Breast Cancer Ultrasound Images Analysis & Auto-Segmentation of Lesions

A dissertation submitted in partial fulfillment of requirement for the degree of Bachelor of Science in Electrical and Electronic Engineering

Islamic University of Technology

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Summary:

Breast cancer is the most common cause of death among patients and one of the main reasons is the lesion is not identified in proper time to seek medical facility. The situation is Bangladesh is alarming as there is a huge female population in the rural areas who don't have proper medical access to detect the early stage of breast cancer.

We have developed a Computer Aided Diagnosis (CAD) system that will detect the cancerous lesion in the BUS (breast ultrasound) image automatically. The algorithm can come up with a Region of Interest (ROI), which not only eliminates human intervention but also highly accurate. Entropy information along with a rule based approach called 'rule of third' is used to obtain the ROI. For edge detection the algorithm uses external energy filtering and thresholding.

Keywords: Ultrasound, Automatic segmentation, ROI, Entropy, Lesion boundary, External energy.

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Contents:

Chapter 1

Introduction

Breast cancer is the most common invasive cancer in females worldwide. It accounts for 16% of all female cancers and 22.9% of invasive cancers in women. 18.2% of all cancer deaths worldwide are from breast cancer. Bangladesh is a vastly populated country and 80% of this population lives in rural areas. As breast cancer is mostly common in female population there are a large number of women at risk of being undiagnosed because of the lack of proper medical care. From fig.1.1 we can see the number of patients diagnosed of different cancers every year in Bangladesh and breast cancer holds the second largest population.

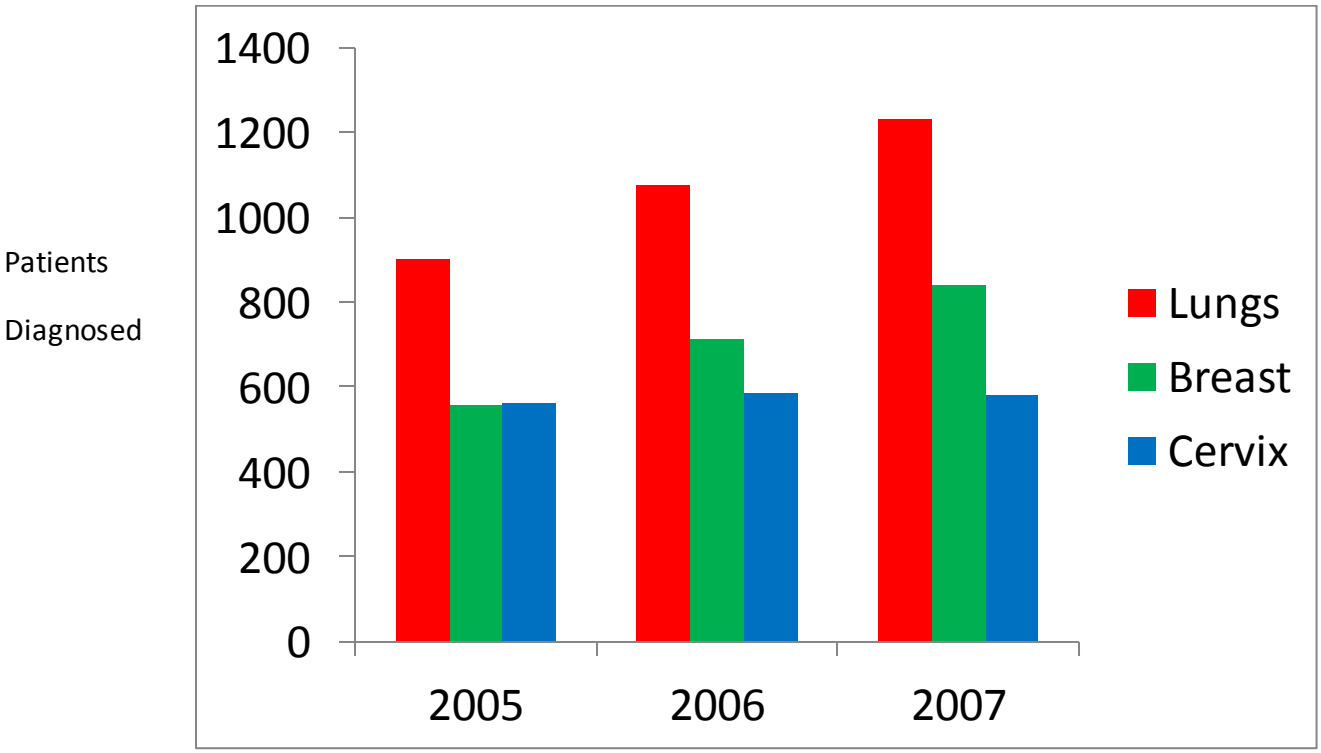


Fig. 1.1: Patients diagnosed on a yearly basis [13]

From fig.1.2 we can see the top malignancies in Bangladeshi female patients and from fig.1.3 the age distribution of diagnosed cancer patients. Breast cancer alarmingly has the highest number of patients diagnosed each year.

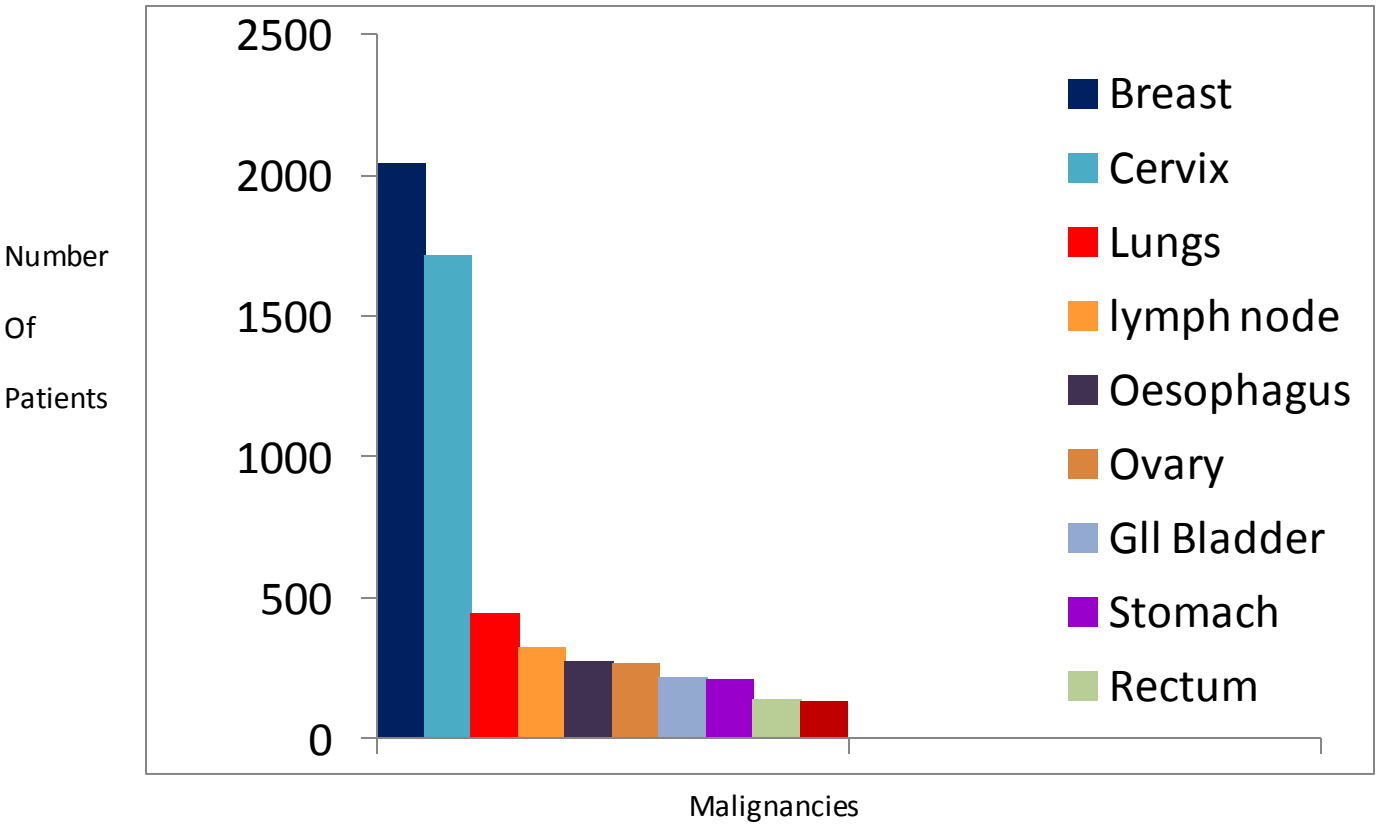


Fig.1.2: Top malignancies in females [13]

The number of deaths every year is increasing because of lack of awareness along with scarce medical facilities to detect breast cancer at an early stage. There is huge number of female population living in the rural areas of Bangladesh. If there is a Computer Aided Diagnosis (CAD) system present in the medical facilities in these areas to help the radiologists and doctors to diagnose and detect breast cancer among the huge number of patients there would be huge medical and social impact.

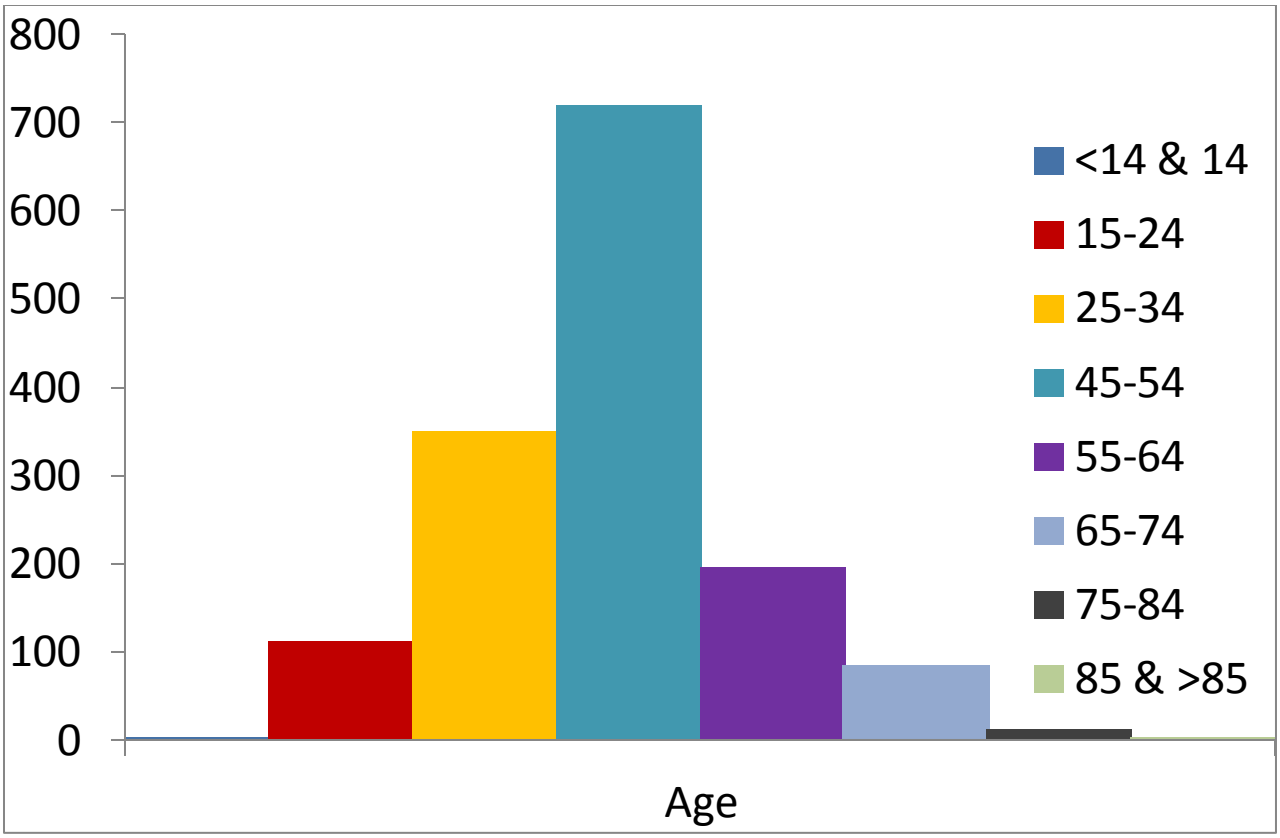


Fig.1.3: Age distribution of female breast cancer patients [13]

The purpose of CAD is to help Radiologists to make accurate diagnosis, provide a second opinion. CAD can minimize the operator dependent nature of Ultrasound Imaging. It can obtain computational and statistical features that cannot be obtained visually. It also Increases efficiency, saves time and effort.

Radiologists need to undergo years of training and experience to properly read Ultrasound images. This is because ultrasonography is an operator dependent process. But still the diagnosis varies for different radiologists because of the randomness of the cancer lesions. Therefore, computer-aided diagnosis (CAD) has been investigated to help radiologists in making accurate diagnoses. One advantage of a CAD system is that it can obtain some features, such as computational features and statistical features, which cannot be obtained visually and intuitively by medical doctors. Another advantage is that CAD can minimize the operator-dependent nature inherent in ultrasound imaging [xx] and make the

diagnosis process reproducible. It should be noted that research into the use of CAD is not done so with an eye toward eliminating doctors or radiologists, rather the goal is to provide doctors and radiologists a second opinion and help them to increase the diagnosis accuracy, reduce biopsy rate, and save them time and effort.

Generally, ultrasound CAD systems for breast cancer detection involve four stages, as shown in fig.1.4 [1]

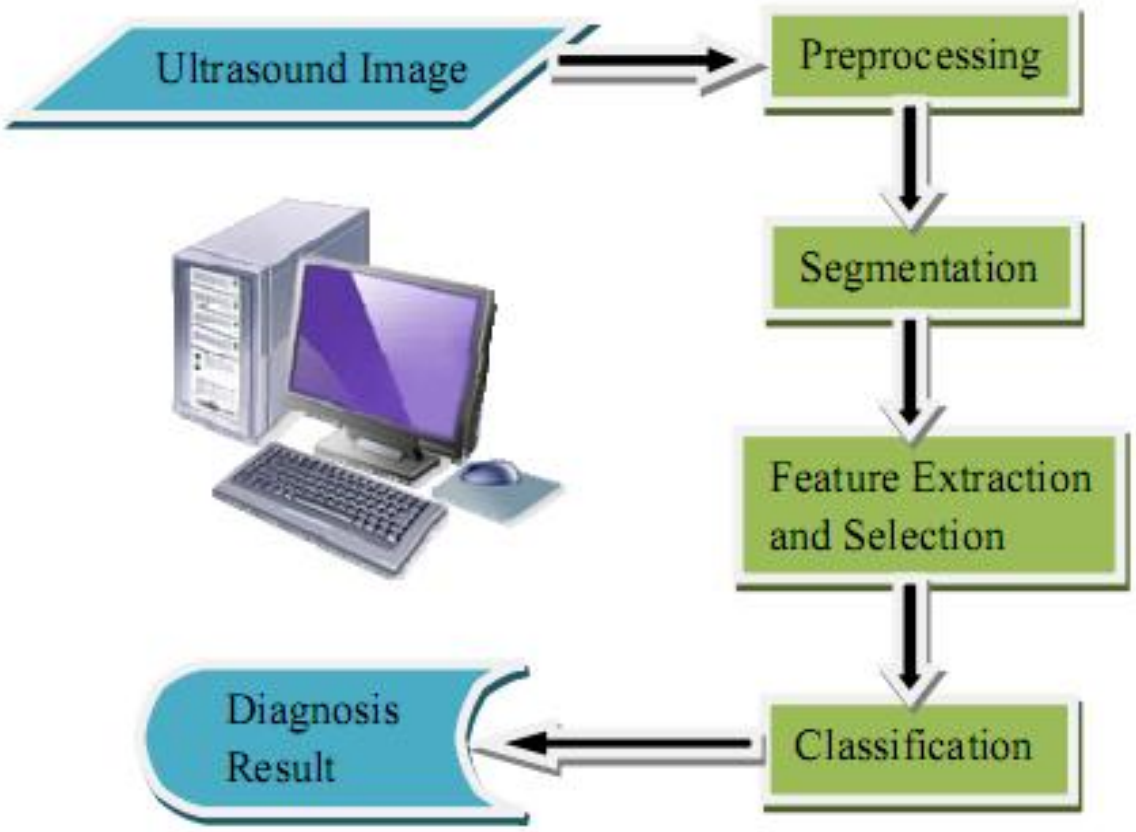


Fig.1.4: A CAD system for breast cancer diagnosis [1]

1. Image preprocessing: The task of image preprocessing is to enhance the image and to reduce speckle without destroying the important features of BUS images for diagnosis.

2. Image segmentation: Image segmentation divides the image into non-overlapping regions, and it separates the objects (lesions) from the background. The boundaries of the lesions are delineated for feature extraction.

3. Feature extraction and selection: This step is to find a feature set of breast cancer lesions that can accurately distinguish lesion/non-lesion or benign/malignant. The feature space could be very large and complex, so extracting and selecting the most effective features is very important.

4. Classification: Based on the selected features, the suspicious regions will be classified into different categories, such as benign findings and malignancy. Many machine learning techniques such as linear discriminant analysis (LDA), support vector machine (SVM) and artificial neural network (ANN) have been studied for lesion classification.

Now, the main objective of this thesis is to develop a CAD system that will automatically segment breast ultrasound images and detect cancerous lesions in an efficient and accurate manner. We collaborated with the National Institute of Cancer Research and Hospital (NICRH) and they provided some very useful data and information about current scenario of Bangladesh. They let us visit their facilities and use their machines for taking ultrasound data. For ROI (region of interest) detection we have used entropy based filtering system along with rule of third. This method avoids the speckle reduction process that makes the whole segmentation process simple and less time consuming. For lesion detection we used external energy filtering with thresholding. We look forward to make a portable and user friendly device in the near future so that the medical representatives in the rural areas can use it to diagnose more number of patients efficiently.

Chapter 2

Literature Review

Researchers working on segmentation mainly emphasize on dividing the process into some parts such as speckle reduction, ROI detection, edge detection and classification. After these comes the diagnosis and error comparison.

For accurate ROI detection it is sometimes crucial to remove noise before wise and do some preprocessing.

Lee et al preprocessed US images by a 4x4 median filter to reduce the speckle noise & to enhance features. For removing noise or spot, image regularization problem was considered. Mean Variance Model was used to solve the problem for smooth image by utilizing the global variation framework.

Rafael et al used Band Pass Filtering to provide valuable information on region transitions of US images while rejecting most of the noise components. The filter is obtained using the McClellan transformation over a 1-D FIR filter. Gaussian Smoothing is also used to reduce the influence of noise. Gaussian smoothing is performed over a series of iterations. The Gaussian filter consists of a 5_5 square matrix. Filter size and standard deviation is constant on all iterations.

Yap et al used a hybrid filtering approach that combines the strength of nonlinear diffusion filtering to produce edge-sensitive speckle reduction, with linear filtering (Gaussian blur) to smooth the edges and to eliminate over segmentation. Subsequent to hybrid filtering, multi-fractals are used to further enhance the partially processed images.

Xu Liu et al applied Anisotropic Diffusion Non-linear filter is applied to smooth the noise.

Now this pre-processing methods and speckle/noise removing algorithms are both time consuming and complex. So if there was a way to avoid this it would actually be very effective and efficient. One of the novel features of this paper is that we can avoid the noise/speckle removal part because we use a textural feature called entropy to select ROI from a general BUS image. By doing so we avoid lots of calculation, save time and effort. From [9] we get a basic idea about textural analysis.

ROI selection is crucial for segmentation because it reduces the computational area and time. It also makes it easier for the computing machine to find the lesion and detect the lesion boundary. In the papers [8, 11, 12] segmentation algorithm concludes ROI detection.

In the paper [8], Level Set Method is used to obtain the ROI. Level Set method is a hybrid speed function method which considers a boundary and region information for masses segmentation.

In the paper [11], ROI selection was automatic. Object Suppressing Operation is used to obtain binary images containing ROI and in most cases, small misclassified isolated objects are considered as noise

A rule based approach is used to identify important ROIs by Yap et al. ROI is detected automatically. The first criterion for the identification of lesions is the size of the segments. The suspect lesions are identified as the largest segments among the likely multiple segments that result from applying the single threshold segmentation. It is observed that 95% of tumors are located at the upper regions of the images.

Some researchers select the ROI manually as in [1,3,4,9] and then try to find the contour/edge of the lesion. We use textural analysis to find the ROI (mainly entropy based filtering). This method is novel and can detect ROI with x% efficiency. Compared to other research works it also takes less computing time. There are many different methods of lesion segmentation. The process must be fast, efficient and automated. Many crucial features for discriminating benign and malignant lesions are based on the-Contour, shape, texture of the lesion. Due to

inherent speckle noise and low contrast of breast ultrasound imaging, automatic lesion segmentation is still a challenging task. An accurate segmentation method is essential for a successful diagnosis. Some characteristics such as attenuation, speckle, shadows, and signal dropout make the segmentation task complicated; these artifacts are due to the orientation dependence of acquisition that can result in missing boundaries. Further complications arise as the contrast between areas of interest is often low. How to do one of the oldest image processing tasks, image segmentation, for breast ultrasound, is a challenging task.

Many techniques have been developed for BUS segmentation. They are categorized into histogram thresholding, region growing, model-based (active contour, level set, Markov random field), machine learning, and watershed methods [Shan].

Histogram Thresholding and Region Growing:

Simple histogram thresholding [19, 20] or region-growing algorithms [21, 22] can find the preliminary lesion boundary. In a histogram thresholding method, an intensity threshold is chosen at the valley of the image histogram to separate the image into background and foreground. For a region growing method, a region is grown from the seed point (start point) by adding similar neighboring pixels. Although efficient, these methods cannot generate a precise boundary because their over-simplified concepts and the high sensitivity to noise. However, they can serve as an intermediate step to provide a rough contour [21] or can be combined with post-processing procedures such as morphological operations [19, 20, 23], disk expansion [24], Bayesian neural network [12], function optimization [25, 26], etc. For example, in the thresholding algorithm [19, 20], firstly, the regions of interest (ROIs) were preprocessed with a 4×4 median filter to reduce the speckle noise and to enhance the features. Second, a 3×3 unsharp filter was constructed using the negative of a two-dimensional Laplacian filter to emphasize the elements with meaningful signal level and to enhance the contrast between object and background. Third, the ROIs were converted to a binary image by thresholding. The threshold was determined by the histogram of ROIs. If a valley of a histogram between 33% and 66% of the pixel population could be found, this

intensity value was selected as the threshold. If there was no such valley in that range, the intensity of 50% of the pixel population was selected as the threshold value. Finally, the selected nodule's boundary pixels were obtained using morphologic operations.

Model-Based Methods:

Model-based methods have strong noise-resistant abilities and are relatively stable at sonography demarcation. Commonly used models include level set, active contours, Markov random fields (MRF), etc.

For instance, Sarti et al. discussed a level set maximum likelihood method to achieve a maximum likelihood segmentation of the target. The Rayleigh probability distribution was utilized to model gray level behavior of ultrasound images. A partial differential equation-based flow was derived as the steepest descent of an energy function taking into account the density probability distribution of the gray levels, as well as smoothness constraints. A level set formulation for the associated flow was derived to search the minimal value of the model. Finally, the image was segmented according to the minimum energy.

Madabhushi and Metaxas [21] combined intensity, texture information, and empirical domain knowledge used by radiologists with an active contour model in an attempt to limit the effects of shadowing and false positives. Their method requires training but in the small database. Using manual delineation of the mass by a radiologist as a reference, and the Hausdorff distance and average distance as boundary error metrics, 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%. Some active contour models have been applied to 3-D ultrasound segmentation, such as [30-33].

Boukerroui et al. [34] used a Markov random field to model the region process and to focus on the adaptive characteristics of the algorithm. Their method introduced a function to control the adaptive properties of the segmentation process, and took into account both local and global statistics during the segmentation process. A new formulation of the segmentation problem was

utilized to control the effective contribution of each statistical component. The merit of MRF modeling is that it provides a strong exploitation of the pixel correlations. The segmentation results can be further enhanced via the application of maximum a posteriori segmentation estimation scheme based on the Bayesian learning paradigm [18].

In most model-based approaches, an energy function is formulated, and the segmentation problem is transformed as finding the minimum (or maximum) of the energy function iteratively. However, the iterations on calculating energy functions and reformulating the models are always time-consuming, especially for complex BUS images; and many models are semi-automatic with the requirement of pre-labeled ROI or manually initialized contour.

Machine Learning Methods:

Machine learning methods (such as neural network and support vector machine) are popular in image segmentation, which transform the segmentation problem into a classification decision based on a set of input features. Dokur and Ölmez proposed a neural network based segmentation method. Images were divided into square blocks, and features were extracted from each block using the discrete cosine transform (DCT). Then a three-layer hybrid neural network was trained to classify the blocks into two categories: background and foreground. The method was applied on the region of interest (ROI) which needed to be selected by the user. Kotropoulos and Pitas [39] employed a support vector machine with a radial basis function kernel to classify different patterns. In this method, patterns were collected by a running window with size of 15x15 over the entire image. To train the SVM, 1128 positive patterns (lesion) and 1128 negative patterns (background) were selected from the training set. Experiments showed that the trained SVM could generate reasonable segmentation result.

For machine learning methods, feature selection and training process are two key steps that play an important role on segmentation result. If features are sufficiently distinguishable and the method is well trained, machine learning methods can generate satisfactory lesion contours. However, over-training or insufficient training (trapped by local minimum) may severely affect the

segmentation performance on new data. And the training process is usually quite time-consuming.

Watershed-Based Methods:

Watershed-based approaches have shown promising performances for ultrasound image segmentation. The methods consider image as topographic surface wherein the grey level of a pixel is interpreted as its altitude. Water flows along a path to finally reach a local minimum. The biggest challenge for such methods is over-segmentation; to address the problem; many approaches have been proposed and can be categorized into two types: marker-controlled and cell competition.

Marker-controlled methods inundate the gradient landscape of image and define watersheds when the flooding of distinct markers rendezvous with each other. Hence, the identification of makers is very crucial in solving the over-segmentation problem. The method proposed in [34] was a texture-based approach that selected the marker candidates as seeds for the water-level immersion. A self-organization map was trained to identify the texture of lesions as the flooding markers. Distinctively, the method in [25] adopted a thresholding and morphological operation scheme to seek flooding markers. It required a heuristic estimation of the best thresholding of markers to achieve the task of lesion delineation. Cell competition approaches, on the other hand, alleviate the over-segmentation problem in a different way. A two-pass watershed transformation [27] was performed to generate the cell tessellation on the original ultrasound image or ROI. In this method, a competition scheme based on the cell tessellation was carried out by allowing merge and split operations of cells. The cost function was devised to characterize boundary saliency and regional homogeneity of an image partition, and it drove the competition process to converge to a prominent component structure. However, neither marker-controlled nor cell competition approaches guarantee to solve the over-segmentation problem completely [28].

In summary, the major drawbacks of current methods are: 1) human interactions such as the pre-labeled ROIs or manually initialized contours are required, which impede full automation; 2) intensity features are most typically used for boundary detection. Since BUS images have low contrast and are degraded by speckle noise, features based on intensity gradients are always sensitive to noise and cannot guarantee accurate segmentation result; 3) reformulating the models and training the methods are always time-consuming, especially for complex BUS images. As the image resolution increases, the computational complexity for processing a BUS image also increases.

The proposed method addresses the problems efficiently. The ROI detection method is automated, edge detection process uses external energy filtering, the whole process consumes very less time and is very simple and straight forward.

Chapter 3

Theories

Ultrasound Imaging

Ultrasound imaging (ultrasonography) is one of the most used modalities in the field of medical diagnosis and therapy. One in five of all diagnostic images is obtained through ultrasound imaging. In physics, ultrasound is an example of an 'acoustic oscillation'. Acoustic oscillation is defined as: movement of particles in an elastic medium about an equilibrium position. Other instances of acoustic oscillation are sound and infra sound. The only difference between these is in the frequency of oscillation. For the acoustic oscillation to be called 'ultrasound', its frequency must be greater than 20 kHz, approximately the upper limit of human hearing. Similarly, 'infra-sound' has a frequency less than 20 Hz, the lower limit of human hearing. Unsurprisingly, 'sound' occupies the in-between frequency range (from 20 Hz to 20 kHz). The frequencies commonly used in biological and imaging applications range from about 500 kHz to more than 50 MHz.[9]

Ultrasound imaging the use of high-frequency sound (several MHz or more) to image internal structures by the differing reflection signals produced when a beam of sound waves is projected into the body and bounces back at interfaces between those structures. Ultrasound diagnosis differs from radiologic diagnosis in that there is no ionizing radiation involved.[13]

Modern Ultrasound Scanner :

Ultrasound images are obtained through a machine known as the " Ultrasound Scanner ". This machine has different components which have particular functions to perform. Basically a modern ultrasound scanner has the following components [9]:

- Pulser
- Beamformer
- Receiver
- Processing Black Box
- Display Storage etc.

Figure 2.1 : A real time modern ultrasound scanner

Pulser : The pulser generates a repetitive sequence of voltage pulses. The rate of pulsing depends on the type of scan and, in particular, the maximum depth of display required.

Beamformer : Each of these pulses is channeled via the beamformer to transducer array. The beam former determines which group of elements in the array is excited. An ultrasound pulse is launched from that group, propagates through the patient, and echoes from boundaries along the path return to the probe face to be converted to electrical signals.

Receiver : This amplifies the raw electrical signals. Echoes from close targets produce signal voltages in the order of milivolts. However, pulse and echo attenuation introduced by soft-tissue interactions during propagation dictates that mean signal levels fall exponentially with time of arrival (target range). The fall in signal strength is compensated by an increase in the receiver gain with time, logarithmically. Such compensation is termed depth compensation, time gain compensation or swept gain compensation. It is implemented at the receiver by user operated controls (Fig. 2.2) [9]

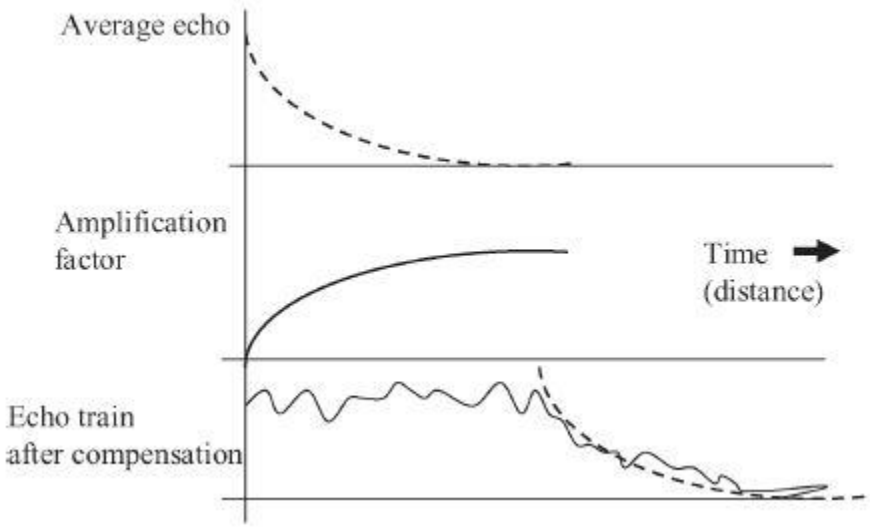


Figure 2.2 : Exponentially increasing amplification is applied to the received echoes to compensate for
attenuation within tissues. This is called variously, depth gain, swept gain, or time gain compensation

Display : The display is invariably a computer monitor which shows the image accumulating in the computer memory. Each time-base line is digitized and echo signals are written into the appropriate location for subsequent display.

Working Principle of the ultrasound scanner :

The creation of an image from ultrasound is done in three step : producing a sound wave, receiving echoes and interpreting those echoes. To understand these steps, we need to go through the block diagram of the modern ultrasound scanner [9], given in the following page.

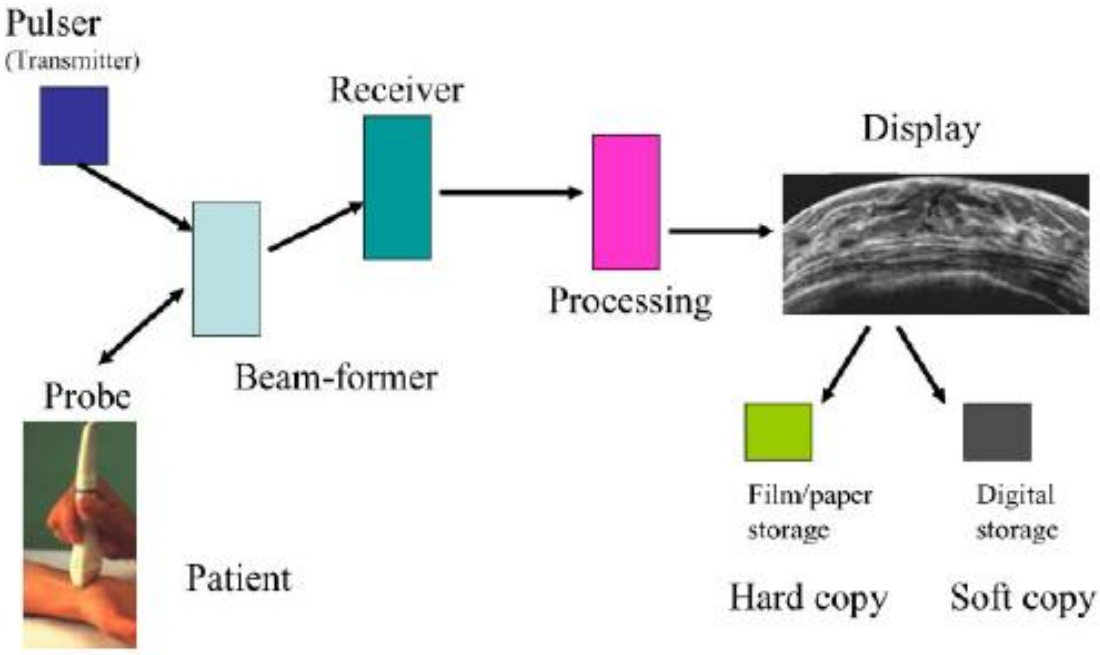


Figure 2.3 : Block diagram of a modern ultrasound scanner [9]

Producing a sound wave :

A sound wave is typically produced by a piezoelectric transducer encased in a housing which can take a number of forms. Strong, short electrical pulses from the ultrasound machine make the transducer ring at the desired frequency. The frequencies can be anywhere between 2 and 18 MHz. The sound is focused either by the shape of the transducer, a lens in front of the transducer, or a complex set of control pulses from the ultrasound scanner machine (Beamforming). This focusing produces an arc-shaped sound wave from the face of the transducer. The wave travels into the body and comes into focus at a desired depth.[13]

Older technology transducers focus their beam with physical lenses. Newer technology transducers use phased array techniques to enable the sonographic machine to change the direction and depth of focus. Almost all piezoelectric transducers are made of ceramic.[13]

Materials on the face of the transducer enable the sound to be transmitted efficiently into the body (usually seeming to be a rubbery coating, a form of impedance matching). In addition, a water-based gel is placed between the patient's skin and the probe.[13]

The sound wave is partially reflected from the layers between different tissues. Specifically, sound is reflected anywhere there are density changes in the body: e.g. blood cells in blood plasma, small structures in organs, etc. Some of the reflections return to the transducer.[13]

Receiving the echoes :

The return of the sound wave to the transducer results in the same process that it took to send the sound wave, except in reverse. The return sound wave vibrates the transducer, the transducer turns the vibrations into electrical pulses that travel to the ultrasonic scanner where they are processed and transformed into a digital image.[13]

Forming the image :

The sonographic scanner must determine three things from each received echo[13]. These things are determined in the " processing black box " (figure 3) :

1. How long it took the echo to be received from when the sound was transmitted.
2. From this the focal length for the phased array is deduced, enabling a sharp image of that echo at that depth (this is not possible while producing a sound wave).
3. How strong the echo was. It could be noted that sound wave is not a click, but a pulse with a specific carrier frequency. Moving objects change this frequency on reflection, so that it is only a matter of electronics to have simultaneous " Doppler sonography ".

After determining these three things, the ultrasound scanner knows which pixels in the US image to light up and to what intensities it should be done.[13]

Displaying the image :

Images from the sonographic scanner can be displayed, captured, and broadcast through a computer using a frame grabber to capture and digitize the analog video signal. The captured signal can then be post-processed on the computer itself. Both soft copy and hard copy images are available in the modern ultrasound scanner.[14]

To have a more clear understanding of the creation of an ultrasound image, we will briefly discuss about the " Pulse Echo Technique ".[9]

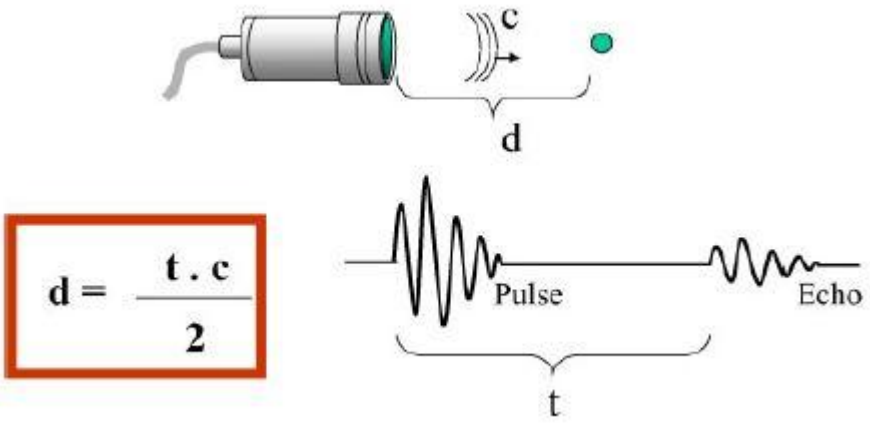


Figure 2.4 : The Pulse Echo Technique [9]

In the pulse echo technique, a hypothetical patient body is considered (figure 4). An ultrasound wave is transmitted in pulse wave fashion from the piezoelectric transducer into the patient body. When the transmitted pulse interacts with the interface between two tissues, a part of the transmitted ultrasound pulse is reflected back towards the transducer, known as the "echo", and the other part continues to transmit. Actually, a train of echoes is received in the transducer.

Now, the transducer converts these echoes into electrical signals and the receiver amplifies these signals so that they are large enough to be processed. The time required for the ultrasound pulse to be transmitted and reflected back to the transducer is measured.

If we multiply this measured time (t) with the average velocity of the transmitted pulse, and divide it by 2, we will get the depth (d) of the tissue interface. By measuring these distances, the scanner knows from where in the body, the signal is coming. These measurements give different depths to different tissues in the ultrasound image.

Modes of ultrasound imaging :

Several modes of ultrasound are used in medical imaging [15][16]. These are :

- **A-mode** : A-mode (amplitude mode) is the simplest type of ultrasound. A single transducer scans a line through the body with the echoes plotted on screen as a function of depth. Therapeutic ultrasound aimed at a specific tumor or calculus is also A-mode, to allow for pinpoint accurate focus of the destructive wave energy.
- **B-mode or 2D mode** : In B-mode (brightness mode) ultrasound, a linear array of transducers simultaneously scans a plane through the body that can be viewed as a two-dimensional image on screen. More commonly known as 2D mode now.
- **C-mode** : A C-mode image is formed in a plane normal to a B-mode image. A gate that selects data from a specific depth from an A-mode line is used; then the transducer is moved in the 2D plane to sample the entire region at this fixed depth. When the transducer traverses the area in a spiral, an area of 100 cm^2 can be scanned in around 10 seconds.[16]
- **M-mode** : In M-mode (motion mode) ultrasound, pulses are emitted in quick succession – each time, either an A-mode or B-mode image is taken. Over time, this is analogous to recording a video in ultrasound. As the organ boundaries that produce reflections move relative to the probe, this can be used to determine the velocity of specific organ structures.

- **Doppler mode** : This mode makes use of the Doppler effect in measuring and visualizing blood flow.

- **Color Doppler** : Velocity information is presented as a color-coded overlay on top of a B-mode image
- **Continuous Doppler** : Doppler information is sampled along a line through the body, and all velocities detected at each time point are presented (on a time line)
- **Pulsed wave (PW) Doppler** : Doppler information is sampled from only a small sample volume (defined in 2D image), and presented on a timeline
- **Duplex** : a common name for the simultaneous presentation of 2D and (usually) PW Doppler information. (Using modern ultrasound machines, color Doppler is almost always also used; hence the alternative name **Triplex**.)

- **Pulse inversion mode** : In this mode, two successive pulses with opposite sign are emitted and then subtracted from each other. This implies that any linearly responding constituent will disappear while gases with non-linear compressibility stand out.

- **Harmonic mode** : In this mode a deep penetrating fundamental frequency is emitted into the body and a harmonic overtone is detected. This way noise and artifacts due to reverberation and aberration are greatly reduced. Some also believe that penetration depth can be gained with improved lateral resolution; however, this is not well documented.

Risks and side-effects :

Ultrasonography is generally considered a safe imaging modality [17]. Diagnostic ultrasound studies of the fetus are generally considered to be safe during pregnancy. This diagnostic procedure should be performed only when there is a valid medical indication, and the lowest possible ultrasonic exposure setting should be used to gain the necessary diagnostic information under the "as low as reasonably achievable" or ALARA principle.

World Health Organizations technical report series 875 (1998).[18] supports that ultrasound is harmless: "Diagnostic ultrasound is recognized as a safe, effective, and highly flexible imaging modality capable of providing clinically relevant information about most parts of the body in a rapid and cost-effective fashion". Although there is no evidence ultrasound could be harmful for the fetus, US Food and Drug Administration views promotion, selling, or leasing of ultrasound equipment for making "keepsake fetal videos" to be an unapproved use of a medical device.

Speckle noise in ultrasound images :

Speckle is another special case of scattering. A speckle pattern is formed by the constructive and destructive interference of ultrasound re-radiated uniformly from randomly positioned closely packed small objects (less than a tenth of the wavelength) in tissue. The speckle pattern is entirely artefactual and is characteristic of the imaging system.[9]

Interference occurs when the spatial separation of the individual scatterers is less than the wavelength. This results in areas of alternating high- and low level echoes. Speckle patterns are strongly wavelength and therefore frequency dependent. They also change as the angle of insonation of the scattering region is altered. Changing this angle alters the relative separation in the beam direction and hence the pattern of interference. For randomly distributed targets the speckle pattern is random noise and entirely artefactual. In real tissues the targets are not purely randomly distributed. The underlying tissue components impose a structure upon which the random speckle pattern is superimposed. The textural pattern of the ultrasound images from tissue combines a random, fine echo texture, component with structural information at a coarser dimension.[9]

Impact of speckle noise in ultrasound images :

An inherent characteristic of coherent imaging, including ultrasound imaging, is the presence of speckle noise. Speckle is a random, deterministic, interference pattern in an image formed with coherent radiation of a medium containing many sub-resolution scatterers. The texture of the observed speckle pattern does not

correspond to underlying structure. The local brightness of the speckle pattern, however, does reflect the local echogenicity of the underlying scatterers.[34]

Speckle has a negative impact on ultrasound imaging. Bamber and Daft show a reduction of lesion detectability of approximately a factor of eight due to the presence of speckle in the image. This radical reduction in contrast resolution is responsible for the poorer effective resolution of ultrasound compared to X-ray and MRI. [34]

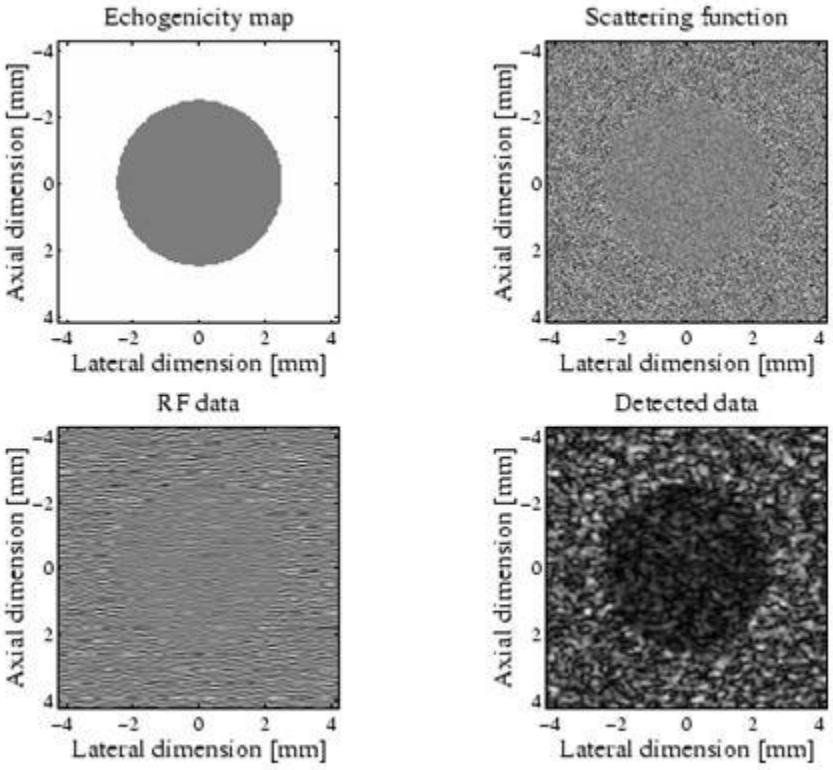


Figure 2.5 : The ultrasound image of a hypo echoic lesion of 5 mm diameter with -9 dB contrast is considered. The echogenicity map corresponding to this object is shown in the top left panel, opposite the corresponding scattering function in the top right panel. The scattering function represents the population of sub-resolution scatterers being imaged, and that are weighted in amplitude by the echogenicity map. This scattering function was convolved with a point spread function to produce the RF echo data is shown in the lower left panel. The RF

echo data is zero-mean and thus does not show what is really of interest, i.e. a map of local echogenicity, or local echo magnitude. Envelope detection removes the carrier, producing the desired image of echo magnitude in the lower right panel. The differences between this image and the original echogenicity map arise from speckle noise.[34]

In Figure 5, we see a simple conceptual demonstration of the impact of speckle noise on information content. The object of interest is a hypo echoic lesion of 5 mm diameter with -9 dB contrast. The echogenicity map corresponding to this object is shown in the top left panel of Figure, opposite the corresponding scattering function in the top right panel. The scattering function represents the population of sub-resolution scatterers being imaged, and that are weighted in amplitude by the echogenicity map. This scattering function was convolved with the point spread function of a hypothetical 7.5 MHz array (60 % bandwidth, imaging at f/1). The resulting RF echo data is shown in the lower left panel. The RF echo data is zero-mean and thus does not show what is really of interest, i.e. a map of local echogenicity, or local echo magnitude. Envelope detection removes the 7.5 MHz carrier, producing the desired image of echo magnitude in the lower right panel. Here it is easy to see how speckle noise obscures the information in the image. While the mean speckle brightness at each region of the image reflects the original echogenicity map, the speckle noise itself does not reflect the structure, or information, in either the echogenicity map or the corresponding scattering function.[34]

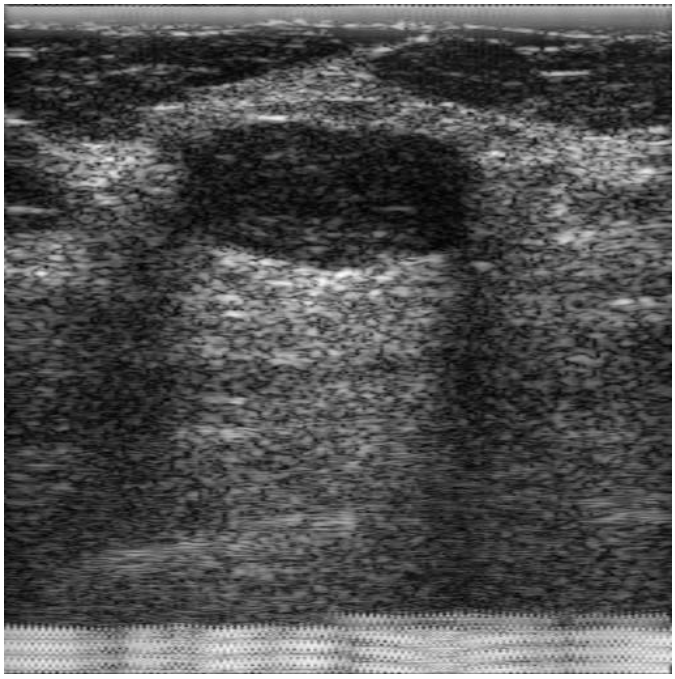


Fig 2.6a: Ultrasound image (speckle not shown)

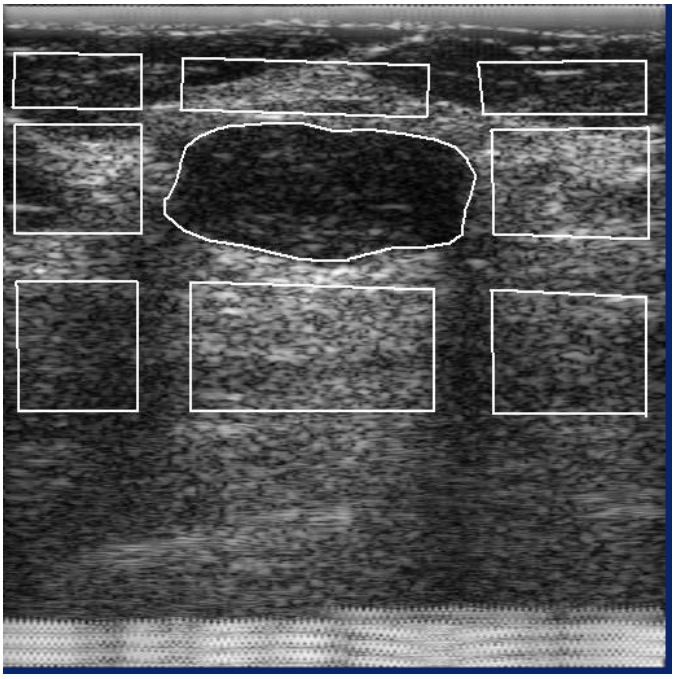


Fig 2.6b: Ultrasound image with speckle noise

Due to the constructive and destructive interference of the ultrasound, there are alternating areas of high and low level echoes. As a result, the ultrasound image quality is degraded. So sometimes it becomes very difficult to detect the breast lesion accurately. [9]

Benign and malignant lesions in breast ultrasound images :

Our thesis work is mainly based on breast cancer ultrasound images analysis. When we are analyzing the breast ultrasound images, we are actually classifying the breast lesions. Breast lesions are mainly classified in two groups : benign and malignant.

Benign means " non-cancerous/non-harmful " and malignant means " cancerous ". **Breast lesions at ultrasound** have a number of characteristics which allows the classification as either malignant or benign. [19]

Malignant characteristics (with positive predictive values) [19] :

- Sonographic speculation : 87-90% [19,22] : alternate hypo-hyper echoic lines radiating perpendicularly from surface of nodules (If lesion is surrounded by echogenic tissue, you will see hypo echoic strands. If lesion is surrounded by fat, echogenic strands may be seen).
- Deeper (taller) than wide : 74-80% [19,22] : except in certain grade III Invasive ductal carcinomas.
- Microlobulations : 75% : small lobulations 1 - 2 mm on the surface; risk of malignancy rises with increasing numbers.
- Thick hyper echoic halo : 74 %
- Angular margins : 70%
- Markedly hypo echoic nodule : 70%
- Sonographic shadowing : 50%
- Branching pattern : 30% : multiple projections from the nodule within or around ducts extending away from the nipple, usually seen in larger tumors.
- Punctuate calcifications : 25% : which usually do not shadow.
- Duct extension : 25% : is seen as projection from a nodule which extends radially within or around a duct towards the nipple
- Shadowing [21]
- Heterogeneous echo texture [21]
- Compressibility : in general terms, benign lesions compress with transducer pressure and malignant lesions displace the breast tissue without changing in height. This is the basis for elastography.

Benign characteristics (with negative predictive values)[19] :

- Well circumscribed markedly hyper echoic tissue: ~ 100%
- Wider than deep: 99%
- Gently curving smooth lobulations (<3 in a wider than deep nodule, i.e. D/W ratio <1) : 99%
- Thin echogenic pseudo capsule in a wider than deep nodule : 99%. It is best seen on anterior / posterior margins, perpendicular to the beam. It probably represents normal compressed tissue consistent with a non infiltrative process.

Textural Analysis

In image processing algorithms, to simply understand the uniformity of intensities in the local image regions, certain simplifying assumptions are always made. Variation of intensities in the images which form certain repeated patterns are known as " visual texture ". These patterns can be the result of physical surface properties (roughness, oriented strands) or they could be the result of reflectance difference (color of the surface).[1]

Definition of texture is very difficult to give and this can be understood by looking into the fact that many vision researchers have attempted to define texture in their own way. Here are a few examples of those :

- " We may regard texture as what constitutes a macroscopic region. Its structure is simply attributed to the repetitive patterns in which elements or primitives are arranged according to a placement rule." [23]

- " The image texture we consider is nonfigurative and cellular. An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives. A fundamental characteristic of texture: it cannot be analyzed without a frame of reference of tonal primitive being stated or implied. For any smooth gray-tone surface, there exists a scale such that when the surface is examined, it has no texture. Then as resolution increases, it takes on a fine texture and then a coarse texture." [24]

- " Texture is an apparently paradoxical notion. On the one hand, it is commonly used in the early processing of visual information, especially for practical classification purposes. On the other hand, no one has succeeded in producing a commonly accepted definition of texture. The resolution of this paradox, we feel, will depend on a richer, more developed model for early visual information processing, a central aspect of which will be representational systems at many different levels of abstraction. These levels will most probably include actual intensities at the bottom and will progress through edge and orientation descriptors to surface, and perhaps volumetric descriptors. Given these multi-level structures, it seems clear that they should be included in the definition of, and in the computation of, texture descriptors." [25]

Image Texture :

The term image texture is a topic of great importance to the researchers because of its usefulness to variety of applications. Image texture can be defined as the function of spatial variation in pixel intensities, also known as the " Gray values ". One immediate application of image texture is the recognition of image regions using texture properties. Let us go through the figures given below [1] :

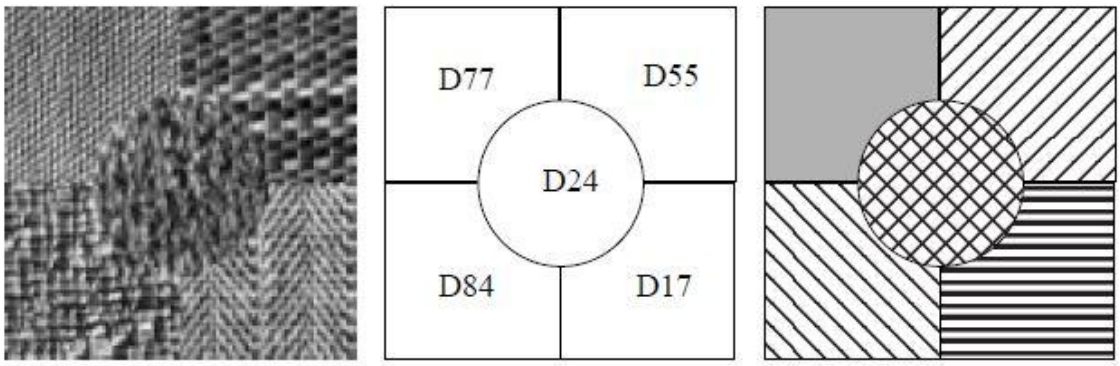


FIGURE 2.7. (a) An image consisting of five different textured regions: cotton canvas (D77), straw matting (D55), raffia (D84), herringbone weave (D17), and pressed calf leather. [26]. (b) The goal of texture classification is to label each textured region with the proper category label: the identities of the five texture regions present in (a). (c) The goal of texture segmentation is to separate the regions in the image which have different textures and identify the boundaries between them. The texture

categories themselves need not be recognized. In this example, the five texture categories in (a) are identified as separate textures by the use of generic category labels (represented by the different fill patterns).[1]

Texture is the most vital characteristic to consider when identifying different homogeneous region types. This is called " Texture Classification ". In Figure 6(a), we can identify the five different textures and their identities as cotton canvas, straw matting, raffia, herringbone weave, and pressed calf leather. The goal of texture classification then is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs to as shown in Figure 6(b). We could also find the texture boundaries even if we could not classify these textured surfaces. This is then the second type of problem that texture analysis research attempts to solve and is known as " Texture Segmentation ". The goal of texture segmentation is to obtain the boundary map shown in Figure 6(c). In computer graphics, where our main object is to render object surfaces which are as much realistic as possible, image compression is very much necessary and we use " Texture Synthesis " for that. [1]

Role of textural analysis in medical image processing :

Several medical applications, in particular those applications which include the automatic extraction of features from images, needed for classification tasks, such as differentiating a cancerous tissue from a non-cancerous tissue, depend greatly on the image analysis technique.

The extracted features capture morphological properties, color properties, or certain textural properties of the image, depending on what type of classification we are going to make.

Harms et al.used image texture in combination with color features to diagnose leukemic malignancy in samples of stained blood cells. They extracted texture micro-edges and "textons" between these micro-edges. The "textons" were regions with almost uniform color. They extracted a number of texture features from the "textons" including the total number of pixels in the textons which have a specific color, the mean texton radius and texton size for each color and various texton shape features. In combination with color, the texture features significantly improved the correct classification rate of blood cell types compared to using only color features. [27]

Lundervold used fractal texture features in combination with other features (such as response to edge detector operators) to analyze ultrasound images of the heart (Figure 7). The ultrasound images in this study are time sequence images of the left ventricle of the heart. Figure 6 shows one frame in such a sequence. Texture is represented as an index at each pixel, being the local fractal dimension within an 11 x 11 window estimated according to the fractal Brownian motion model proposed by Chen et al. [29]. The texture feature is used in addition to a number of other traditional features, including the response to a Kirsch edge operator, the gray level, and the result of temporal operations. The fractal dimension is expected to be higher on an average in blood than in tissue due to the noise and backscatter characteristics of the blood which is more disordered than that of solid tissue. In addition, the fractal dimension is low at non-random blood/tissue interfaces representing edge information. [28]

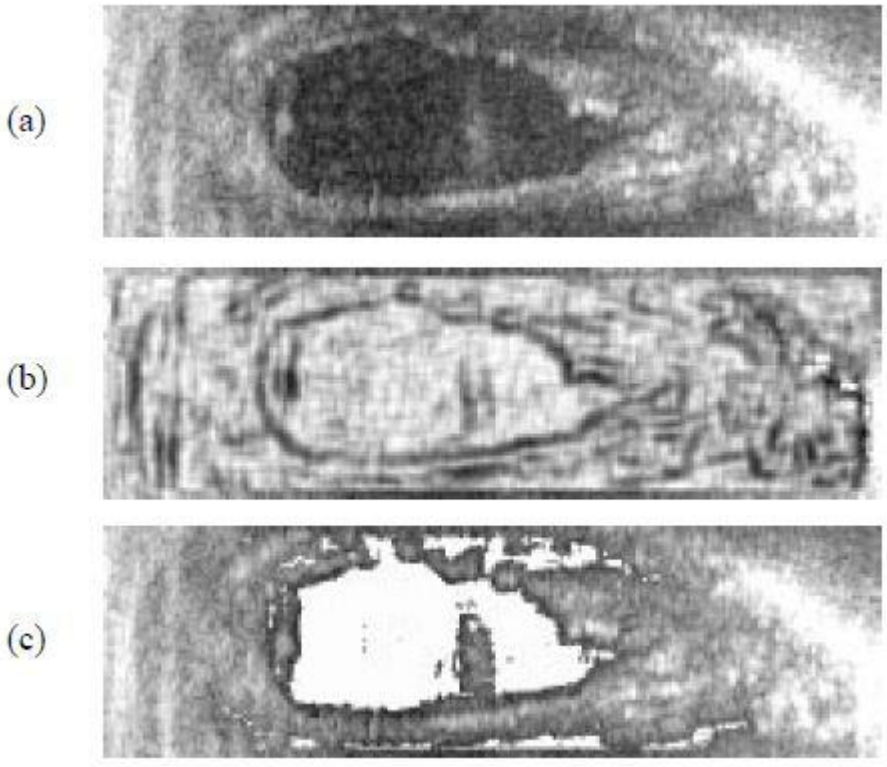


FIGURE 7. The processing of the ultrasound images of the heart using textural features. (a) A 128 x 432
ultrasound image from the left ventricle of the heart. (b) The fractal dimension used as the

texture feature. The fractal dimension is lower at the walls of the ventricle. (c) Image segmentation from a
k-means clustering algorithm. The white region is cluster 2 which corresponds to the blood. The
clustering uses four features, one of which is the fractal texture feature. [1]

Classification of pulmonary disease using texture features was discussed by Sutton and Hall [30]. Some diseases, such as interstitial fibrosis, affect the lungs in such a manner that the resulting changes in the X-ray images are texture changes as opposed to clearly delineated lesions. To distinguish the normal lung from the diseased lung, Sutton and Hall proposed three types of texture features, namely, computed based on an isotropic contrast measure, a directional contrast measure, and a Fourier domain energy sampling. In their classification experiments, the best classification results were obtained using the directional contrast measure.

Chapter 4

Proposed Method

The algorithm can come up with a Region of Interest (ROI), which not only eliminates human intervention but also highly accurate. Entropy information along with a rule based approach called 'rule of third' is used to obtain the ROI. Even though the area of the ROI detected by our algorithm is bigger than those mentioned by literature, this bigger area, however, increases the chance to locate the lesion.

Novelty of our work

For accurate ROI detection, it is sometimes crucial to perform some pre-processing steps. One of these steps is removing noise such as speckle noise. Speckle noise removing algorithms are time consuming and complex. So if there were a way to avoid the step, the lesion detection and classification process would actually be very effective and efficient. One of the novel features of this work is that it can bypass the noise/speckle removal step. This is because we use a textural feature called entropy to select ROI from a BUS image.

Step 1: Entropy filtering

We take a BUS image and run a textural analysis on it. Entropy is a textural feature and can be defined as a measure of randomness.

$\text{Entropy} = -\sum p(z_i) \log_2 p(z_i)$

z is a random variable,

p(z) is the histogram of the intensity levels,

L is the number of possible intensity levels

We observed that the entropy values are different for different regions. We categorized entropy values based on these regions. These values are tabulated in Table 1. The entropy values in the dark (anechoic) region inside the lesion vary from 3 to5. The white (hyoerechoic) region found near the boundary of the lesion has very high entropy values ranging from 6 to 7.5. The rest of the image with mostly gray regions (hypoechoic) has values from 5 to 6.5. The regions can be seen in the original BUS image shown in Fig. 4.3. Corresponding entropy image along with a range of obtained values shown in Fig. 4.2. The minimum and maximum values are 3.5 and 7.5 respectively. Low entropy values indicate that randomness is small inside the lesion, i.e. the grayscale-intensity values within the lesion do not vary much compared to that of the region near boundary. Due to high variation of grayscale-intensity values, entropy is higher near boundary.

This is shown in dark-red color near the lesion boundary in Fig. 4.2. We used this information for automatic ROI detection.

Table 4.1. Entropy values and their respective regions

Regions (in terms of location)	**Regions (in terms of echogenicity)**	**Entropy Value**	**Comments**
Boundary of the lesion	Hyperechoic	>6.5	This is general for all test images
Inside the lesion	Anechoic	5~6	Varies with images but mostly the entropy value is lesser than the values around the lesion
Rest of the image	Mostly hypoechoic	5~6.5	With some anechoic regions

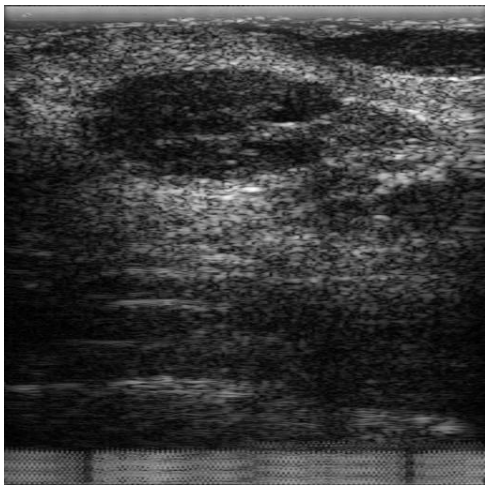


Fig 4.1: A BUS image

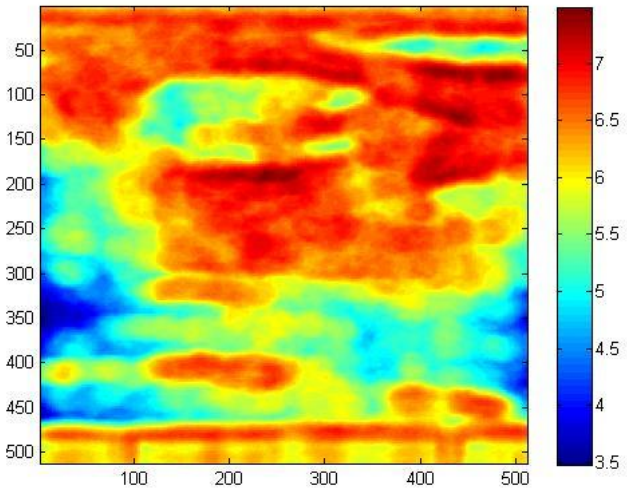


Fig 4.2: A BUS image after Entropy filtering

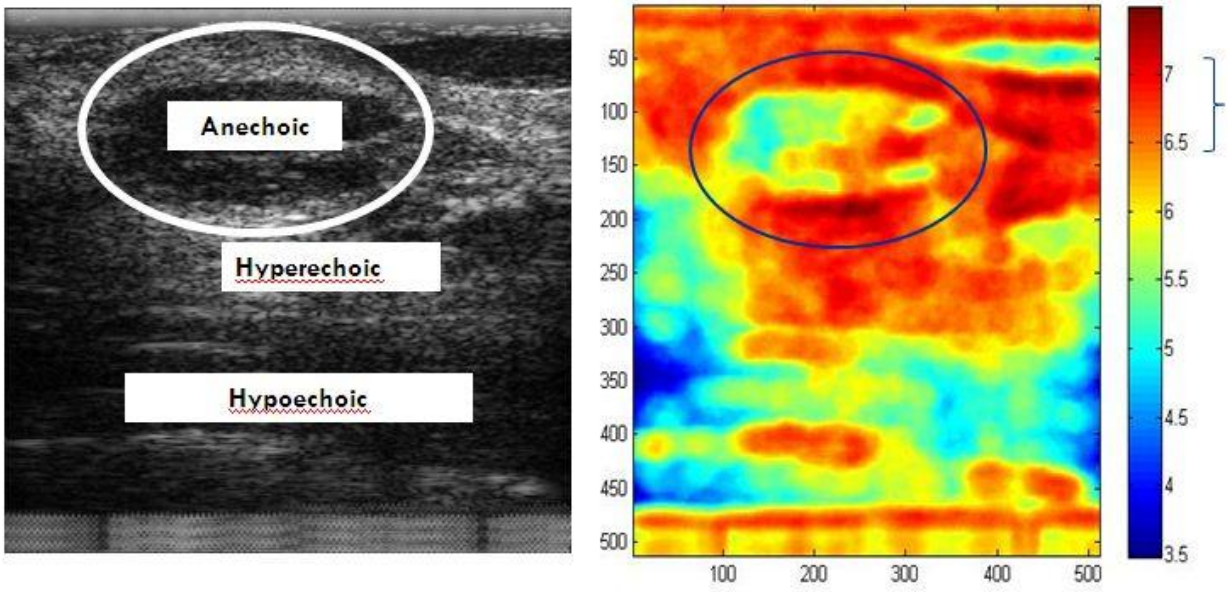


Fig 4.3: BUS image and entropy image showing echogenic regions

We observed that for all the BUS images, the entropy values around the lesion boundary fall within a certain range. Considering this threshold we removed the region from the original image.

Step 2: Automatic ROI selection

Our objective is to isolate the anechoic or darker region of the lesion. But dark areas from other regions such as the bottom part of the image have similar grayscale-intensity values, which makes it very difficult to differentiate. We used a rule based ROI detection process stated below.

Rule of third:

The idea of rule of thirds comes from photography. It is a guideline used for composition while taking photographs. Three vertical and horizontal imaginary lines divide the rectangular vision seen through viewfinder by the photographer. This results in three horizontal and vertical blocks in the image. It is advised, generally, to put elements of higher interest on these lines or at the intersections to attract viewers' attention. In our work, however, we modify the rule of third in the following way. We divide the image into three horizontal blocks only. This is because we observed that high entropy values are concentrated in any two

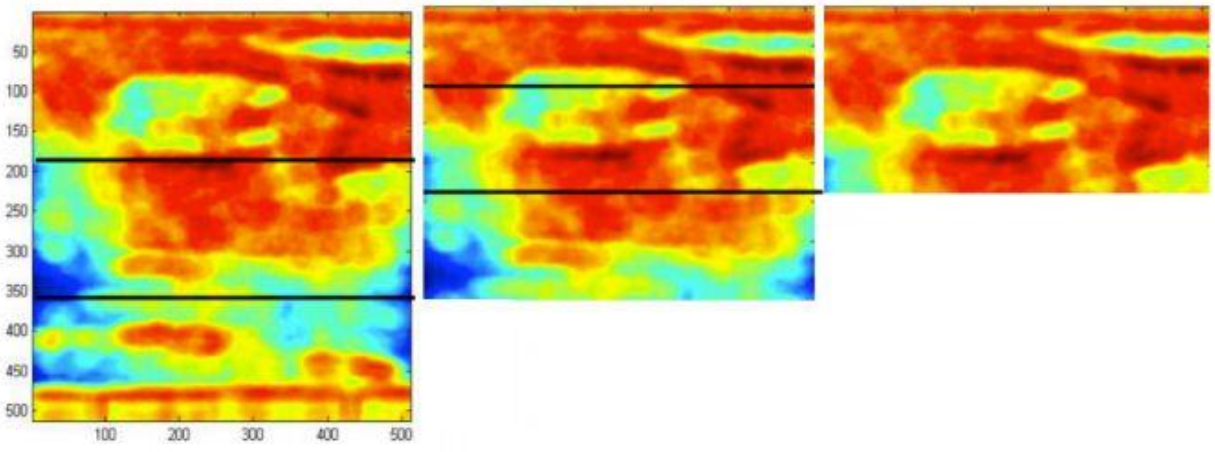


Fig 4.4: Applying modified rule of third for ROI detection

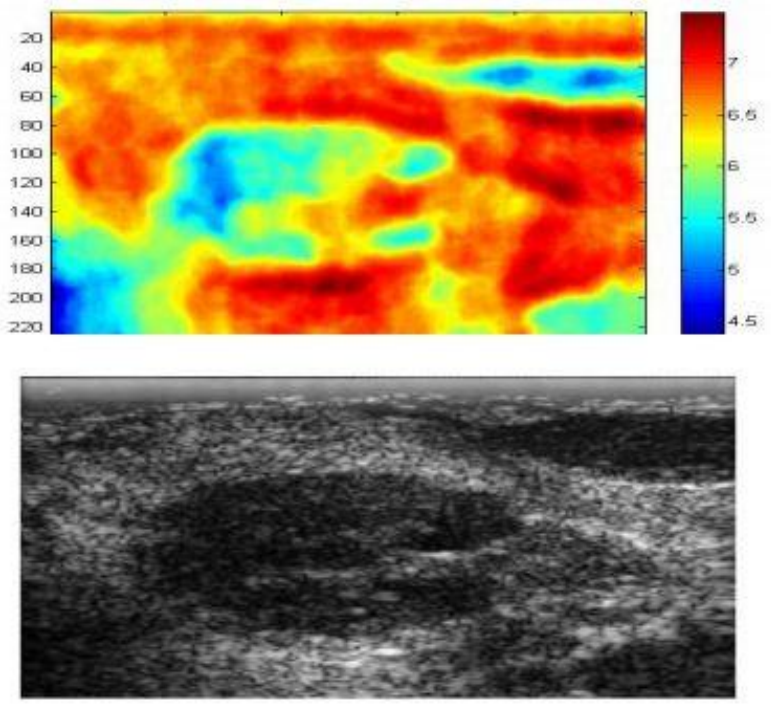


Fig 4.5: ROI shown in entropy image (upper), ROI in original image (lower)

horizontal blocks (either upper two or lower two depending on the location of the lesion) of the image. These two blocks have greater chance to contain the lesion since, as stated earlier, entropy values are the highest near boundary of the lesion. We discard the third horizontal block (the upper-most or lower-most) since it does not contain high concentration of entropy values greater than 6. We repeated this step two more times to obtain a smaller ROI. The ROI detection process is shown in Fig. 4.3 and 4.4.

Step 3: Lesion segmentation

External Energy:

The concept of external energy comes from the active contour model, also called snakes.

Snakes are boundary descriptors used to identify shapes in an image. They are energy minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges [Kass, 1988].

The energy consists of an internal and external energy. The external energy is supposed to be minimal when the snake is at the object boundary position. The most straightforward approach consists in giving low values when the regularized gradient around the contour position reaches its peak value. The internal energy is supposed to be minimal when the snake has a shape, which is supposed to be relevant considering the shape of the sought object. The most straightforward approach grants high energy to elongated contours (elastic force) and to bended/high curvature contours (rigid force), considering the shape should be as regular and smooth as possible [Wikipedia]. For this work, however, we calculated only the external energy for lesion segmentation. The external energy image is shown in Fig 4.5.

Then we converted this external energy image to a BW image with a threshold value ranging from 0.3 to 0.4. The threshold value is crucial for good segmentation and currently it has to be selected empirically. Then we observed the connected components of the image. Usually the lesion is always the largest connected component of the image and we detect it and extract from the ROI. The final result is shown in Fig 4.6 which can be compared with the manual segmentation shown in Fig 4.7.

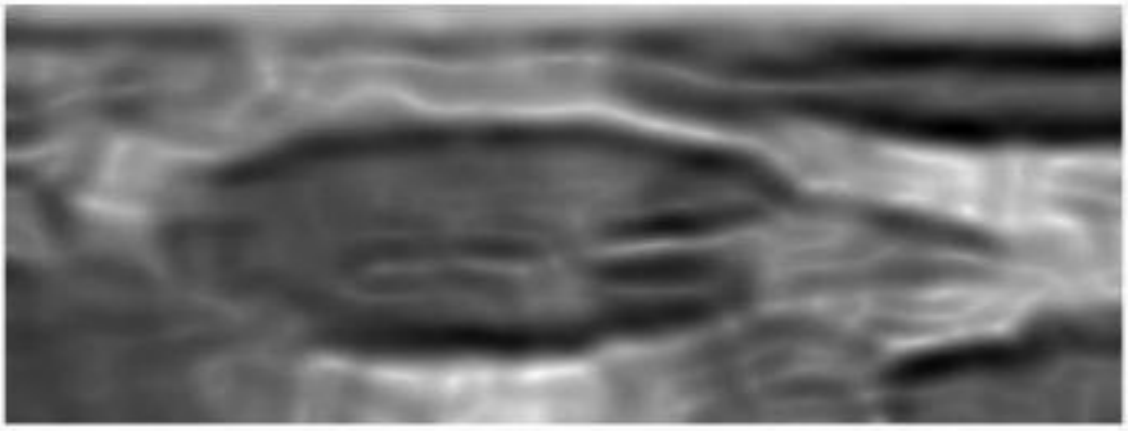


Fig 4.6: External energy from the snake model of ROI image

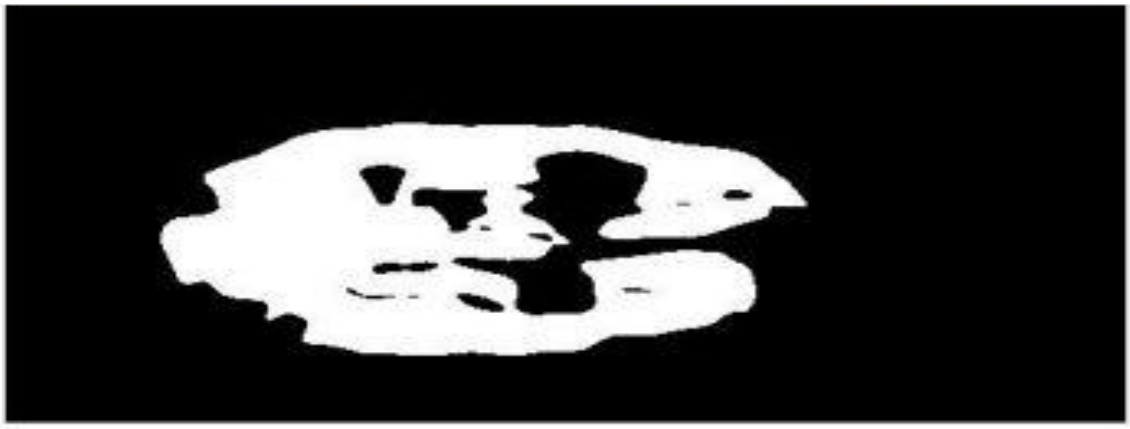


Fig 4.7: Threshold image shows segmented lesion

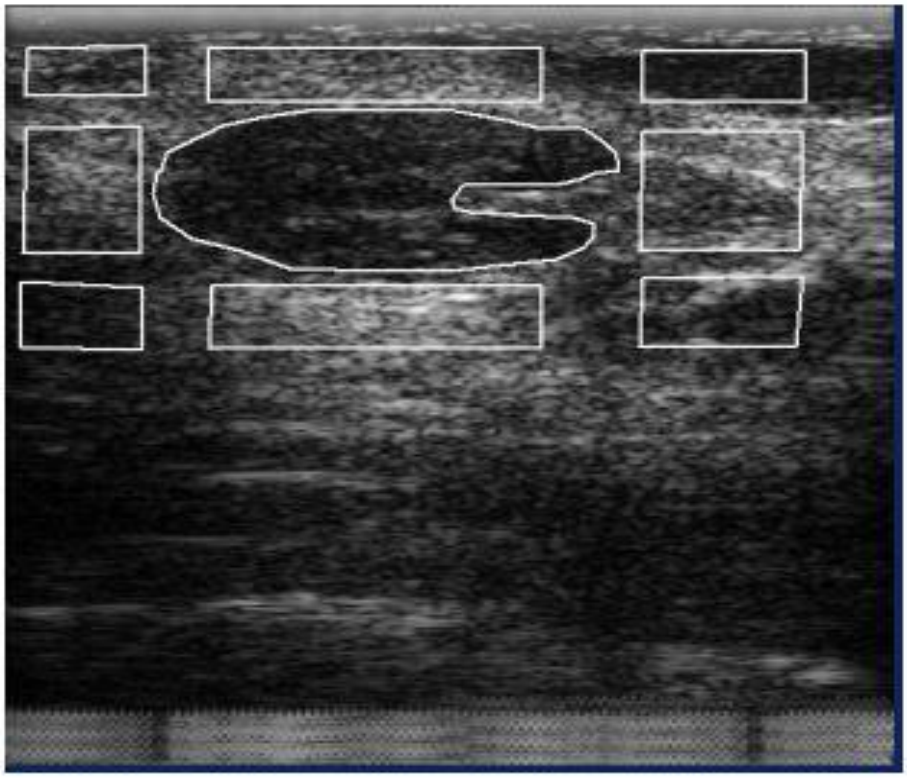


Fig 4.8: Manually segmented lesion

Now let's take a look at the overall outline of the whole proposed method in the fig 4.9.

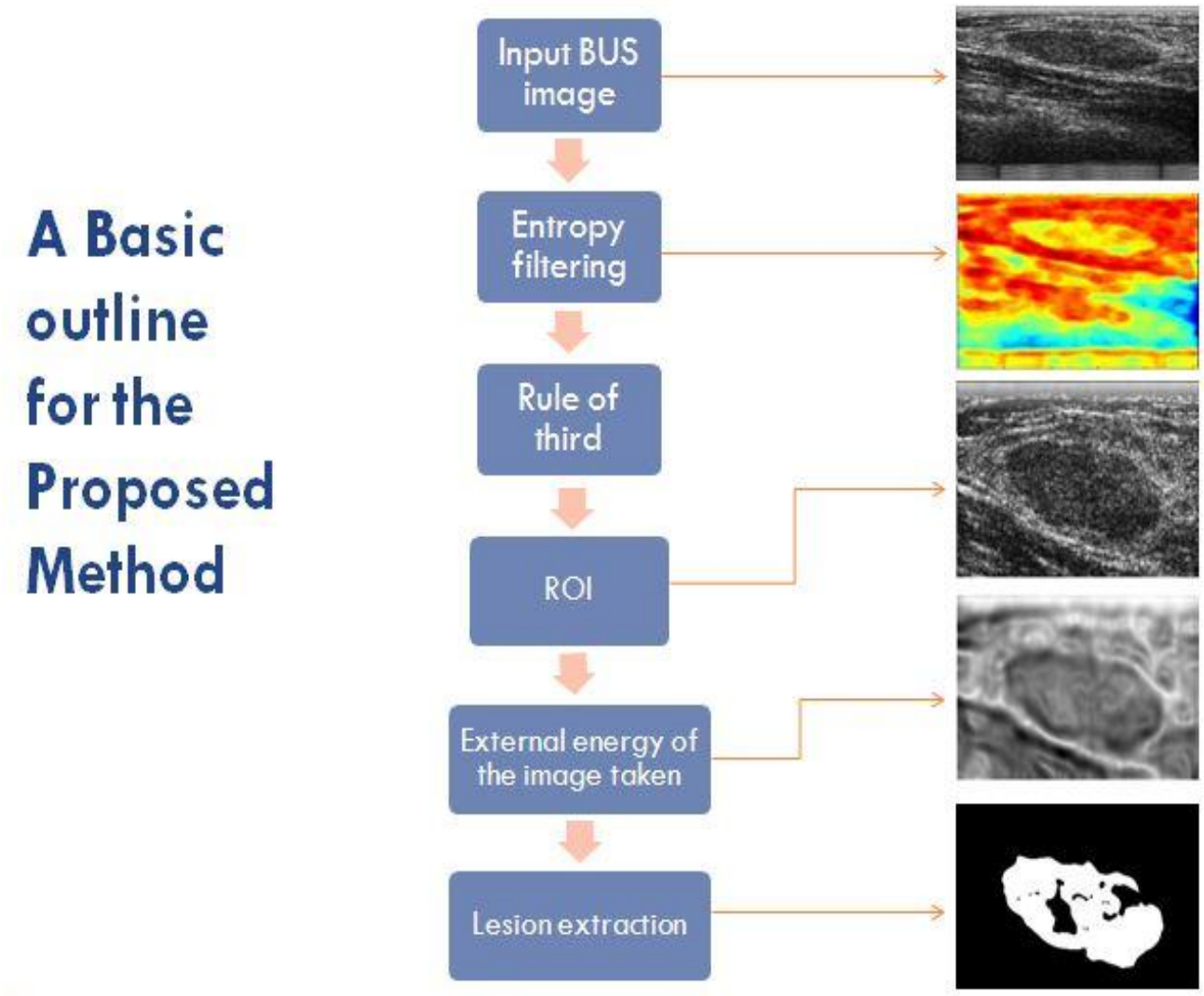


Fig 4.9: A basic outline for the proposed method

Chapter 5

National Institute of Cancer and Research

The following part is collected from the NICRH cancer registry report 2005-2007 [13],

"The National Institute of Cancer Research and Hospital (NICRH), Dhaka, started a cancer registry in 2005 for the first time in Bangladesh with technical assistance from the World Health Organization. Current report covers three years from 2005 to 2007. Data were collected from 24,847 cancer patients who attended the NICRH for the first time.

Essential information (confirmed diagnosis) could be made available for 18,829 cases, and they are included in this analysis. Among them 10,847 (57.6%) were males. Lung cancer was the leading cancer (17.3%), followed by cancers of breast (12.3%), lymph nodes and lymphatics (8.4%) and cervix (8.4%) for sexes combined in all ages. In males lung (25.5%) and in females breast (25.6%) and cervical (21.5%) cancers were predominant. In children aged 14 years or younger (n=657) lymphoma, retinoblastoma, osteosarcoma, leukaemia and kidney cancers were most prevalent.

Cancer registries are systems for collection, storage, analysis and interpretation of data from people with cancer. There are two main types of cancer registries; population-based and hospital-based cancer registries (PBCR and HBCR). Other registries of syndromes, diseases or special situations could be of interest in order to collect information about special populations at high risk of developing cancer. The objective of registries is to collect as complete and accurate information as possible. This would include clinical description of the disease, as well as the information to identify the patient, tumour, hospital, and relevant physicians. When these data are put together with the additional information describing treatment and follow-up, relapses, metastases as well as date and cause of death, a complete and invaluable database is created.

These data could be used in many fields: aetiological and epidemiological investigations, care planning, primary and secondary prevention, benefiting both patients and society. The older the registry and wider the area covered (in PBCR), the more useful it is. Description of temporal tendencies is also an essential endpoint of cancer registries1.

Like many other countries in the world cancer in Bangladesh is one of the major killer diseases.

Its personal, social and economical bearing is huge. To control cancer proper data on cancer trend is essential. Cancer registry is the tool which can provide such information.

Hospital-based registries use information abstracted from medical records to assess the number of diagnoses per year and frequencies by sites. The information collected consists of demographics, site of cancer, type of cancer, type of treatments, stage of disease at diagnosis and vital status. Hospital registry data are used to evaluate diagnostic and treatment practices; assess quality of patient care and hospital programmes; and track outcomes. Registry data are also used to develop standards of care; develop strategic plans and measure progress; and assist hospital administrators and physicians in setting up screening programme2. It is important to note that

HBCR contribute to PBCR also. Both HBCR and PBCR are important tools for any successful cancer control programme3. This first ever cancer registry was established in Bangladesh with an objective to obtain an overview of cancer pattern among the patients at the National Institute of Cancer Research and Hospital (NICRH) located in the capital city of Dhaka.

Breast cancer

Breast cancer was the commonest cancer among the female patients who attended NICRH, which formed the second most common cancer as a whole. The mean age of patients was 41 years, with largest proportion of patients in 35-54 year age group (Figure 5). Among all breast cancer patients 89% were married. About three in five were multipara and one in four were grand multipara. At the time of first reporting two-third had histopathological diagnosis and one-fourth had cytological diagnosis (Table 5). A vast majority (96%) had duct cell carcinoma

A total of 1,116 breast cancer patients received treatment prior to NICRH. Among them three in five had surgical treatment. Tumour Board of NICRH decided to give chemotherapy for 39%, 35% for radiotherapy, and 19% for combined radio and chemotherapy (Figure 6), while only 8% were recommended for surgery."

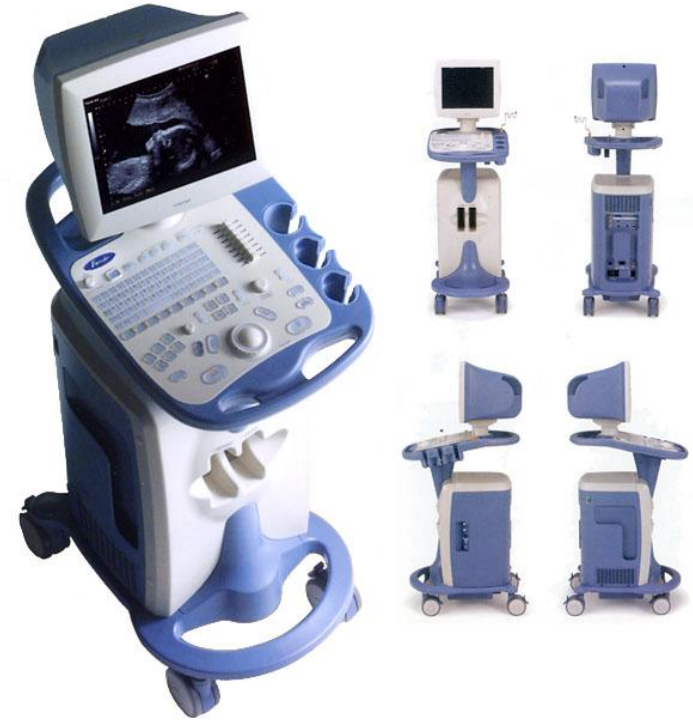
<u>Collavoration with NICRH</u>

We visited National Institute of Cancer Research & Hospital (NICRH), Dhaka as a part of our final year project titled "**Breast Cancer Ultrasound Images Analysis & Auto-Segmentation of Lesions** ".

Objectives:

1. To observe US image and data acquisition process
2. To obtain firsthand experience with the US equipments and patient handling
3. To collect US image and raw RF data
4. To explore current scenario of breast cancer research in Bangladesh

Equipments used:



1. Toshiba Famio 8 Ultrasound system

At NICRH,Toshiba Famio 8 is used for ultrasound imaging and it is handled manually by an operator. The machine is a compact ultrasound system that rivals full size console systems with its versatility and performance. It features a 14" high-definition monitor to display images with exceptional clarity. One of the advantages is that it doesn't force the user to sacrifice performance like other portable ultrasound machines.

Students obtained US images with the help of the operator. However, raw RF data was not available and the technician was unable to obtain one.

Detailed Component Description:

The Toshiba Famio 8 Ultrasound Machine has the following features:

- Digital continuous beam former
- Smart Optimization technology
- Tissue Harmonic Imaging (THI)
- 14" high definition monitor that tilts and swivels

- Fully programmable key functions
- Lightweight and easy to transport
- Integrated hard disk and CD-R drive

System Applications:

- Radiology
- Small Parts
- OB-GYN
- Portable Ultrasound
- Internal Medicine
- Cardiac

2. Probes

It uses two probes/ultrasound arrays:

- PLQ 703a 7.5MHz
- PVQ 375a 3.75MHz

Although both of the probes are specified for abdominal ultrasound imaging, but at NICRH, they are used for breast ultrasound imaging.

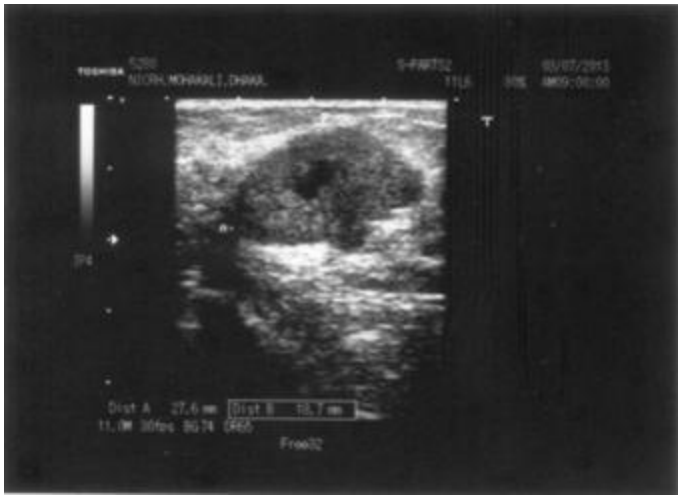
PLQ 703a 7.5MHz:

- The Toshiba PLQ-703A is a linear array ultrasound transducer probe.
- The Toshiba PLQ-703A is compatible with the Toshiba Famio 8.
- It is used with peripheral vascular applications and has a frequency range of 6-11MHz (At NICRH, they use 7.5 MHz probe).

PVQ 375a 3.75MHz:

- The Toshiba PVQ-375A is a convex ultrasound transducer probe that is used with abdominal applications.
- It has a frequency range of 3-6MHZ and is compatible with the Famio series ultrasound systems.
- The transducer size is about 50mm.

Collected data from NICRH (Breast ultrasound images)



Experience at NICRH

We observed the diagnosis procedure and collected US images. However, there was no facility to obtain the raw RF data from the machine. Also a real-time video of the ultrasound could not be obtained due to some technical difficulties. The diagnosis room contains a Toshiba Famio 8 ultrasound system with two probes attached to it. But both of the probes are specialized for abdominal US imaging.

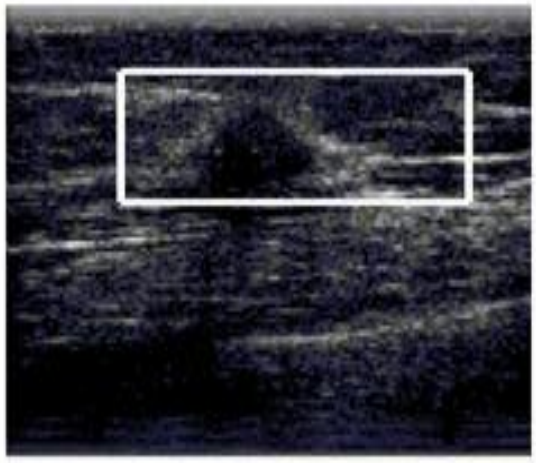
Most of the research conducted in NICRH is statistical; i.e. finding a pattern of various types of cancers in different age and sex groups in Bangladesh. The technology at NICRH is not up to date for biomedical research and hence there is a scope to improve that.

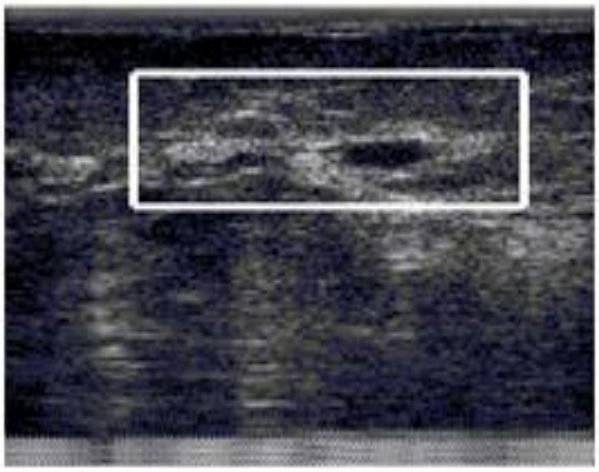
Chapter 6

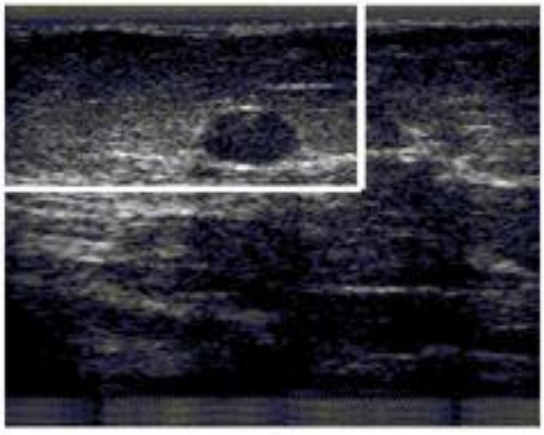
Result Analysis

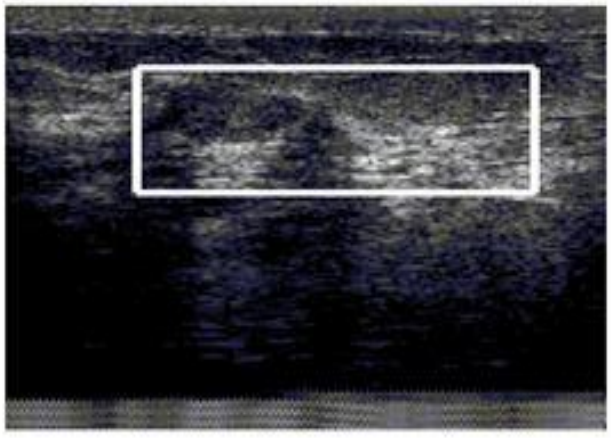
At first we will observe the ROI detection done by the algorithm using entropy based filtering and rule of third method.

Below we are showing some BUS images with ROI detected and marked on them.









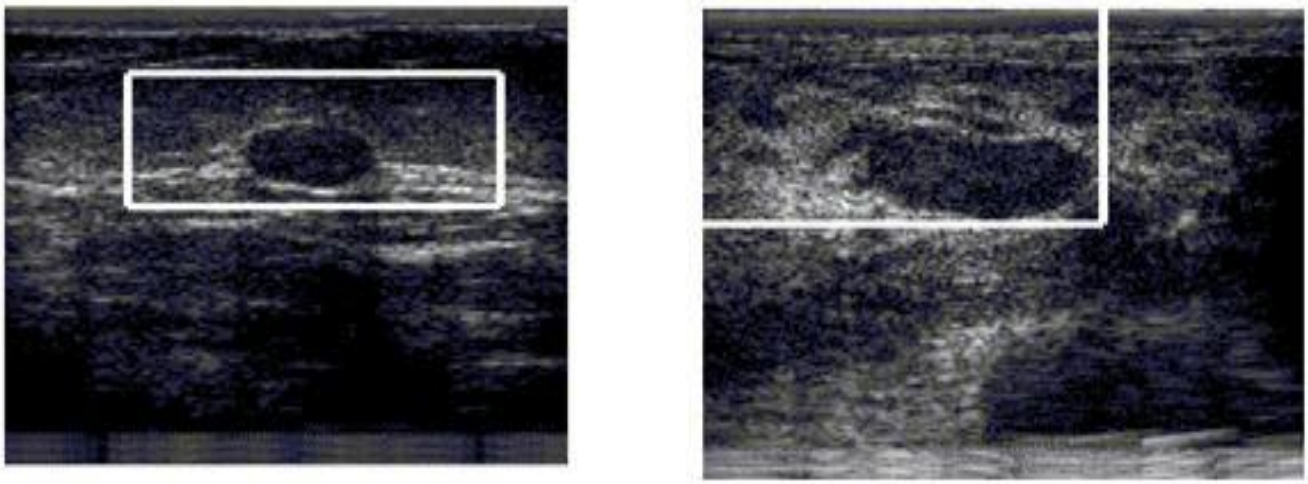


Fig 5.1 a,b,c : Different BUS images with ROI detected

Now we will observe edge detection from BUS image.

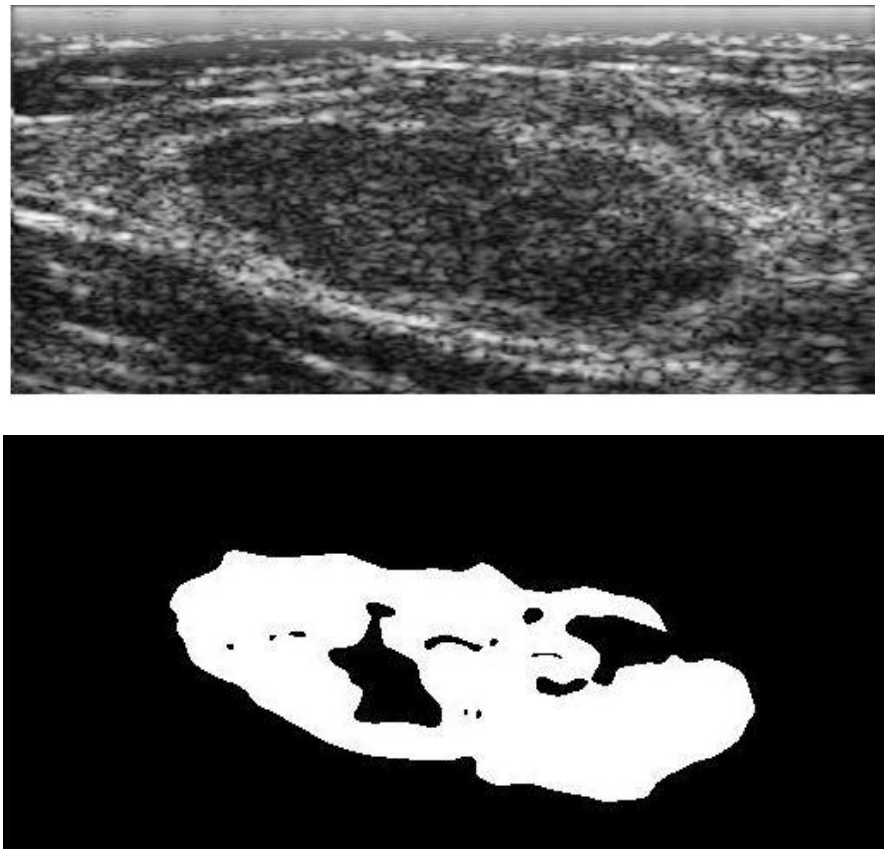
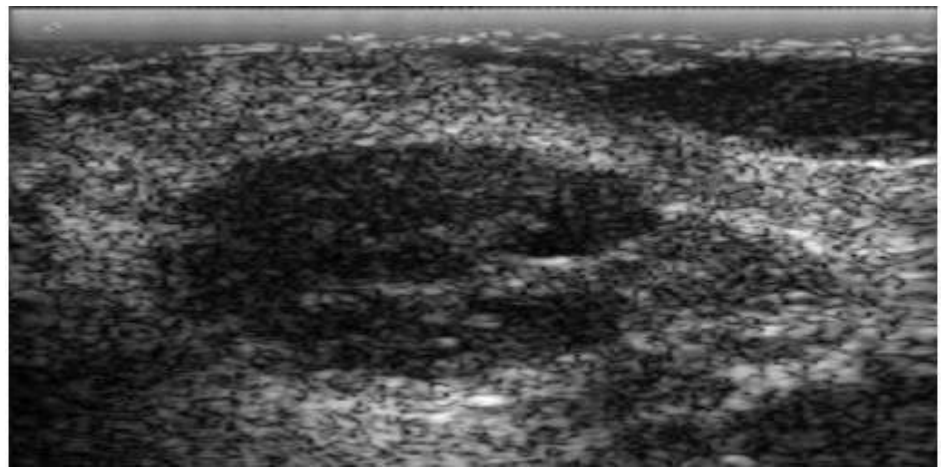


Fig 5.2 a

.



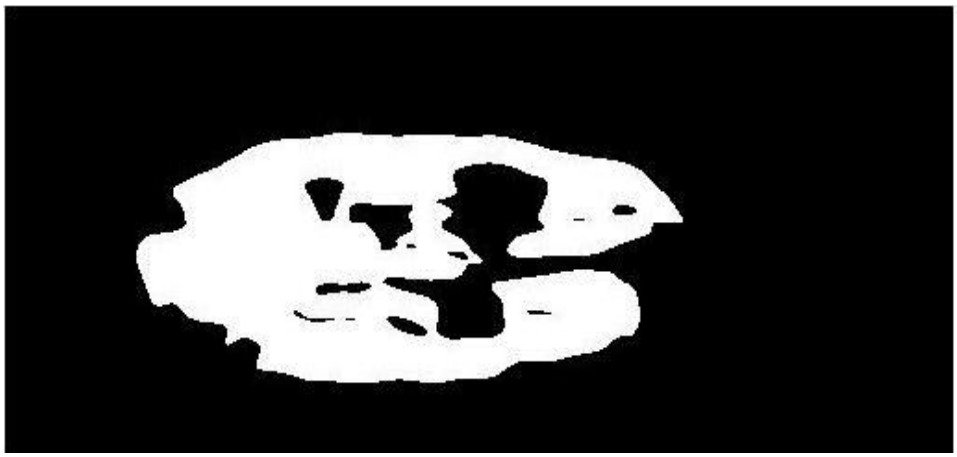
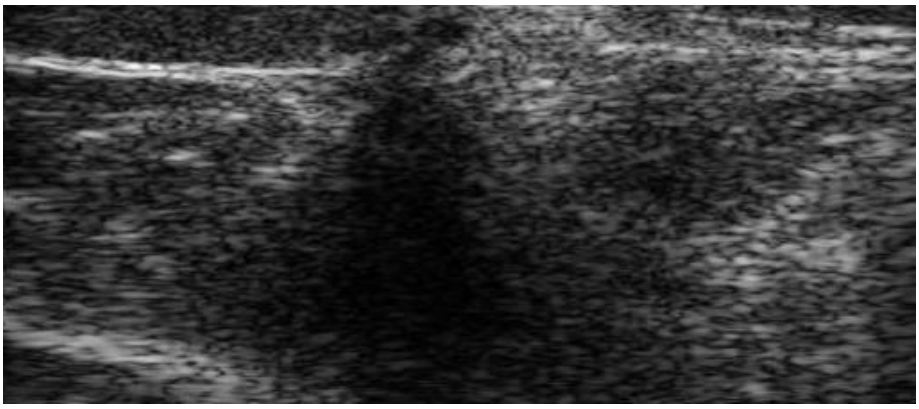


Fig 5.2b



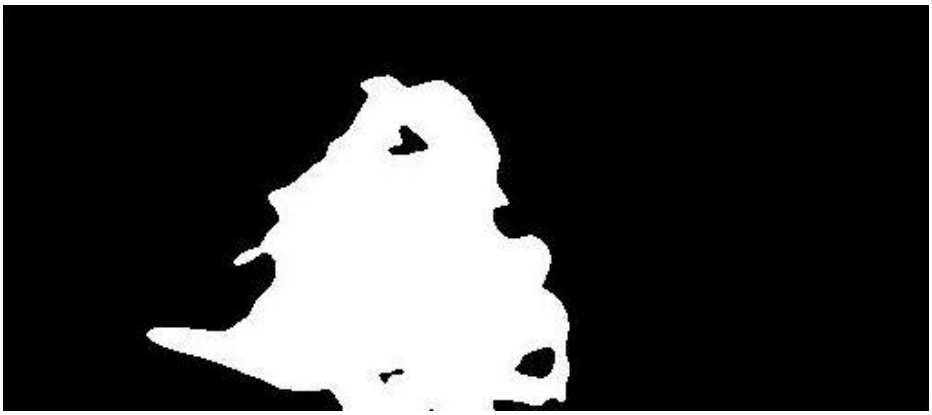


Fig 5.2 c

Fig 5.2 a,b,c : Different BUS image ROIs and their detected lesions

Finally we will observe a manually detected lesion of a BUS image and lesion detected by the CAD.

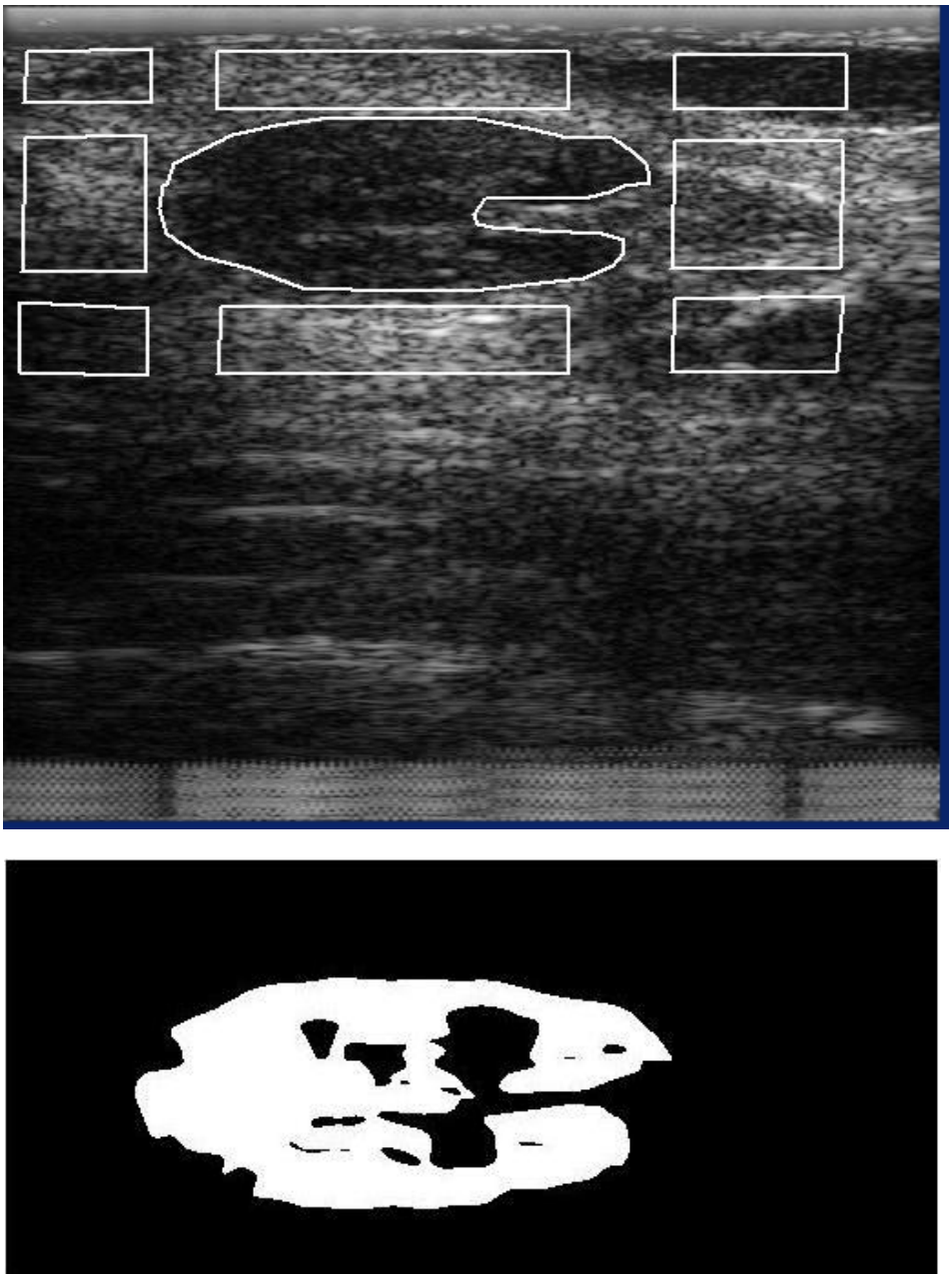


Fig 5.3: Manual vs. Automatic Detection

We have taken BUS images with cancerous lesions and extracted the ROI from it and then from the ROI we finally detect the lesion boundary through CAD process. The results that come up are quite accurate and they match with manually detected lesion boundary by the radiologists.

So by observing the above sample figures of different BUS images we can say that our CAD process can detect the lesion boundary from a sample BUS image efficiently.

Chapter 7

Conclusion and Future Development

So far we have come up with a computer aided diagnosis system that detects the lesion boundary by segmenting the BUS image, extracting the ROI and then applying external energy filtering and thresholding.

Now we want to extend our work in the future. We have some probable viewpoints in mind as follows:

- ☐ Diagnosis of malignant-benign lesions: We want the CAD to not only detect the lesion boundary but also give a diagnosis if the lesion is malignant or benign. We can do this by using some statistical and textural features, also by running the CAD through a classifier.
- ☐ Practical implementation: We want the CAD to be user friendly and very simply designed so that it can be used by medical personalities with a very little training and knowledge.
- ☐ Portable device/ mobile application: We want to further make a portable device or maybe a mobile application (android is more feasible) so that that it can be carried to any place and can be used in all kinds of environment.

We have tried to design the CAD system as simple and accurate as possible. The research will be continued further to achieve the probable future goals. The thesis was motivated by the fact that in our country the radiologists don't have the ability to give proper breast cancer detection facility to the large number of people (mainly women) and we would like to extend our cooperation to make them more efficient and give a second opinion with the CAD system. We also hope to provide NICRH with our CAD and portable device in the future for more efficiency in breast detection process.

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