

CURVATURE AND SHAPE ANALYSIS FOR THE DETECTION OF SPICULATED MASSES IN BREAST ULTRASOUND IMAGES

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Abstract- Detection and classification of spiculated masses in ultrasound images is still a challenge due to the interference of speckle noise and fuzziness of boundaries. Ultrasound (US) is an important adjunct to mammography in breast cancer detection as it doubles the rate of detection in dense breasts do a dynamic analysis of moving structures in breast. This paper presents technique to detect spiculations and boundary of spiculated masses in breast ultrasound images. In the proposed method, ultrasound images are preprocessed using Gaussian smoothing to remove additive noise and anisotropic diffusion filters to remove multiplicative noise (speckle noise). Active contour method has been used to extract a closed contour of filtered image which is the boundary of the spiculated mass. Spiculations which make breast mass unstructured or irregular are marked by measuring the angle of curvature of each pixel at the boundary of mass. To classify the breast mass as malignant or benign we have used the structure of mass in accordance with spiculations and elliptical shape. We have used receiver operating characteristic curve (ROC) to evaluate the performance. We have validated the proposed algorithm on 100 sub images(40 spiculated and 60 non spiculated) and results shows 90.5% of sensitivity with 0.87 Area Under Curve. Proposed techniques were compared and contrasted with the existing methods and result demonstrates that proposed algorithm has successfully detected spiculated mass ROI candidates in breast ultrasound images.

Key words - ultrasound, spiculated mass, Gaussian filter, mean and median filter, angle of curvature.

INTRODUCTION

Breast cancer is the most common, life-threatening cancer which has been reported to have the highest mortality rates of any women's cancer. It is the second leading cause of cancer deaths among women in United States and it is the leading cause of cancer deaths among women in the 40 – 55 age groups. Approximately 182,000 new cases of breast cancer are diagnosed and 46,000 women die of breast cancer each year in the United States. In 2009, about 40,610 women died from breast cancer in the United States. According to the recent statistics, one out of nine women will develop breast cancer during her lifetime [1, 2]. There is no effective way to prevent the occurrence of breast cancer. Therefore, early detection is the first crucial step towards treating breast cancer. Mammography and ultrasonography are currently the most sensitive noninvasive modalities for detecting breast cancer. A panel report issued from Institute of Medicine and National research council of National Academics concurred that Mammography though useful wasn't always enough and health practitioners needed to investigate other complementary screening methods like ultrasound. It also says that mammography depicts about three to four cancers per 1000 women. But in women with dense breasts ultrasound depicts another three cancers per 1000 women [3]. In addition, mammography produces a high

false positive rate, and only about 525 of 1800 lesions that were sent to biopsy are malignant. Mammography has limitations in cancer detection in the dense breast tissue of young patients. Most cancers arise in dense tissue, so lesion detection for women in this higher risk category is particularly challenging. The breast tissue of younger women tends to be dense and full of milk glands, making cancer detection with mammography problematic. In mammograms, glandular tissues look dense and white, much like cancerous tumor. The reasons for the high miss rate and low specificity in mammography are, low conspicuity of mammographic lesions, noisy nature of the images, overlying and underlying structures that obscure features of the mammographic images [4, 5]. The cancers found on ultrasound are almost all small invasive cancers that have not yet spread to the lymph nodes and therefore have good prognoses. Reports generated by screening process be interpreted and diagnosed by relatively few radiologists. In order to improve the accuracy of interpretation, a variety of computer systems have been proposed.

Wild and Neal [6] were the first to propose the use of ultrasound imaging in breast examination. Consequently, ultrasonography is more effective for women younger than 35 years of age. Thus, it has proven to be an important adjunct to mammography. It is superior to mammography in its ability to detect local abnormalities in

the dense breasts of adolescent women. Results suggest that the denser the breast parenchyma, the higher the detection accuracy of malignant tumors using ultrasound. Breast ultrasound examination is playing an increasingly significant role in detecting breast cancers, due to the fact that ultrasonography can reveal a mass otherwise obscured mammographically by dense tissue, it is low cost, portable, and requires no ionizing radiation. However, the ultrasound image itself has some limitations, such as low resolution and low contrast, speckle noise, and blurry edges between various organs, so it is more difficult for a radiologist to read and interpret an ultrasound image. In addition, ultrasound diagnosis is heavily dependent on a doctor's personal experience.

Some of the important signs of breast cancer radiologists normally look for are: spiculated masses, micro calcifications, architectural distortions and bilateral asymmetry. Spiculated masses are characterized by radiating lines or spicules from a central mass of tissue. Spiculated masses carry a much higher risk of malignancy than calcifications or other types of masses. The performance figures for the leading mass detection algorithms are not as good as those for microcalcification detection algorithms [7]. Masses appear as ill-defined local increases in brightness, are highly variable in appearance, and share many characteristics with normal background tissue. Almost 50% of malignant masses are, however, characterized by a radial pattern of linear structures known as spicules [7,8]. In this paper, we present a computational technique that detects the spiculations in masses in ultrasound images.

LITERATURE

The literature directly relevant to the proposed research, are highlighted here. Abdul Kadir[9] presented the application of Snake for the segmentation of masses on breast ultrasound images. The boundaries of the masses identified may be used in classification of cancers or non-cancerous masses. They have attempted to segment masses on the breast ultrasound images using Balloon Snake by combining the mathematical optimization conception together with the computer technology. The accuracy of segmentation results was 95.53%. Yan and Toshihiro [10] proposed segmentation scheme using fuzzy c-means (FCM) clustering incorporating both intensity and texture information of images is proposed to extract breast lesions in ultrasound images. The proposed spatial FCM is more tolerant to noise than the conventional one. Based on the speckle texture and image intensity, it copes with the speckle noise and fuzziness of boundaries in ultrasound images. The low-level segmentation techniques are known to be fast and simple, but these methods simply analyze an image by reducing the amount of data to be processed. This problem can result in loss of important information. Moreover, the low-level segmentation techniques may incorrectly identify region or boundary of an object due to the distraction of noise in an image. The boundary of the abnormality should be identified accurately so that all of the important information required by the radiologist from the object such as shape, margin, and area can be

determined. In order for the image to be interpreted accurately, the image must be segmented accurately into regions that correspond to objects or parts of an object. The iterative algorithm namely active contours were proven to be the effective high level techniques in line and edge detection, image segmentation, shape modeling, and motion tracking as claimed through research carried out by Kass [11].

Cheng and Itoh[12] proposed a novel method for the automated detection of breast tumors in three dimensional ultrasonic images using fuzzy reasoning. 10 cases of malignant and 10 cases benign tumors are successfully extracted by the proposed method. Horsch [13] presented a method which involved thresholding a preprocessed image that has enhanced mass structures. Madabhushi and Metaxas [14] combined intensity, texture information, and empirical domain knowledge used by radiologists with a deformable shape model in an attempt to limit the effects of shadowing and false positives. Their method requires training but in the small database. They showed that their method is independent of the number of training samples, shows good reproducibility with respect to parameters, and gives a true positive area of 74.7%. Yuji Ikedo and Daisuke [15] proposed a scheme for mass detection in whole breast ultrasound images using bilateral subtraction technique based on a comparison of the average gray values of a mass candidate region and a region with the same position and same size as the candidate region in the contra lateral breast. The sensitivity was 83% (5/6) with 13.8 (165/12) false positives per breast before applying the proposed reduction method. By applying the method, false positives were reduced to 4.5 (54/12) per breast without removing a true positive region.

Dar and Chang [16] in their research used morphology operation, histogram equalization, and fractal analysis for classifying ultrasound images. The fractal analysis is applied to obtain the fractal texture features to classify the test cases of masses into benign and malignant. The accuracy rate was up to 88.80%.

Yuji and Takako [18] proposed a computerized classification scheme to recognize breast parenchyma patterns in whole breast ultrasound (US) images. They employed Canonical discriminant analysis with stepwise feature selection for the classification of parenchymal patterns. The classification scheme resulted in the accuracy of 83.3% (10/12cases) in mottled pattern cases. Ruey-Feng and Wen-Jie [19] worked on segmenting the tumors in ultrasound images using the newly developed level set method at first and then six morphologic features are used to distinguish the benign and malignant cases. In the experiment, the accuracy of SVM with shape information for classifying malignancies was 90.95% (191/210) and the sensitivity was seen to be 88.89% (80/90).

It has to be understood that the works in medical image processing generally or medical image segmentation specifically are not trying to substitute the appreciation of the physicians or radiologist, but to introduce approaches in order to improve the diagnosis by giving second opinion to the radiologist that hopefully reduce the requirement of

biopsy which is expensive, time-consuming and uncomfortable technique. In a way to overcome the shortcomings of existing works and to improve the sensitivity we are proposing a method to classify spiculated masses in ultrasound images.

MATERIAL AND METHODS

In this paper, we have used 100 US images (40 Spiculated mass and 60 non spiculated). For each image, a rectangular ROI including the tumor and the area around it were determined by an experienced radiologist. The radiologist also depicted tumor contours and has classified them as regular or irregular.

We aim at early detection of breast cancer by detecting the sites of spiculations in ROI of ultrasound images. The organization of this paper is as follows: Preprocessing, Feature analysis and extraction, classification and detection of spiculated masses, results and finally the concluding remarks and future work.

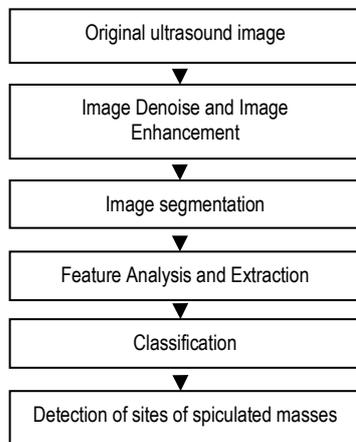


Fig. 1- Flow diagram showing the overall methodology

Preprocessing

Ultrasound medical imaging uses low-power, high frequency sound waves to visualize the body's internal structures and they are regarded as a noninvasive, practically harmless, portable, accurate, and cost effective method for diagnosis. Image data are generally contaminated by noise. Noise occurs in images for many reasons including imperfect instruments, problems with the data acquisition process, and interfering natural phenomena. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Unfortunately, the quality (resolution and contrast) of ultrasound image is generally degraded due to the existence of Gaussian noise and speckle noise. In our preprocessing steps we have removed additive (Gaussian) noise using Gaussian smoothing. Anisotropic diffusion method is used to reduce multiplicative (speckle) noise. Anisotropic diffusion filter can get rid of major drawback of conventional special filters and improve the image quality significantly and can preserve important boundary information.

Gaussian smoothing is the result of blurring an image by Gaussian function. It is a widely used to reduce image noise and reduce detail. Gaussian blur to an image is same as convolving the image with a Gaussian function. Since the Fourier transform of a Gaussian is another Gaussian, applying a Gaussian blur has the effect of reducing the high-frequency components of image. A Gaussian blur is thus a low pass filter. Breast ultrasound images have low contrast and some degree of fuzziness such as indistinct cyst borders, ill-defined mass shapes, and different tumor densities. Anisotropic diffusion reduces the speckle noise and also blurs the image without compromising with the image quality. The main idea in anisotropic diffusion is to smooth the homogenous areas of the image while enhancing the edges. This creates a piecewise constant image from which the segmentation boundaries can be easily obtained. Perona and Malik [10] first proposed anisotropic diffusion. They apply an inhomogeneous process that reduces the diffusivity at those locations which have a larger likelihood to be edges. Following is the nonlinear partial differential equation used for smoothing image on a continuous domain:

$$\frac{\partial I}{\partial t} = \text{div}[c(\|\nabla I\|)] - \nabla I$$

$$I(t=0) = I_0 \tag{1}$$

Where ∇ is the gradient operator, div the divergence operator, $\|\cdot\|$ denotes the magnitude, $c(x)$ the diffusion coefficient, and I_0 the initial image. Two diffusion coefficients are:

$$c(x) = \frac{1}{1+(x/k)^2} \tag{2}$$

and

$$c(x) = e^{-[(x/k)^2]} \tag{3}$$

Where k is an edge magnitude parameter (acts as an edge strength threshold). Gradient magnitude is used to detect an image edge or boundary as a step discontinuity in intensity.

If $\|\nabla I\| > k$, $c(\|\nabla I\|) \rightarrow 0$ we have an all-pass filter
 If $\|\nabla I\| < k$, $c(\|\nabla I\|) \rightarrow 1$ we achieve isotropic diffusion (Gaussian filtering).

Proposed diffusion model not only provides different degrees of smoothing for intra-regions but also actively provides different degrees of sharpening for edges in inter-regions. The resulting images preserve linear structures while at the same time smoothing is made along these structures. Anisotropic diffusion is an iterative process where a relatively simple set of computation are used to compute each successive image in the family and this process is continued until a sufficient degree of smoothing is obtained. In our work we have considered 15 iterations to obtain the enhanced image. Later the

preprocessed image is used for segmentation process. Segmentation remains a necessary step in medical imaging to obtain qualitative measurements such as the location of objects of interest as well as for quantitative measurements such as area, volume or the analysis of dynamic behavior of anatomical structures over time. There are four layers in US image: skin, subcutaneous tissue, mammary gland and muscle as shown in "Fig. (3)". The boundaries between these layers are quite blurry.

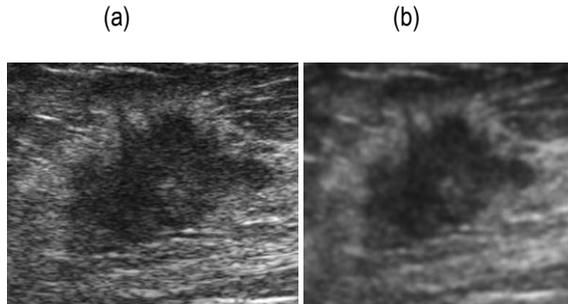


Fig. 2- (a) Original ROI of ultrasound with spiculated Mass, (b) Image after Preprocessing

Image segmentation

Segmentation remains a necessary step in medical imaging to obtain qualitative measurements such as the location of objects of interest as well as for quantitative measurements such as area, volume or the analysis of dynamic behavior of anatomical structures over time. There are four layers in US image: skin, subcutaneous tissue, mammary gland and muscle as shown in "Fig. (3)". The boundaries between these layers are quite blurry. The mammary gland region is located between the subcutaneous tissues and muscle layers, which are characterized as a line-like area with high gray levels. The regions with high gray levels are known as layers of subcutaneous tissues and the chest muscle.

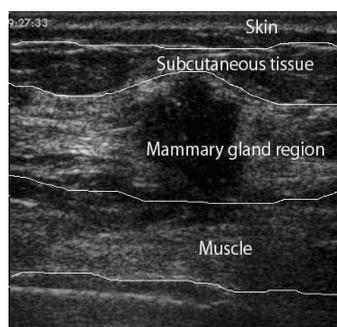


Fig. 3- Breast structure in Ultrasound images

Active contours were proven to be the effective high level techniques in edge detection and image segmentation. In this method, a curve is evolved towards the object boundary under a force, until it stops at the boundary. In the classical active contour methods, the curve moves to minimize the energy,

$$\varepsilon(l) = \int_1 (\frac{1}{2} \alpha |l'(s)| + \frac{1}{2} \beta |l''(s)| - \lambda |\nabla I(x, y)(l(s))|^2) ds \tag{4}$$

Where $l(s)$ represents a parameterized curve, $l(x, y)$ is the image gray-level function, and constants $\alpha, \beta, \lambda > 0$. The first two terms in the energy functional smooth the curve. The third term attracts the curve to the object boundary, where the value of image gradient is large. The dynamics of the curve is given by the Euler-Lagrange equation,

$$l_t(s) = \alpha l'(s) - \beta l''(s) + \lambda \nabla |\nabla I(x, y)(l(s))|^2 \tag{5}$$

Later, a constant force (balloon force) was added in the normal direction of the curve to accelerate the motion of the curve and increase the capture range. In, the level set framework was used to handle the topological changes such as merging or splitting of the moving curve. The dynamic equation can be summarized as,

$$\phi_t = g(\nabla I(x, y)) (\nabla \cdot \left(\frac{\nabla \phi}{|\nabla \phi|} \right) + v) |\nabla \phi| \tag{6}$$

Where $\phi(x, y)$ is the level set function whose zero level set represents the curve. The terms before $|\nabla \phi|$ form the velocity of the curve in its normal direction. The first term in the bracket is the effect of the curvature of the curve, which smoothes and shortens the curve. The second term in the bracket is a constant v , which corresponds to the balloon force mentioned above, making the curve expand or shrink depending on its sign. The function $g(\nabla I(x, y))$ is chosen such that it is very small at the boundary, where the value of image gradient is large, so that the velocity of the curve is small and the curve will stop there. One choice of $g(\nabla I(x, y))$ is $g(\nabla I(x, y)) = 1 / (1 + |\nabla G\sigma(x, y) * I(x, y)|^p), p \geq 1$. There are some modifications to the level set formulation, stated in Eq. (6), rewriting the right-hand-side as the minimization of an energy which gives some additional terms to attract the curve to the boundary from its both sides. However, for these methods, without the balloon force, the capture range is short and the curve cannot reach the narrow concave parts of the boundary. This is because the effect of (x, y) , in Eq.(5) or $g(\nabla I(x, y))$ in Eq.(6), is localized near the boundary. By applying active contour on ROI of ultrasound which contains mass or spiculated mass we get the boundary of mass as shown in "Fig. (4)".



Fig. 4- ROI after segmentation

Feature Extraction

A key stage of mass detection and classification is feature analysis and extraction. Several features might be derived from an image. But not all of the features are suitable for classification. Too many irrelevant features not only make the classifier complicated, but also will reduce the accuracy of the classification. The most important issue is to select features that are able to represent the characteristics of spiculated masses in the breast ultrasound images. Spiculations are the small needlelike structures found in malignant mass which shows uncontrollable multiplication of breast cells. These spiculations will make the breast masses unstructured and irregular.

Spiculation feature: The first feature retrieved is the spiculation feature of mass by finding angle of curvature at each pixel of contour. Most benign masses tend to be wider and roughly ellipse. Thus as a second feature we consider shape of the mass by fitting the contour to ellipse. Based on these features the spiculated malignant mass can be significantly discriminated from the benign masses by the classifier. In breast ultrasound images, spiculations and angular margins are the significant characteristics. Spiculations produce the higher positive predictive value of malignancy. Also, the hyperechogenicity, well-circumscribed lobulation, ellipsoid shape and a thin capsule are the significant characteristics of benign masses in breast ultrasound images [15].

Based on the characteristics of the breast ultrasound image, we first detect the presence of spiculations in the segmented image. We start by clearing the unwanted structures in the segmented image. The angle of curvature of every pixel at that boundary of the ROI is considered. At every pixel the angle of curvature is found by projecting lines from that pixel to some appropriate pixels and the angle between the lines are found and is as shown in "Fig. (5)". The spiculated regions will be having lesser angle of curvature and thus the measured angle of curvature at each pixel is compared with certain range of angle, showing the spiculated region. Here we have considered spiculated angle range as 45° to 60° and if any pixels showing this feature are found, they are marked for analysis as shown in "Fig. (6)".

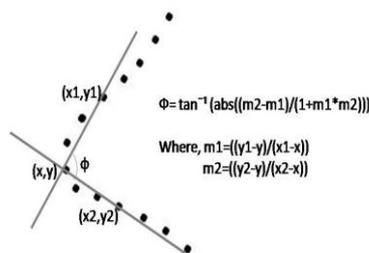


Fig. 5- Angle of curvature at pixel (x,y) found by projecting lines from that pixel

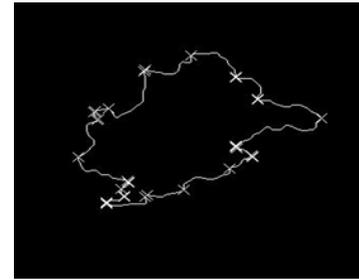


Fig. 5- ROI to which spiculations are marked with "x"

Shape feature: This section deals with those factors which refer to shape of the mass. The proportion of width and height of the mass and the ellipsoid shape are considered to classify it as benign or malignant. Consider the contour of mass which is already retrieved in previous section. Let (c1,c1) be the centroid of mass contour with the maximum path passing the point (c1,c1) is considered to be the major axis 'a' and the minimum path through (c1,c1) is considered as a minor axis 'b'. Angle between X-axis and major axis is considered to be 'θ'. Mathematically an ellipse may be specified as:

$$x(t) = c1 + a \cos t \cos \theta - b \sin t \sin \theta \quad (7)$$

$$y(t) = c2 + b \sin t \cos \theta + a \cos t \sin \theta \quad (8)$$

Where t is interval angle (0 < t < 2π)

The standard deviation of the shortest distance is the best fit of mass contour by an ellipse. Shortest distance can be defined as

$$S(i) = |E_i H_i| \quad i=1,2,3,\dots,N \quad (9)$$

Where N is number of pixels on mass contour

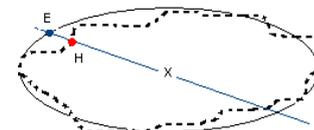


Fig. 7- Shows the shortest distance in the best fit ellipse. Point "X" in the centre is centroid of mass contour

Standard deviation of shortest distance is given by

$$SD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N [S(i) - \frac{1}{N} \sum_{i=1}^N S(i)]^2} \quad (10)$$

The shape and spiculated features retrieved in previous section are sent as input to SVM classifier to classify the ROI's as malignant or benign. Using support vectors SVM finds adequate hyper plane to separate the groups. After separation cases belonging to one category remains in one side of the plane and other cases on the other side of the plane [17] as shown in "Fig. (8)". The features we have considered are discriminative and effective in identifying spiculations in ultrasound images which is

shown in "Fig. (8)". Using a single feature as parameter to discriminate benign and malignant cases, there is always a tradeoff between the sensitivity and specificity. The tradeoff is due to that each feature parameter is mainly related to its nature. So we have considered two main features: spiculated feature and elliptical shape feature for discrimination. We evaluated the performance of both features in classifying benign and malignant tumors by performing the ROC analysis and calculating the area under the ROC curve.

In breast ultrasound images, the spiculation and the angular margins are the significant characteristics of the spiculation and produce higher positive predictive value of malignancy. Ellipsoid shape is also significant characteristic of benign masses in breast ultrasound images. These two features have high sensitivities and negative predicted values. We have effectively used SVM classifiers with the help of Angle of curvature and ellipsoidal features to classify the ROI's as malignant or benign.

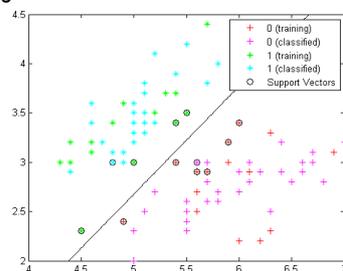


Fig. 8- Shows the classification using SVM

EXPERIMENTAL RESULTS

The proposed methods are applied on 100 ROI's of ultrasound images. First set of features related to spiculations were retrieved using angle of curvature method. Second set of features related to shape were retrieved by fitting an ellipse to mass contour to find the elliptical shape of mass. Classification is done using SVM toolbox by considering 70% of dataset for training and 30% for testing. We have evaluated the method of classification to classify the breast mass in ultrasound images as malignant or benign. For cross validation we used leave-one-out scheme. Performance analysis is done by plotting Receiver Operating Curve (ROC). ROC graphically represents the true positive rate as a function of false positive rate. The performance of the classifier is assessed in terms of sensitivity and specificity as shown in "Fig. (9)". Where sensitivity is the proportion of actual positives which are correctly identified and specificity is the proportion of negatives which are correctly classified. ROC curve shows the performance of SVM classifier for classification of masses as malignant or benign in ultrasound images with sensitivity 90.5%, area under curve (AUC) is 0.87. Table 1 gives the comparison of our method with other existing methods which have addressed similar type of problems.

Conclusion and Future work

In this work, we have proposed new approaches for measuring angle of curvature and elliptical shape feature to classify the masses as benign or malignant. The improved method is expected to allow early detection of

breast cancer. Increased sensitivity in breast cancer diagnosis may be expected to reduce mortality due to the disease, and to improve the prognosis of patients with breast cancer. As the features retrieved from one modality are not sufficient to classify masses and to detect the breast cancer in earlier stage, future research will concentrate on designing image processing algorithms to extract features from different modalities and combining these features to improve the performance of detection.

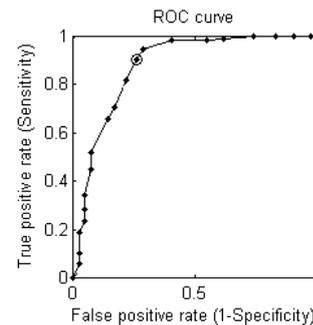


Fig. 9-ROC Curve depicting the performance of SVM classifier with sensitivity of 90.5% and AUC=0.87.

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Table-1 - Comparison of our method with other existing methods:

Technique	Problem addressed	Sensitivity (%)
Fuzzy reasoning [12]	Spiculated Mass detection	86
Combined intensity, texture and shape information [14]	Mass detection	74.7
Bilateral subtraction technique[15]	Mass detection	83
Morphology operation, histogram equalization, and fractal analysis[16]	Mass detection	88.8
Canonical discriminant analysis [18]	Recognize breast parenchyma patterns	83.3
Six morphologic features and SVM [19]	Segmenting the tumors in ultrasound	88.89
Angle of curvature and Elliptical shape features (our method)	Spiculated Mass detection	90.05