dams, called watershed lines or simply watersheds which is shown in Fig. 1 [13]. In practice, a direct computation of the Watershed transform on the image to be segmented produces an over segmentation, which is due to the presence of spurious minima. Therefore, the segmentation function must be filtered by minima imposition technique in order to remove all irrelevant minima. This technique requires the determination of a marker function to point the relevant structures within the image to control the flooding only to the catchment basins associated to each marker. This technique is known as marker-controlled watershed transformation and it is a robust and flexible method for segmenting objects with closed contours.

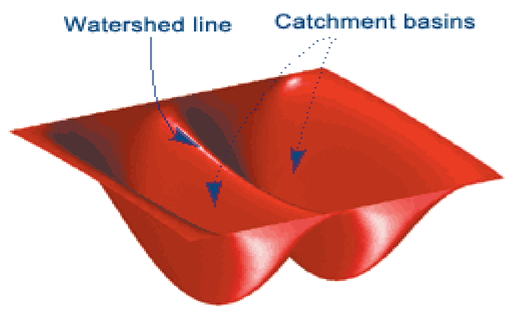

Fig. 1 Watershed Transform

3.3 Marker Function

Marker functions are selected to remove spurious minima. The marker is a connected component used to control over segmentation results from the watershed algorithm. The marker function is calculated from the internal marker and external marker. Internal markers are object marker calculated from watershed function on the gradient image. External markers are the background marker calculated by imposing the irrelevant regional minima. The internal markers and external markers are combined to obtain the desired marker function.

3.4 Feature Extraction and Selection

Feature extraction and selection are important steps in breast cancer detection and classification. An optimum feature set should have effective and discriminating features, feature vectors highly affects the performance of the classification Thus, how to extract useful features and make a good selection of the features is a crucial task for CAD systems. The features of breast US images can be divided into four categories: texture, morphologic, model-based and descriptor features [6]. Extraction and selection of effective features is a necessary step. The general guidelines for selecting significant features mainly include four considerations: discrimination, reliability, independence and optimality. The goal of feature extraction and selection is to maximize the discriminating performance of the feature group. In this work, extracted 32 GLCM features [8, 9], all the features are extracted with a 0 and 90 degree angles and with a distance 1 and 2; they show discrimination between malignant and benign lesions.

The extracted GLCM features are;

Energy:

$$Ene = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)^2 \quad (5)$$

Correlation:

$$Cor = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x\sigma_y} \quad (6)$$

Contrast:

$$Con = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}|i-j|^2\, p(i,j) \quad (7)$$

Entropy:

$$Ent = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\log(p(i,j)) \quad (8)$$

Homogeneity:

$$Homo = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{p(i,j)}{1+|i-j|} \quad (9)$$

Cluster Shade:

$$Sha = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i+j-\mu_x-\mu_y)^3\, p(i,j) \quad (10)$$

Sum of Square Variance:

$$sosv = \sum_{i}\sum_{j}(i-\mu)^2\, p(i,j) \quad (11)$$

Cluster Prominence:

$$\Pr = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i+j-\mu_x-\mu_y)^4\, p(i,j) \quad (12)$$

Where, μx, μy, бx and бy are the mean and standard deviation of px and py. N - number of distinct gray level in the quantized image. P(i,j) gray tone spatial dependency matrix.

3.5 SVM

Support vector machine [14], is a supervised learning technique that seeks an optimal hyperplane to separate two classes of samples. Kernel functions are used to map the input data into a higher dimension space where the data are supposed to have a better distribution, and then an optimal separating hyperplane in the high dimensional feature space is chosen. The database is organized equally for Training set (Benign-19, Malignant-6) and Testing set (Benign-19, Malignant-6).

4 Results

The test image used in this research comes from our breast US image database and the lesion's boundary is manually outlined by experienced radiologists. Fig. 2(a) shows the original BUS image used as input to our algorithm. Fig. 2(b) shows the output after anisotropic diffusion preprocessing. Fig. 2(c) shows the final segmentation result of the proposed method and Fig. 2(d) shows the manually outlined lesion by radiologist. The most common means of measuring diagnostic accuracy for reconstructed images is based on Area under receiver operating characteristic (ROC) curve. The area AZ under the ROC curve is an index of the quantitative measure of the overall performance of a diagnosis. Table 1, shows the performance for the proposed SVM system in the classification of malignant and benign tumors. The proposed method achieves Area under ROC curve ie. AZ=0.89. Matthew's correlation coefficient (MCC) is a powerful accuracy evaluation criterion of machine learning methods. Especially, when the number of negative samples and positive samples are obviously unbalanced.

$$MCC = \frac{TP*TN - FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (13)$$

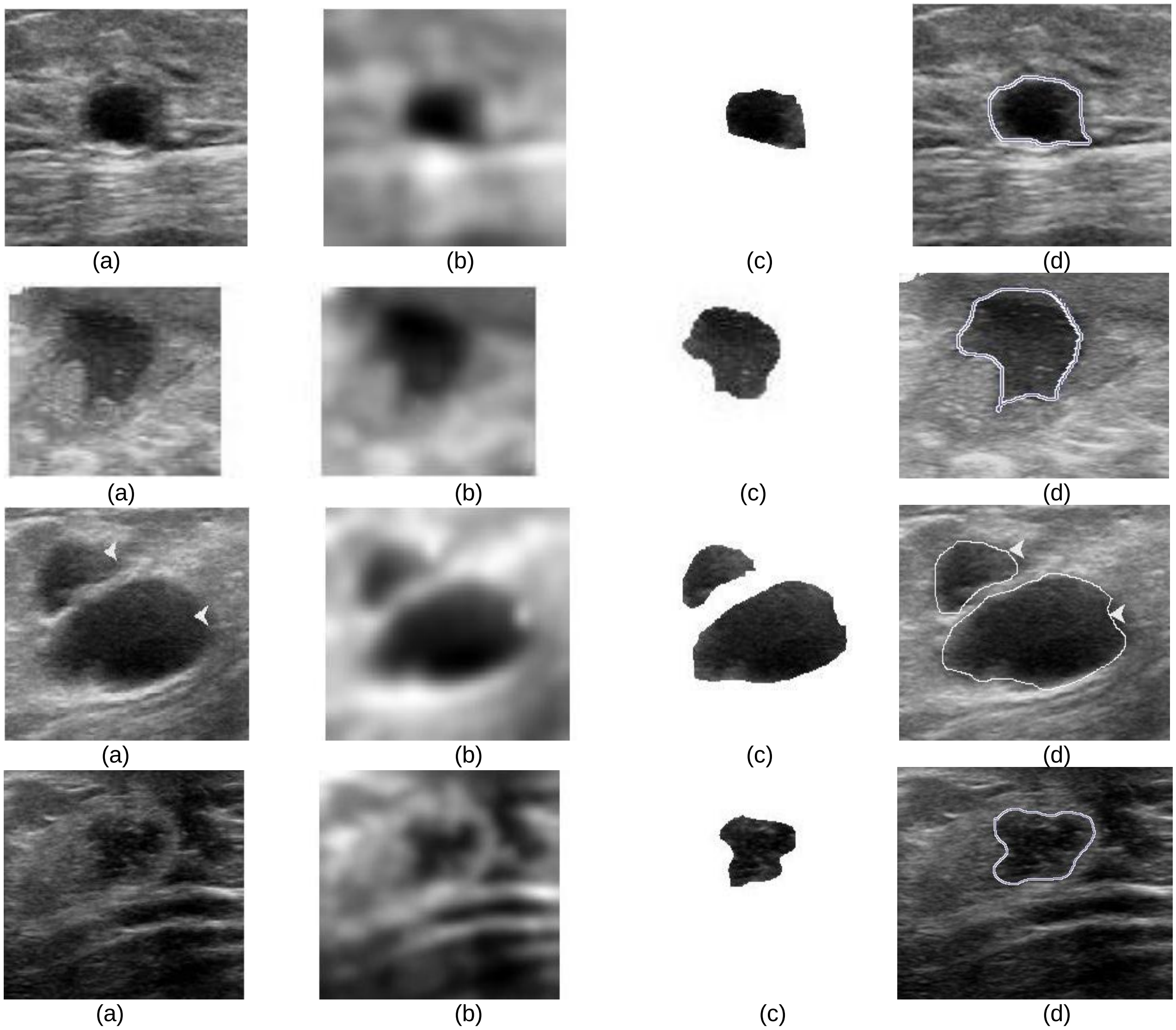

Fig. 2 Experiment results: (a) original image; (b) preprocessed image; (c) final segmented image; (d) manually outlined lesion image

Table I
The performance of the proposed CAD method.

Item	Proposed Method
Accuracy	92.00
Sensitivity	94.736
Specificity	83.34
MCC	0.78

Accuracy = (TP+TN)/(TP+TN+FP+FN); sensitivity = TP/(TP+FN); specificity = TN/(TN+FP); TN true-negative, FN false-negative, FP false-positive, TP true-positive, MCC Matthew's Correlation Coefficient.

5 Conclusion

This work presents a segmentation and classification method for breast lesions in BUS images. This technique preprocesses the image with an anisotropic diffusion filtering, in order to preserve and enhance useful information in the lesion boundaries, unlike from other filtering techniques that blur the image. The marker function plays an important role to remove the spurious minima which results in over segmentation. The MCC is used to measure along with the other performance evaluation parameters because it is efficient evaluation parameter of machine learning methods when data is unbalanced. The Marker-controlled watershed transformation is defined as a robust and flexible method for segmenting objects with closed contours, such as breast lesions. One advantage of our method is its simplicity to be implemented, because it does not require large computational cost to solve complex mathematical models, such as snake-deformation. SVM classifier efficiently classifies the Benign from Malignant and also works faster than ANN. The techniques are used in the CAD system to give support to the detection and diagnose of breast lesion in BUS image.

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