BREAST CANCER DETECTION BASED ON COMBINED ANALYSIS OF ULTRASOUND ELASTOGRAPHY AND B-MODE IMAGE FEATURES

PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Breast cancer is one of the leading causes of death for the female population in both developed and developing countries. Earlier treatment requires early diagnosis, and early diagnosis requires an accurate and reliable diagnostic procedure that allows physicians to differentiate benign breast tumors from malignant one. Sonoelastography and Ultrasonography are currently the most sensitive noninvasive modalities for detecting breast cancer. This study presents a diagnosis system with various features from B-mode and Sonoelastography images for classifying benign and malignant breast tumors on medical ultrasound systems. The image obtained is first given to the filter for reduction of noise. Here a wavelet-based thresholding scheme for speckle noise reduction is used. The noise removed images of the tumors are segmented using the level set method to separate the tumor area from the normal tissue. Twenty eight features regarding stress, strain, shape and texture features are computed. The features have been reduced using PCA and LDA method to improve the accuracy of the system and are normalized. BPN classifier and SVM classifier has been used for classifying the image as benign or malignant tumors by the use of above features and results were compared.

Accuracy of the neural network using BPN for the classification of solid breast tumors for the Elastographic features and B-mode features individually are calculated. The results are compared with the combination of the Elastographic and B-mode feature values. Accuracy is also obtained using SVM classifier and the results are compared to select the best classifier. BPN along with the PCA reduction technique yields greater accuracy than the other methods. Hence it is proved that the combined method yields the better result than to the Elastography and Ultrasonography methods done individually. It is concluded that Ultrasound and Sonoelastographic images and neural network analysis of features has the potential to increase the accuracy of the use of Ultrasound for the classification of benign and malignant breast tumors.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BPN	Back Propagation Network
CAD	Computer Aided Design
CT	Computer Tomography
DCT	Discrete Cosine Transform
DWT	Discrete Wavelet Transform
LDA	Linear Discriminant Analysis
MLP	Multi Layer Perceptron
MRI	Magnetic Resonance Imaging
NPV	Negative Predictive values
OFDM	Orthogonal Frequency Division Multiplexing
PCA	Principal Component Analysis
PPV	Positive Predictive values
ROC	Region Of Curves
SVM	Support Vector Machine
SWE	Shear Wave Elastography
US	UltraSound

CHAPTER 1

INTRODUCTION

Breast cancer is one of the most common forms of cancer in women. Worldwide, breast cancer is the second most common type of cancer after lung cancer (10.4% of all cancer incidence), and the fifth most common cause of cancer death. In 2005, breast cancer caused 502,000 deaths worldwide (7% of cancer deaths; almost 1% of all deaths).Statistics shows that one in 9 women is expected to develop breast cancer during her lifetime and one in 28 will die of it. In 2013, an estimated 232,340 new cases of invasive breast cancer were expected to be diagnosed in women in the U.S., along with 64,640 new cases of non-invasive breast cancer. Worldwide it is estimated that around 522,000women died from breast cancer in 2012, with mortality rates varying across the world. 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.

Elastography is a noninvasive imaging method developed to evaluate the stiffness of soft tissues. With the use of sonoelastography, the difference in hardness between normal and diseased tissue of the breast can be estimated by measuring the tissue strain induced by probe compression. Several clinical studies have reported that sonoelastography has the potential to differentiate between benign and malignant breast masses. Elastography works in the following steps: first, elastography receives digitized radiofrequency echo lines from the tissue; second, it gives slight compression to the tissue by the transducer along the radiation axis to make some displacement; and third, it receives a second, post compression digitized radiofrequency echo line from the same tissue.

The most common form of ultrasound imaging used in breast diagnosis is B-mode ultrasonography. It is based on broadcasting short bursts of ultrasound energy from transducer elements, then listening to the echoes from tissues at different depths along the path of ultrasound propagation. The strength (amplitude) of the echo received from the tissue is used to control the brightness (B-mode) of the display monitor. The brightness of an ultrasonic image represents a complex combination of sonographic properties of the tissue and also that of the ultrasound equipment that has been used.

CHAPTER 2

LITERATURE SURVEY

Bartolotta et al (2011) [1] evaluated the role of Ultrasound (US) Elastography to characterize breast lesions classified as indeterminate on B-mode US. 84 focal breast lesions, 64 benign and 20 malignant detected but not characterized on B-mode US. BI-RADS US category 3 or category 4 was studied with US Elastography and the lesions are classified according to a five-point color scale. Sensitivity, specificity and positive and negative predictive values (PPV and NPV) of US Elastography compared with conventional US were calculated in relation to other methods such as microhistology and cytology, which were used as the reference standard. In the evaluation of BI-RADS 3 lesions a statistically significant difference was noted in which US Elastography parameters as compared with BI-RADS 4 lesions. The results concluded that the high NPV of US Elastography may help to reduce the use of biopsy in BI-RADS 3 lesions.

V.Landoni, et al (2012) [2] developed a quantitative method for breast cancer diagnosis based on Elastography images. Images in DICOM format were exported into software, written in Visual Basic. The lesion was contoured after removing the noise, and then the mean grey value and softness inside the region of interest (ROI) were determined. The variables have certain correlations which were examined and receiver operating characteristic (ROC) curve analysis was performed to assess the diagnostic accuracy of the proposed method. The statistical measures were performed by using MedCalc, version 11.1.0.0 software. The limitation is that large prospective trials are necessary to determine whether quantitative analysis of images can help to overcome pitfalls of this method.

Çebi Olgun et al (2014) [3] proposed a method to determine the correlations between the elasticity values of solid breast masses and histopathological findings in differentiating malignant from benign lesions. Minimum, mean and maximum elasticity values were calculated in ROI over the lesion areas on two different images. Correlation of elastographic measurements with histopathological results was studied and they calculated mass/fat elasticity ratios. 83 benign and 32 malignant lesions were diagnosed histopathologically. The result showed that the above mentioned elasticity values and elasticity ratios of malignant lesions, were significantly higher than those of benign lesions. The authors concluded that SWE yields additional valuable and informative quantitative data to Ultrasonographic examination on solid breast lesions. Limitation is that more clinical studies are required to accurately select lesions requiring biopsy.

Tsutomu Tateishi, et.al (1999) [4] evaluated the ability of B-mode Ultrasonographic images in vitro study to distinguish metastatic from nonmetastatic axillary lymph nodes on a node-by-node basis. Four B-mode features such as size, circularity, border demarcation and internal echo were evaluated for their ability to distinguish between the nodes. Sensitivity and specificity were compared for all the combinations of features. ROC curves were created to identify the best combination of features. The advantage is that this method precisely correlated Ultrasonographic findings with histologic determinations. Results showed that a circular shape was the best single feature for distinguishing metastatic from nonmetastatic lymph nodes. The use of all four features provided the best combination of sensitivity and specificity. The present method in vitro study had some limitations, although the size and shape of lymph nodes in vitro may not be changed compared to in vivo, the measurable longest and shortest axis of a node may differ because in vitro scanning can be optimized.

Segyeong Joo, et al (2004) [5] developed a computer-aided diagnosis (CAD) algorithm identifying breast nodule malignancy using multiple ultrasonography (US) features and artificial neural network (ANN) which is used to differentiate between benign and malignant lesions. Five morphological features representing the shape, edge characteristics, and darkness of a nodule were extracted. Sonographic features were extracted automatically from an image by digital image processing techniques and by providing multiple sonographic feature values to the ANN, the performance of the decision algorithm can be improved. This scheme was expected to reduce processing time as well as to minimize false detection. The structure of ANN was selected using -fold cross-validation method with = 10. The developed CAD algorithm has the potential to increase the specificity of US for characterization of breast lesions.

Zhong Ling, et al (2007) [6] classified breast tumors through the contour complexity parameter estimated by divider-step method using a hybrid neural network. The combination of an unsupervised self-organizing mapping network (SOM) and a multilayer perceptron (MLP) network with error back propagation (BP) algorithm is used. It has shown that an impressive performance could be achieved when using a diagnostic system with the hybrid neural network as classifier, through the contour complexity parameter measured by divider-step method for benign and malignant differentiation. Further work is to integrate more additional features such as texture features should be used, to improve the accuracy of diagnosis.

Elizabeth S. Burnside, et al (2007) [7] evaluated the sensitivity and specificity of Ultrasonographic (US) strain imaging for distinguishing between benign and malignant solid breast masses. Receiver operating characteristic (ROC) curves were constructed by using the probabilities obtained. It is found that strain imaging has the potential to improve the decision of whether to perform breast biopsies. And the average area under the ROC curve for all those readers after US strain imaging was found to be greater than that after the B-mode US that is done alone. The results of this method also demonstrated that inter observer variability and image quality can influence reader performance. The case selection also limits the ability to generalize the results to other practices with full ranges of image quality. It will be important to determine the quality that must be achieved before using strain imaging data for clinical decisions.

Hamid Behnam et al (2010) [8] calculated the efficiency of novel shape features for classification of benign and malignant sonographic breast masses. Anisotropic diffusion filter on coefficients of wavelet transform is used to remove the speckle noise. The level set method is a numerical technique used for segmentation. Six novel shape features were extracted difference area, mean variation, variance variation, skewness variation, kurtosis variation, entropy variation. Mass classification was done by using MLP neural networks. The experimental results showed that this diagnostic system with the features proposed can improve the positive rate of biopsies. This is limited to the textural features as it can be affected by changes in sonographic machine settings and the use of different kinds of machines. To achieve a precise system for clinical examination the effects of automatic and manual segmentation and investigating the effects of other classifiers on obtained results can be regarded as subjects for future research.

Xiangjun Shi , H.D. et al (2010) [9] developed a novel CAD system based on fuzzy support vector machine to automatically detect and classify masses using ultrasound (US) images. The Metropolis Sampler approach is used for segmentation. Textural, fractal and histogram-based features were extracted. Classification is done using Fuzzy Support Vector Machine (FSVM). The results demonstrated that the textural features, fractal dimensions, and histogram-based features can represent the characteristics of masses in BUS (B-mode Ultrasound) images well. The stepwise regression method that is used to select the optimal features is quite effective. They have also studied different kinds of features and compared the performance of radiologist assessment, ANN, SVM, and FSVM in classifying masses. This approach is valuable to improve the accuracy of the diagnosis of breast cancer and to reduce the number of unnecessary biopsies.

Eriko Tohno and Ei Ueno (2008) [10] proposed a method where digital beam formers contributed to improving both contrast and special resolution of B-mode images. Elastography may reduce false-positives and unnecessary intervene procedures, especially in asymptomatic patients. The lesions were judged by their scores. Four-dimensional images are obtained by moving or shaking the transducer very fast and reconstructing 3-D images almost in real time. Results showed that the Elastography score is less helpful in cases of bloody nipple discharge and ductal carcinoma in situ (DCIS) and that very few invasive ductal carcinomas have a score of 1.

Woo kyung moon, et al (2009) [11] evaluated the accuracy of neural network analysis of elastographic features at Sonoelastography for the classification of biopsy-proved benign and malignant breast tumors. Once the segmentation process of the tumors is over, five elastographic strain features and six B-mode shape features were computed. With these features, a neural network was used to classify tumors. The Sonoelastographic images and neural network analysis of these features has the potential to increase the accuracy of ultrasound for the classification of benign and malignant tumors. Further studies are needed to automate the segmentation of tumor contours to reduce observer variability and to evaluate the potential of the neural network system to improve physician performance and to distinguish benign from malignant breast tumors.

Todd R. Kumm, et al (2010) [12] assessed the application and diagnostic performance of Elastography for the characterization of breast lesions in patients referred for biopsy. Clinical Application of Elastography in Breast Imaging includes two methods Color Elastography Imaging and Strain Ratio Measurement. BIRADS categories 1, 2 and 3 are the lesions that are affirmed as benign tumors and they are considered to have a higher probability of benign outcome. Category 3 lesions are said to be indistinct, while lesions that are graded as categories 4 and 5 are generally said to be malignant. Once the strain ratio increases, then the probability of invasive breast cancer also increases. The result obtained from this method showed lower sensitivity, specificity, and negative and positive predictive values. Strain ratio imaging in the evaluation of breast cancer is very limited, but combining this Strain ratio imaging technique with color Elastography may improve the overall performance than this as done alone.

Jae Jeong Choi, et al (2011) [13] evaluated the diagnostic utility of sonographic Elastography in differentiating benign and malignant axillary lymph nodes in breast cancer. They accessed B-mode sonograms by the sum of scores based on 4 criteria: short diameter, shape, hilum, and cortical thickening. Elastographic images were given scores of 1 to 4 according to the percentage of high-elasticity areas in the lymph nodes. Results suggested that there was a significant difference in the elasticity scores between benign and malignant lymph nodes. Combined B-mode method improved the sensitivity of axillary node metastasis detection. Further study has to done for precise node-to-node correlation using the sizes from pathologic and radiologic findings will be needed.

Jung Min Chang, et al (2011) [14] evaluated the diagnostic performance of Shear wave Elastography (SWE) for the differentiation of breast lesions as benign or malignant compared with conventional Ultrasound (US). For each lesion, quantitative elasticity was measured in terms of the Young's modulus with SWE and BI-RADS final categories were assessed with conventional US. There were significant differences in the elasticity values of benign and malignant masses as well as invasive and intraductal cancers with SWE. The results obtained using this method suggested that SWE has the high potential to differentiate between benign and malignant breast lesions. There is no specific guideline for the combination of BI-RADS score and elasticity values. More clinical studies are needed on how best to combine both methods to enhance benign and malignant differentiation are necessary.

Shirley Selvan, et al (2012) [15] proposed an automatic feature extraction method in ultrasound Elastography and Echography for characterization of breast lesions. The two sets of images are initially preprocessed by anisotropic diffusion filtering and then by an automatic threshold technique. Segmentation of the tumor images is done using the level set method in the combined image. The texture, strain and shape features are computed from the segmented lesions. Some of the features are distinct in an elastogram for the three specified conditions and hence elastogram increases the specificity of diagnosis. Classification of breast lesions using texture and strain features obtained from ultrasound images and elastograms is under implementation.

Richard G. Barr (2012) [16] reviewed the basics of the techniques such as how to perform the examination, image interpretation and artifacts. Compression Elastography produces an image based on the displacement of the tissue from an external or patient source. This technique allows for a qualitative assessment of the lesion. Shear wave Elastography applies a special "push pulse" which results in shear wave propagation that can be measured as a velocity. There are three methods of interpreting elastograms that includes all evaluating the size change between the B-mode image and the elastogram, the relative stiffness, and the ratio of the lesion stiffness to fat. The bull's eye artifact seen with compression Elastography is extremely helpful in characterization of cystic lesions. Further work is needed to determine whether Elastography will be able to downgrade BI-RADS category 4B, 4C, and 5 lesions.

Amani Ezzat Mousa, et al (2012) [17] detected the diagnostic performance of the combined use of Sonoelastographic scoring and strain ratio in differentiation of benign and malignant breast masses. The hardness was determined with 5-point scoring method and SRs of the lesions were calculated. Scores 1, 2 and 3 represent benign lesions while scores 4 and 5 represent malignant lesions. The receiver operating characteristic (ROC) curves for B-mode, ES and combination of ES and SR images for differentiating benign and malignant lesions were obtained. The combined use of both ES and SR had a high significant difference compared to B-mode US alone or ES alone. The limitation is that the wide range of SR values where some malignant lesions showed low SR while some benign lesions showed high SR. This has caused some overlapping in the diagnoses of some benign and malignant breast lesions.

Miki Mori, et al (2012) [18] used Elastography to evaluate the elasticity of mucinous carcinoma. Results showed that mucinous carcinoma and then both mixed mucinous carcinoma and pure-type mucinous carcinoma have a high elasticity score similar to that of the usual malignant lesions. In B-mode images, mucinous carcinoma and myxomatous fibroadenoma are delineated as high-echoic masses that have a similar circumference. They concluded that distinguishing between the 2 types of tumors is complicated. The limitation of Elastography is that some mucinous carcinomas have lower scores and some fibroadenomas have higher scores.

A Evans, et al (2012) [19] assessed the performance of shear wave Elastography combined with BI-RADS classification of greyscale ultrasound images for benign/malignant differentiation. Benign and malignant classification was by BI-RADS scoring of grayscale ultrasound and by shear wave Elastography using the defined cutoff value. The combination of SWE and BI-RADS is resulted as positive from either and was counted as malignant which yielded specificity, PPV and accuracy as same compared with BI-RADS and shear wave separately. It may be possible to reduce the number of women subjected to biopsy or short-term follow-up for benign-appearing solid breast masses. Limitation of such an approach would be that a number of benign lesions of uncertain malignant potential would remain as undiagnosed and not removed.

Marwa A.Shaaban and Abo El-Ata K. Aly (2012) [20] evaluated the sensitivity and specificity of the real-time Sonoelastography as compared with B-mode US for distinguishing between benign and malignant solid breast masses. The lesions were classified according to the density of the glandular breast tissue into low density group (D1) and a high density group (D2) and were categorized with the BIRADS and elasticity score. Elastographic images were assigned an elasticity score of 1 to 5 where 1–3 are called benign and then 4 and 5 are called malignant. Limitation is in evaluating focal lesions located at a depth of more than 1 cm because of the incomplete coloring present in the images. Further improvement for the perfection of Elastography is required in addition to the amount of compression applied to the tissues, patient positioning, and subjective computation of elastograms in the course of the examination.

Nesreen Mohey, et al (2014) [21] evaluated the value of ultrasound Elastography (UE) in differentiating benign versus malignant solid breast lesions discovered in mammography and compare it with grey scale ultrasound (US) and mammography. UE was the most specific (95.1%) of the 3 modalities. The accuracy (81.7%) of UE was equal to mammography and was higher than those of US (82.5% and 71.9%, respectively). A combination of UE and US had the best sensitivity (90.9%) and accuracy (93.8%). As compared to the false-negative rate, there is no significant difference between the 3 modalities was noted. Detection accuracy can be greatly improved and the combination potentially could reduce unnecessary biopsy especially for elasticity score 1–2

TABLE 2.1 COMPARISONS OF PERFORMANCE METRICS

Paper Reference No.	*Parameters*	*Accuracy(%)*	*Sensitivity(%)*	*Specificity(%)*
1	US Elastography	-	50	86
2	Elastography	-	81.1	87.5
3	Elastography Mean elasticity	-	96	95
	Maximum elasticity	-	95	94
	Maximum elasticity	-	96	95
	Mass/fat elasticity ratio	-	97	95
4	B-mode Size, shape, border, echo	-	30	90
	Any three features	-	85	73
5	B-mode	-	99.3	
6	B-mode	93.8	91.8	96
7	B-mode	-	96.8	13.2
	Strain	-	99.3	25.7
8	B-mode	93.83	91.18	95.74
9	B-mode(All features)	94.25	91.67	96.08
	Radiologist	74.71	88.89	64.71

	Texture features	88.51	83.33	92.16
11	Elastography	86.2	83.8	87.6
	B-mode	82.3	70.6	89.4
	Combined	90.6	95.6	87.6
12	Elastography Scoring(ES)	79	76	81
	Strain Ratio(SR)	77	79	76
13	Elastography	73.4	80.7	66.7
	B-mode	76.6	74.2	78.8
	Combined	70.3	87.1	54.6
14	Shear wave Elastography Elasticity value (100 kPa)	84.6	80.9	88.2
	Conventional US Between 4 and 5	75.3	100	87.9
17	B-mode	75.8	90.1	63.1
	ES	86.3	87.4	85.4
	ES + SR	94.2	94.3	94.2
19	BI-RADS	86	95	69
	Shear wave	89	95	77
	Combined	86	100	61
20	B-mode	-	85	94
	Elastography	-	80	97
21	Mammography	82.5	72.7	86.4
	Elastography	81.7	69.7	95.1
	B-mode	71.9	69.7	72.8
	Combined	93.8	90.9	95.1

CHAPTER 3

PROPOSED WORK

3.1 INTRODUCTION

The goal of screening exams for early breast cancer detection is to find cancers before they start to cause symptoms. Screening refers to tests and exams used to find a disease, such as cancer, in people who do not have any symptoms. Early detection means using an approach that lets breast cancer get diagnosed earlier than otherwise might have occurred. Breast cancers that are found because they are causing symptoms tend to be larger and are more likely to have already spread beyond the breast. In contrast, breast cancers found during screening exams are more likely to be smaller and still confined to the breast. The size of a breast cancer and how far it has spread are some of the most important factors in predicting the prognosis (outlook) of a woman with this disease.

3.1.1 BREAST ULTRASOUND

Ultrasound, also known as sonography, uses sound waves to look inside a part of the body. A gel is put on the skin of the breast and a handheld instrument called a transducer is rubbed with gel and pressed against the skin. It emits sound waves and picks up the echoes as they bounce off body tissues. The echoes are converted by a computer into a black and white image on a computer screen. This test is painless and does not expose you to radiation.

Breast ultrasound is sometimes used to evaluate breast problems that are found during a screening or diagnostic mammogram or on physical exam. Breast ultrasound is not routinely used for screening. Some studies have suggested that it may be helpful to use ultrasound along with a mammogram when screening high risk women with dense breast tissue (which is hard to evaluate with a mammogram). But at this time, ultrasounds cannot replace mammograms. More studies are needed to figure out if ultrasound should be added to routine screening mammograms for some groups of women.

Ultrasound is useful for taking a closer look at some breast masses, and it‘s the only way to tell if a suspicious area is a cyst without putting a needle into it to take out (aspirate) fluid. Breast ultrasound may also be used to help doctors guide a biopsy needle into an area of concern in the breast. There is a newer system, called a 3-dimensional automated ultrasound, which can be used on the breast. The FDA has approved it to be used along with mammography. The 3-D ultrasound can be done with a handheld transducer, but more often the breast is covered with gel before a larger unit is placed over the entire breast area and left in place as the machine gets images from different angles.

LIMITATIONS OF BREAST ULTRASOUND

Ultrasound has become a valuable tool to use along with mammograms because it‘s widely available, non-invasive, and costs less than other options. But the value of an ultrasound test depends on the operator‘s level of skill and experience—though this is less important with the new automated ultrasound systems. Ultrasound is less sensitive than MRI (that is, it detects fewer tumors), but it has the advantages of costing less and being more widely available.

3.1.2 ELASTOGRAPHY METHOD

Elastography is a non-invasive method in which stiffness or strain images of soft tissues are used to detect and classify tumors. The cancerous growth will be 5-28 times stiffer than the background of normal soft tissue. The strain of tissue is less than the surrounding tissue. Elastography method is a medical imaging modality that maps the elastic properties of soft tissue. This modality emerged in the last decade. It includes Ultrasound Elasticity Imaging, Magnetic Resonance Elasticity Imaging and Tactile Imaging. Organ is mechanically stressed by either external or internal forces. Measurement of tissues movement induced. Qualitative evaluation of tissue elastic properties is done from the measured displacement of tissues.

3.1.3 METHODOLOGY

In this proposed method as shown in Fig 3.1 Elastography and B-mode images are initially preprocessed by wavelet transform filtering and then by an automatic threshold technique. The level set method is utilized to segment the lesion in the combined images of Elastography and B-mode. The texture, strain and shape features are computed from the segmented lesions. Some of the features are distinct in an Elastogram image for the three specified conditions than to the Ultrasound B-mode.

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic.

Feature extraction is the main step in the detection and classification of the tumors. Once the features are extracted feature reduction is performed to improve the accuracy. PCA and LDA methods are used for the feature reduction. 28 features are reduced to 15 features in both PCA and LDA methods. They are normalized to bring all the values between the same levels. The extracted values are combined, randomized and then they are given to the classifier. BPN and SVM classifier is used to classify the randomized data and the accuracy is measured individually and by combining the data sets. The results obtained from different classifiers using different reduction methods have been compared.

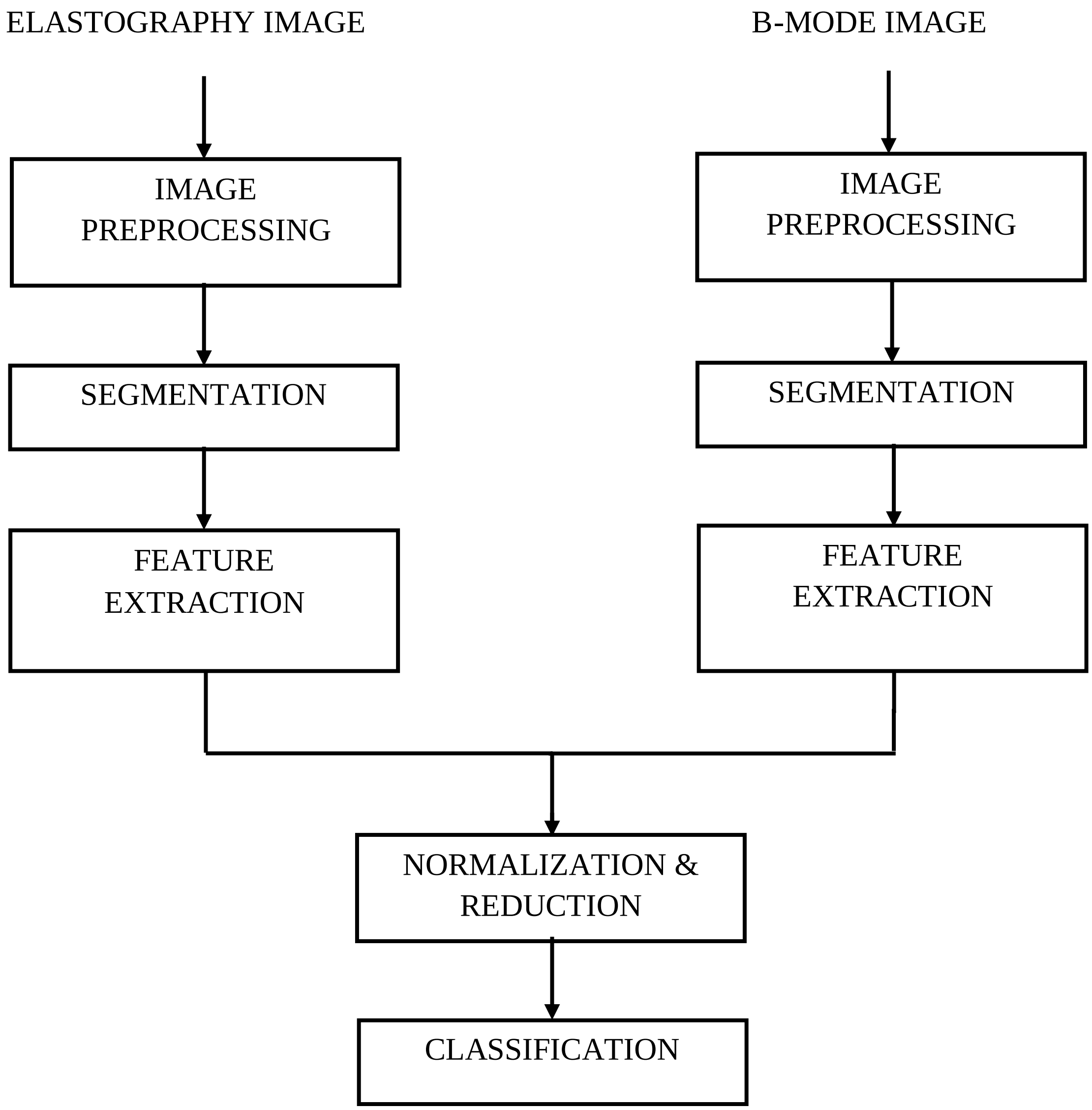


Fig 3.1 Work flow

CHAPTER 4

IMAGE PREPROCESSING & SEGMENTATION

4.1 DATABASE

The proposed algorithm was tested on 56 pairs of biopsy proven ultrasound elastography and ultrasound B mode images of which 40 are benign and 16 are malignant lesions. The images are obtained from the Sonoscan, Ultrasonic Scan Centre, Coimbatore and from the website http://www.ultrasoundcases.info/Case-List.aspx?cat=605. From the above set of images the database has been created and tested with different classifiers.

4.2 SPECKLE NOISE REDUCTION

This is to reduce speckle noise without losing its significant information in ultrasound images in an efficient way in order to improve the diagnosis. In the compression stage some useful information about the imaged object may be deteriorated or even lost. Any processing which works with envelope detected data has more information at its disposal and preserves more useful information. Compared to processing the scan converted image, envelope detected data has fewer pixels and thus incurs lower computational cost.

4.3 SPECKLE NOISE IN ULTRASOUND IMAGING

Ultrasound-based diagnostic medical imaging technique used to visualize muscles and many internal organs, their size, structure and any pathological injuries with real time tomographic images. It is also used to visualize a fetus during routine and emergency prenatal care. Obstetricsonography is commonly used during pregnancy. It is one of the most widely used diagnostic tools in modern medicine. The technology is relatively inexpensive and portable, especially when compared with other imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). It has no known long-term side effects and rarely causes any discomfort to the patient. Since it does not use ionizing radiation, ultrasound yields no risks to the patient. It provides live images, where the operator can select the most useful section for diagnosing thus facilitating quick diagnoses. This work aims to suppress speckle in Ultrasound images.

Speckle noise affects all coherent imaging systems including medical ultrasound. Within each resolution cell a number of elementary scatterers reflect the incident wave towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that delays the interpretation of the image content. A speckled image is commonly modeled as

$v_1 = f_1 \xi$:

where

$f = \{ f_1, f_2, f_3, ... f_n\}$ is a noise-free ideal image,

$V = \{v_1, v_2, v_3 ...... v_n\}$ speckle noise and

$\xi = \{\xi_1, \xi_2, \xi_3 ...... \xi_n\}$ is a unit mean random field.

The desired grade of speckle smoothing preferably depends on the specialist's knowledge and on the application. For automatic segmentation, sustaining the sharpness of the boundaries between different image regions is usually preferred while smooth out the speckled texture. For visual interpretation, smoothing the texture may be less desirable. Physicians generally have a preference of the original noisy images more willingly than the smoothed versions because the filters even if they are more sophisticated can destroy some relevant image details.

An appropriate method for speckle reduction is one which enhances the signal to noise ratio while preserving the edges and lines in the image. To address the multiplicative nature of speckle noise, Jain developed a homomorphic approach, which is obtained by taking the logarithm of an image, translates the multiplicative noise into additive noise, and consequently applies the Wiener filtering. Recently many techniques have been purposed to reduce the speckle noise using wavelet transform as a multi-resolution image processing tool. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One of the widespread method which is mainly exploited for speckle reduction is the wavelet method. A comparative study between wavelet coefficient filter and several standard speckle filters that are being largely used for speckle noise suppression which shows that the wavelet-based approach is deployed among the best for speckle removal.

4.4 WAVELET DEFINITION

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "revert, shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

A wavelet could be created to have a frequency of Middle C and a short duration of roughly a 32nd note. If this wavelet were to be convolved at periodic intervals with a signal created from the recording of a song, then the results of these convolutions would be useful for determining when the Middle C note was being played in the song. Mathematically, the wavelet will resonate if the unknown signal contains information of similar frequency - just as a tuning fork physically resonates with sound waves of its specific tuning frequency. This concept of resonance is at the core of many practical applications of wavelet theory. As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including - but certainly not limited to - audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based compression/decompression algorithms where it is desirable to recover the original information with minimal loss. In formal terms, this representation is a wavelet series representation of a square-integrable function with respect to either a complete, orthonormal set of basis functions, or an over complete set or frame of a vector space, for the Hilbert space of square integrable functions.

4.4.1 SCALING FILTER

An orthogonal wavelet is entirely defined by the scaling filter - a low-pass finite impulse response (FIR) filter of length *2N* and sum 1. In biorthogonal wavelets, separate decomposition and reconstruction filters are defined. For analysis with orthogonal wavelets the high pass filter is calculated as the quadrature mirror filter of the low pass, and reconstruction filters are the time reverse of the decomposition filters. Daubechies and Symlet wavelets can be defined by the scaling filter.

4.4.2 SCALING FUNCTION

Wavelets are defined by the wavelet function $\psi(t)$ (i.e. the mother wavelet) and scaling function $\phi(t)$ (also called father wavelet) in the time domain. The wavelet function is in effect a band-pass filter and scaling it for each level halves its bandwidth. This creates the problem that in order to cover the entire spectrum, an infinite number of levels would be required. The scaling function filters the lowest level of the transform and ensures all the spectrum is covered. For a wavelet with compact support, $\phi(t)$ can be considered finite in length and is equivalent to the scaling filter *g*. Meyer wavelets can be defined by scaling functions.

4.5 WAVELET TRANSFORM

A wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as "daughter wavelets") of a finite-length or fast-decaying oscillating waveform (known as the "mother wavelet"). Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.

Wavelet transforms are classified into discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs). Note that both DWT and CWT are continuous-time (analog) transforms. They can be used to represent continuous-time (analog) signals. CWTs operate over every possible scale and translation whereas DWTs use a specific subset of scale and translation values or representation grid.

4.5.1 CONTINUOUS WAVELET TRANSFORM

In continuous wavelet transforms, a given signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the L^p function space $L^2(R)$).

For instance the signal may be represented on every frequency band of the form $[f^2\ f]$ for all positive frequencies $f>0$. Then, the original signal can be reconstructed by a suitable integration over all the resulting frequency components.

The frequency bands or subspaces (sub-bands) are scaled versions of a subspace at scale *1*. This subspace in turn is in most situations generated by the shifts of one generating function ,$\psi \in L^2(R)$, the mother wavelet. For the example of the scale one frequency band [1,2] this function is

$$\psi(t)= 2\ \mathrm{sinc}(2t)-\mathrm{sinc}(t)= \sin(2\pi t)- \sin(2\pi t)/ \pi t$$

4.5.2 DISCRETE WAVELET TRANSFORM

It is computationally impossible to analyze a signal using all wavelet coefficients, so one may wonder if it is sufficient to pick a discrete subset of the upper half plane to be able to reconstruct a signal from the corresponding wavelet coefficients. One such system is the affine system for some real parameters $a>1$, $b>0$. The corresponding discrete subset of the half plane consists of all the points $(a^m,\ na^m b)$ with integers .m, $n \in z$. The corresponding *baby wavelets* are now given as

$$\psi_{m,n}(t)= a^{-m/2}\psi(\ a^{-m}t-nb)$$

A sufficient condition for the reconstruction of any signal x of finite energy by the formula

$$x(t)= \Sigma_{m\in z}\ \Sigma_{n\in z}\ (x,\ \psi_{m,n}).\ \psi_{m,n}(t)$$

is that the functions $\psi_{m,n}$:m, $n \in z$ form a tight frame of $L^2(R)$.

4.6 APPLICATION OF WAVELETS

An approximation to DWT is used for data compression if signal is already sampled, and the CWT for signal analysis. Thus, DWT approximation is commonly used in engineering and computer science, and the CWT in scientific research.

Wavelet transforms are now being adopted for a vast number of applications, often replacing the conventional Fourier Transform. Many areas of physics have seen this paradigm shift, including molecular dynamics, ab initio calculations, astrophysics, density matrix localization, seismology, optics, turbulence, and quantum mechanics. This change has also occurred in image processing, blood-pressure, heart-rate, and ECG analyses, brain rhythms, DNA analysis, protein analysis, climatology, general signal processing, speech recognition, computer graphics and multi fractal analysis. In computer vision and image processing, the notion of scale-space representation and Gaussian derivative operators is regarded as a canonical multi-scale representation.

One use of wavelet approximation is in data compression. Like some other transforms, wavelet transforms can be used to transform data, then encode the transformed data, resulting in effective compression. For example, JPEG 2000 is an image compression standard that uses biorthogonal wavelets. This means that although the frame is overcomplete, it is a *tight frame* and the same frame functions (except for conjugation in the case of complex wavelets) are used for both analysis and synthesis, i.e., in both the forward and inverse transform. For details see wavelet compression.

A related use is for smoothing/denoising data based on wavelet coefficient thresholding, also called wavelet shrinkage. By adaptively thresholding the wavelet coefficients that correspond to undesired frequency components smoothing and/or denoising operations can be performed.

Wavelet transforms are also starting to be used for communication applications. Wavelet OFDM is the basic modulation scheme used in HD-PLC (a power line communications technology developed by Panasonic), and in one of the optional modes included in the IEEE 1901 standard. Wavelet OFDM can achieve deeper notches than traditional FFT OFDM, and wavelet OFDM does not require a guard interval (which usually represents significant overhead in FFT OFDM systems).

4.7 WAVELET FILTERING

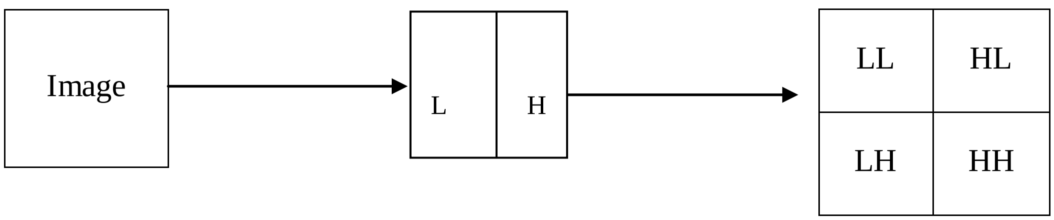
Recently there has been significant investigations in medical imaging area using the wavelet transform as a tool for improving medical images from noisy data. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal.

Several properties of the wavelet transform, which make this representation attractive for denoising, are

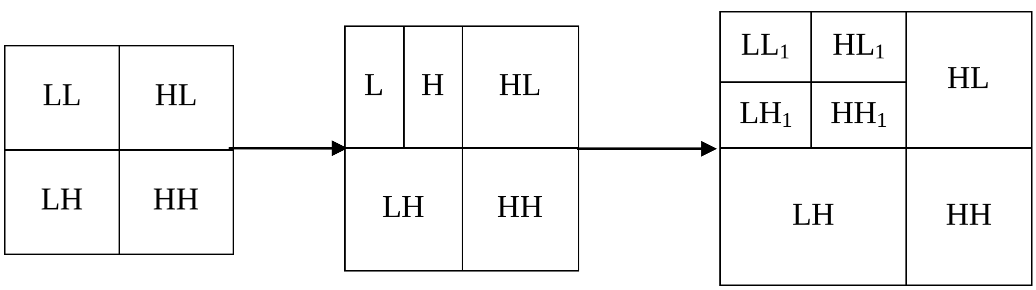
- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- Sparsity - the majority of the wavelet coefficients are small in magnitude.
- Edge detection - large wavelet coefficients coincide with image edges.
- Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters

During a two level of decomposition of an image using a scalar wavelet, the two-dimensional data is replaced with four blocks. These blocks correspond to the sub bands that represent either low pass filtering or high pass filtering in each direction. The procedure for wavelet decomposition consists of consecutive operations on rows and columns of the two-dimensional data. The wavelet transform first performs one step of the transform on all rows. This process yields a matrix where the left side contains down sampled low pass coefficients of each row, and the right side contains the high pass coefficients. Next, one step of decomposition is applied to all columns; this results in four types of coefficients, HH, HL, LH and LL. The HH subband gives the diagonal information of the ultra sound image; the HL subband gives the horizontal features while the LH subband represents the vertical structures of the US image. The LL subband is the low-resolution residual consisting of low frequency components.

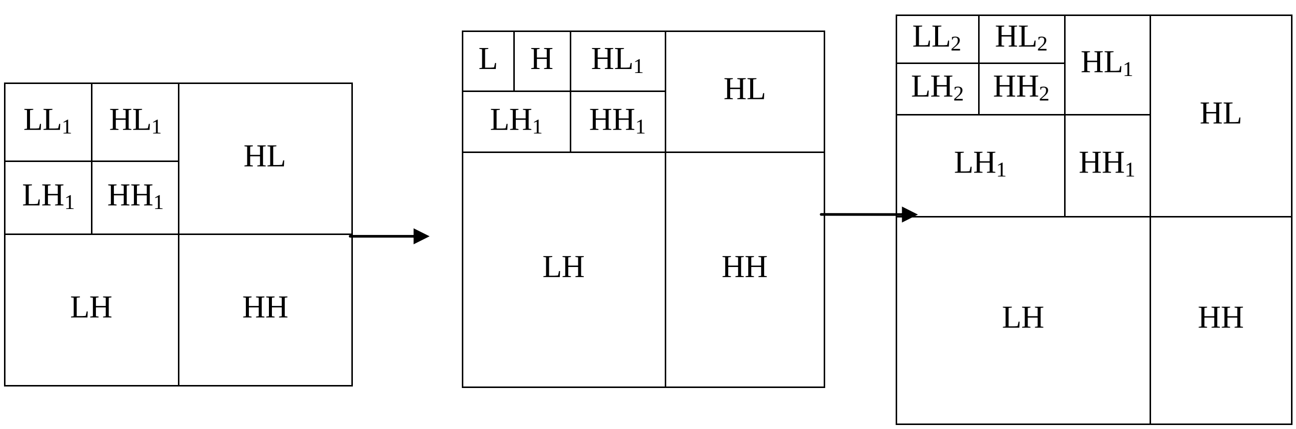
LEVELS OF DECOMPOSITION



Level 1



Level 2



Level 3**Fig 3.2 Decomposition of Wavelets**

4.8 WAVELET THRESHOLDING

All the wavelet filters use wavelet thresholding operation for denoising .Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One widespread method exploited for speckle reduction is wavelet thresholding procedure. The basic Procedure for all thresholding method is as follows:

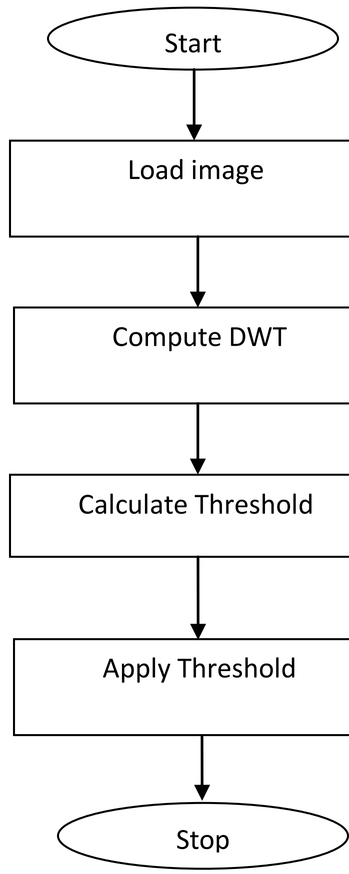


Fig 3.3 Flow Chart of Algorithm

This section depicts the image-denoising algorithm, which achieves near optimal soft thresholding in the wavelet domain for recovering original signal from the noisy one. The wavelet transform employs Daubechies' least asymmetric compactly supported wavelet with eight vanishing moments with four scales of orthogonal decomposition. It has the following steps.

Transform the multiplicative noise model into an additive one by taking the logarithm of the original speckled data.

- Log I(x, y) = log S(x, y) + log η(x, y).
- Perform the DWT of the noisy image
- Obtain noise variance.

- Calculate the weighted variance of image.
- Compute the threshold value for each pixel.
- Perform the inverse DWT to reconstruct the denoised image.
- Take Exponent.

In general a small threshold value will leave behind all the noisy coefficients and subsequently the resultant denoised image may still being noisy. On the other hand a large threshold value makes more number of coefficients as zero which directs to smooth the signal destroys details and the resultant image may cause blur and artifacts. So optimum threshold value should be found out, which is adaptive to different sub band characteristics. Thus the innovative aspects of the present work consist of the estimating appropriate threshold by analyzing the statistical parameters of the wavelet coefficients. Our threshold is based on Universal thresholding function. Threshold is calculated by estimating a parameter weighted variance (δ). The parameter weighted variance (δ) involves neighboring coefficients of the wavelet decomposition for the estimation of the local variance. Weighted variance (δ) of a given wavelet coefficient is determined by the weight in a local window.

$$\delta = \Sigma_{i\,,\,j\in N}\, w_{i\,,\,j}\, Y[x,y]^2 \,/\, \Sigma_{I\,,\,j\in N}\, w_{i\,,\,j}$$

Y[x,y] is pixcel value of the image. w is the weight of the local window. The selection of weights for the calculation of weighted variance would be in such a way that the estimated threshold minimizes the Mean square error.

Threshold (λ) is calculate from noise variance(σ) by weighted variance(δ).

$$\lambda(x\,,\,y) = \sigma(x\,,\,y) / \delta(x\,,\,y)$$

The parameter noise variance (σ) needs to be estimated. It may be possible to measure variance (σ) based on information other than the corrupted image and it is estimated from the sub band *HH* by the robust median estimator,

$$\sigma^2(x\,,\,y) = [\text{median}/0.6745]^2$$

where 0.6745 is the experimental value.

For quantitative analysis parameters MSE (Mean Square Error), PSNR (peak signal to noise ratio) are calculated for all the standard images with their noisy and denoised counterparts,

$$PSNR = 10\log10\ (255*255/MSE)$$

$$MSE = 1/MN\Sigma\Sigma[X(i,j)-Y(i,j)]^2$$

where X and Y are the original and noisy or denoised image respectively. M and N represent the width and height of image.

Soft threshold shrinks coefficients above the threshold in absolute value. The false structures in hard thresholding can overcome by soft thresholding. Now a days, wavelet based denoising methods have received a greater attention. Important features are characterized by large wavelet coefficient across scales, while most of the timer scales.

The soft thresholding operator is defined as:

$$D(U,\lambda) = \text{sgn}(U)\max(0, |U| - \lambda)$$

Soft thresholding overcome the following disadvantages of hard Thresholding

- Hard thresholding makes algorithms mathematically more tractable
- Hard thresholding does not even work with some algorithms such as the GCV procedure
- Sometimes, pure noise coefficients may pass the hard threshold and appear as annoying ’blips’ in the output.

4.9 IMAGE SEGMENTATION

Due to noise and speckles in the ultrasound B mode and elastographic images, noise filtering and edge-enhancement are required. The Speckle Reducing Anisotropic Diffusion (SRAD) filter (Yongjian Yu and T. Scott Acton, 2002) meets these requirements of noise filters and also improves the image quality significantly while preserving the important boundary information and hence, in present study, speckle reducing anisotropic diffusion filtering of real elastography and ultrasound B mode images is done to reduce noise and peckles. Segmentation is required to separate the tumor region from its background. Segmentation algorithms for grey scale images are based on one of the two basic properties of image intensity values: discontinuity and similarity. In the first category, the approach is to partition the image based on abrupt changes in the intensity, such as edges in an image.

The principal approaches in the second category are based on partitioning an image into two regions that are similar according to a set of predefined criteria. In present study, automatic threshold and level set active contour method, based on the above criteria are used for segmentation. An automatic threshold-determination method, proposed by Otsu (1997), can choose the threshold to minimize the infraclass variance of the black and white pixels automatically. An additional control scheme is allowed to enable the user to change the threshold value when he is not satisfied with the threshold value assigned by this automatic method.

4.9.1 LEVEL SET METHODS

The level set method was initially proposed to track moving interfaces by Osher and Sethian in 1988 and has spread across various imaging domains in the late nineties. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner. The central idea is to represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour. The level set method encodes numerous advantages: it is implicit, parameter free, provides a direct way to estimate the geometric properties of the evolving structure, can change the topology and is intrinsic. Furthermore, they can be used to define an optimization framework as proposed by Zhao, Merriman and Osher in 1996.

Therefore, one can conclude that it is a very convenient framework to address numerous applications of computer vision and medical image. Furthermore, research into various level set data structures has led to very efficient implementations of this method. a fast algorithm for topology independent tracking of moving interfaces under curvature- and velocity field-dependent speed laws. This is usually done in the level set framework using the narrow-band algorithm, which accurately solves the level set equation but is too slow to use in real-time or near real-time image segmentation applications. In this paper we introduce a fast algorithm for tracking moving interfaces in a level set-like manner.

The algorithm relies on two key components: First, it tracks the interface by scheduling point-wise propagation events using a heap sorted queue. Second, the local geometric properties of the interface are defined so that they can be efficiently updated in an incremental manner and so that they do not require the presence of the signed distance function.

4.9.2 THE LEVEL SET FORMULATION

As pointed out above, the level set technique is an implicit method, i.e. it does not track points on the interface itself but instead the interface is embedded as the zero level set of a time-dependent scalar function. The chain rule is

$$\frac{\delta\phi(\mathscr{S}(t),t)}{\delta t} = \phi_t + \frac{\delta\mathscr{S}(t)}{\delta t}\cdot\nabla\phi = 0$$

along with

$$F(\mathscr{S}(t)) = \frac{\delta\mathscr{S}(t)}{\delta t}\cdot\boldsymbol{n} = \frac{\delta\mathscr{S}(t)}{\delta t}\cdot\frac{\nabla\phi}{|\nabla\phi|}$$

yields the initial value problem

$$\phi_t + F|\nabla\phi| = 0, \quad \text{given } \phi(\boldsymbol{x},0).$$

Here, /ðx; 0Þ is usually the signed distance function of the closed surface S. However, /ðx; tÞ will not remain a signed distance function in general and therefore there is also a need for reinitializing / at regular intervals. An alternative level set equation where / is always the signed distance function.

CHAPTER 5

FEATURE EXTRACTION & REDUCTION

5.1 FEATURE EXTRACTION

Feature Extraction is a method of capturing visual content of images for indexing & retrieval. Primitive or low level image features can be either general features, such as extraction of color, texture and shape or domain specific features. It involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects.

In image processing algorithms are used to detect and isolate various desired portions or shapes (features) of a digitized image or video stream. It is the process of selecting a subset of relevant features for use in model construction. In this stage a set of features related to the shape, texture and size are selected. 28 parameters are considered for feature extraction. The texture features computed are Entropy, Uniformity, Mean, Median, Standard deviation, Smoothness, Tamura texture and Moments. The shape feature includes Edge density, Perimeter difference, Contour difference, Width-Height, Solidity. The strain feature includes Strain ratio, Strain difference, and Average gradient. And the other features include Intensity variation, Angularity, Orientation, Undulation, Wavelet, Spectral, Average inner, Average outer, Probability and Skewness features.

The five features (strain difference, strain ratio, mean, median and mode value) were computed by two of the investigators to evaluate the findings of benign and malignant tumors. The two features strain difference and strain ratio, were determined by comparing the average hue values in the bands five pixels inside and outside of the tumor contour. The mean, median and mode value of the strain were determined by calculating the hue values of pixels within the tumor contour. At first, the distant map is used to separate the inside and outside of tumor boundary.

Six features (orientation, undulation, angularity, average gradient, gradient variance and intensity variance) were also computed by two investigators to evaluate the findings of benign and malignant tumors. The former three features were used to evaluate the morphology of tumors and the latter three features were used to evaluate the echo patterns of tumors. The feature extraction method according to the BI-RADS US lexicon used in this study has been described and will be briefly summarized here.

The orientation was defined as the angle of the major axis of the best-fit ellipse and was used to measure the parallel degree of the mass contour. For computing the feature, undulation, the maximum inscribed circle of the lesion was applied to locate the lobulate areas and the number of lobulate areas was defined as the undulation. In addition, the local maximum within each lobulate area was found and defined as the angularity. The average gradient magnitude within the bands five pixels inside and outside of the tumor contour was calculated and defined as the average gradient. The variation of the echogenicity within the tumor was calculated by using the gradient magnitude within the tumor and was defined as the gradient variance. The intensity variance was also calculated to evaluate the extent of the differences between the gray intensity values within the tumor.The extracted values are normalized in order to improve the efficiency.

Skewness

Skewness was defined as a measure of symmetry. A distribution, or data set, is symmetric if it appears the same to the left and right of the center point.

Edge density

Edge density was defined as the mean value of edge pixels in a unit area. A pixel location (m, n) was declared as an edge location if its gradient g(m, n) exceeded some threshold t. The location of edge points constituted an edge map å (m, n), which was defined as follows:

$$\varepsilon(k,l) = \begin{cases} 1, & (k,l) \in Ig \\ 0, & \end{cases}$$

where

$$I_g \in \{(m,n);\ g(m,n) > t\}$$

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

Mean

The arithmetic mean is the "standard" average, often simply called the "mean". In mathematics and statistics, the arithmetic mean of a list of numbers is the sum of all the members of the list divided by the number of items in the list.

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$$

Where xi is the i th random variable, n-number of pixels

Standard deviation

The standard deviation of a discrete random variable is the root-mean-square (RMS) deviation of its values from the mean

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2}$$

Where xi is the i th random variable, N-number of items

Variance

The variance is the averaging the squared distance of its possible values from the expected value (mean). Whereas the mean is a way to describe the location of a distribution, the variance is a way to capture its scale or degree of being spread out.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2$$

Where xi is the ith random variable, N-number of item

Entropy

The entropy measure from the pixel intensity distribution is given by

$$E = \sum_{K=1}^{100} p_K \log(p_k)$$

Where pk is the probability that the kth intensity value falls between I and I+ΔI.

5.2 FEATURE REDUCTION

5.2.1 PRINCIPLE COMPONENT ANALYSIS

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data. If a multivariate dataset is visualised as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a projection or "shadow" of this object when viewed from its (in some sense; see below) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

PCA is closely related to factor analysis. Factor analysis typically incorporates more domain specific assumptions about the underlying structure and solves eigenvectors of a slightly different matrix.PCA is also related to canonical correlation analysis (CCA). CCA defines coordinate systems that optimally describe the cross-covariance between two datasets while PCA defines a new orthogonal coordinate system that optimally describes variance in a single dataset. PCA is useful for finding new, more informative, uncorrelated features; it reduces dimensionality by rejecting low variance features.

APPLICATIONS

- Analysis of expression data
- Analysis of metabolomics data

The objectives of principal components analysis are

- Data reduction
- Interpretation
- The results of principal components analysis are often used as inputs to
- Regression analysis
- Cluster analysis

The first principal component is the linear combination of maximum variance, The second principal component is the linear combination of maximum variance that is uncorrelated with the first principal component, The third principal component is the solution to the nonlinear optimization problem.

ALGORITHM

1. X ← Create N x d data matrix, with one row vector x_n per data point
2. X subtract mean x from each row vector x_n in X
3. Σ ← covariance matrix of X
4. Find eigenvectors and eigenvalues of Σ

PC's ← the M eigenvectors with largest eigenvalues

LIMITATIONS

- As noted above, the results of PCA depend on the scaling of the variables.
- The applicability of PCA is limited by certain assumptions made in its derivation.

5.2.2 LINEAR DISCRIMINANT ANALYSIS (LDA)

There is growing recognition that a variety of statistical classification problems can be approached advantageously using tools from the field of optimization. Reexamination of those problems and their underlying model assumptions can sometimes lead to refreshing new prospective and alternate lines of attack. Discriminant analysis is high on the list of problems of this type and has been drawing increased attention recently because it straddles the area of management science, artificial intelligence as well as statistics. Artificial Intelligence applications involve the challenging realm of pattern recognition, including problems of signal differentiation, diagnostic classification, and code signatures and data types.

An effort to wed statistical discrimination with optimization has come about through proposals to capture the goals of discriminant analysis in a collection of linear programming formulations. Linear Discriminant Analysis (LDA) is a technique that has been successfully used for many classification problems, such as voice recognition, face recognition, and multimedia information retrieval. In statistical theory, LDA arises in those classification problems assuming that the densities of all classes are multivariate Gaussian with a common covariance matrix. In such assumption, it is very easy to deduce the decision boundaries of each class and use them for classification. For recognition, the aim of LDA is also to find a projection matrix as in PCA that maximizes the so called Fisher criterion.

Although successful in many cases, many LDA-based algorithms suffer from the so-called “small sample size problem” (SSS) which exists in high-dimensional pattern recognition tasks, where the number of available samples is smaller than the dimensionality of the samples. An active field where such problem appears is image retrieval/classification.

DIMENSION REDUCTION

Finds linear combinations of the features $\mathbf{X}=X_1,...,X_d$ with large ratios of between-groups to within-groups sums of squares - discriminant variables.

APPLICATIONS

- Image retrieval
- Gene expression data analysis
- Text mining
- Medical image analysis

CHAPTER 6

CLASSIFICATION

NEURAL NETWORK

Neural networks are similar to biological neural networks in performing functions collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned. The term "neural network" usually refers to models employed in statistics, cognitive psychology and artificial intelligence. Neural network models which emulate the central nervous system are part of theoretical neuroscience and computational neuroscience.

6.1 BACKPROPAGATION ALGORITHM

Backpropagation, an abbreviation for "backward propagation of errors", is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respects to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function. Backpropagation requires a known, desired output for each input value in order to calculate the loss function gradient. It is therefore usually considered to be a supervised learning method, although it is also used in some unsupervised networks such as autoencoders. It is a generalization of the delta rule to multi-layered feedforward networks, made possible by using the chain rule to iteratively compute gradients for each layer. Backpropagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

The goal of any supervised learning algorithm is to find a function that best maps a set of inputs to its correct output. An example would be a simple classification task, where the input is an image of an animal, and the correct output would be the name of the animal. Some input and output patterns can be easily learned by single-layer neural networks (i.e. perceptrons). However, these single-layer perceptrons cannot learn some relatively simple patterns, such as those that are not linearly separable.

A single-layer neural network however, must learn a function that outputs a label solely using the intensity of the pixels in the image. There is no way for it to learn any abstract features of the input since it is limited to having only one layer. A multi-layered network overcomes this limitation as it can create internal representations and learn different features in each layer.[1] The first layer may be responsible for learning the orientations of lines using the inputs from the individual pixels in the image. The second layer may combine the features learned in the first layer and learn to identify simple shapes such as circles. Each higher layer learns more and more abstract features such as those mentioned above that can be used to classify the image. Each layer finds patterns in the layer below it and it is this ability to create internal representations that are independent of outside input that gives multi-layered networks their power. The goal and motivation for developing the backpropagation algorithm was to find a way to train a multi-layered neural network such that it can learn the appropriate internal representations to allow it to learn any arbitrary mapping of input to output.

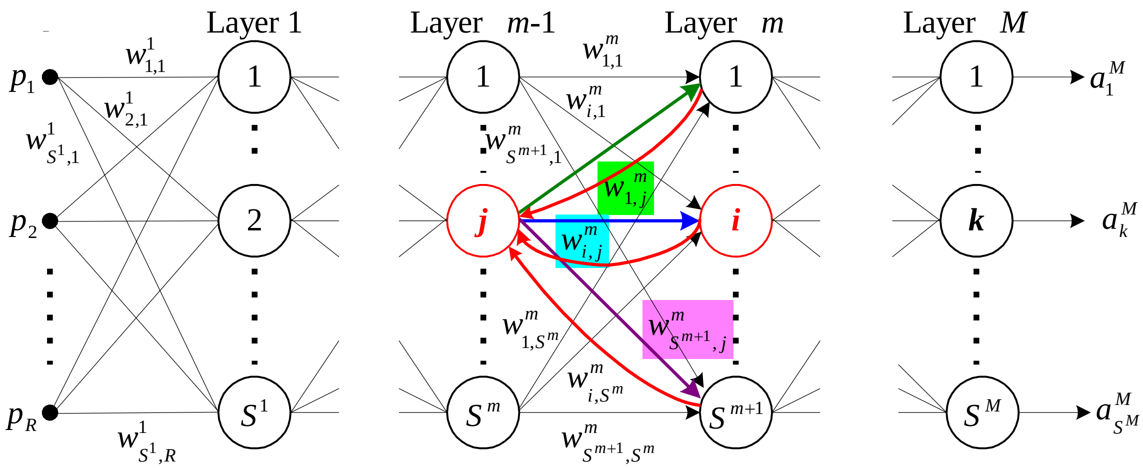


Fig 6.1 BP Neural Network

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.

2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.

2. Subtract a ratio (percentage) of the gradient from the weight.

This ratio (percentage) influences the speed and quality of learning; it is called the *learning rate*. The greater the ratio, the faster the neuron trains; the lower the ratio, the more accurate the training is. The sign of the gradient of a weight indicates where the error is increasing; this is why the weight must be updated in the opposite direction.

Phase 1 and 2 are repeated until the performance of the network is satisfactory.

As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes. Technically speaking, backpropagation calculates the gradient of the error of the network regarding the network's modifiable weights. This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "backpropagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Backpropagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Backpropagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and Gaussian function.

The backpropagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode.

6.1.1 CLASSIFICATION OF MASSES USING BPN

Based on the features extracted, the masses are classified as benign, malignant or normal tissue. The proposed work uses Back Propagation Neural network (BPN) for the classification of the suspicions. Back propagation algorithm is a supervised learning method for multilayer network. It is used as a learning method in feed forward multilayer neural networks and classification problems.

In the training, the input pattern and the corresponding target output are applied to the input layer of BPN. The input produces a response to the neurons of the first layer, which in turn produce a response to the neurons of the upper hidden layer, and so on, until a response is produced at the output layer. The obtained response is then compared with the target output and the error is computed. The weights between the last hidden layer and the output layer are recalculated using the error value obtained so that the output error is reduced. This process is repeated up to the input layer. Now, the weights are updated to new value. When the weights have reached a steady state, the algorithm takes the next set of input-target patterns and repeats the above steps. The testing is done with different set of inputs.

6.2 SUPPORT VECTOR MACHINE

Support Vector Machine is an unsupervised or self organized neural network. SVM have recently found considerable attention in classification problems due to its generalization capabilities. These classifiers maximize the distance (margin) between the training examples and the decision boundaries by mapping the training examples to higher dimensional space [II]. The dimension of the new space is considerably larger than that of the original data space. Then the algorithm finds the hyper plane in the new space having the largest margin of separation between the classes of the training data using an optimization technique known as the risk minimization. For a binary classification problem where there are only two classes in the training data = $\{-1,1\}$, a hyper plane can be defined as:

$W.x + b = 0$

where W is the normal to the hyper plane and b / W is the shortest distance of the plane from the origin. For a good classification model, the positive and negative examples of the training data should fulfill the following two conditions:

$(W.x_i) + b > 0 \quad \text{if } Y_i = 1$

$(W.x_i) + b < 0 \quad \text{if } Y_i = -1$

These inequalities can be combined into one set of Inequalities

$y(W.x + b) \geq 1$ for all i

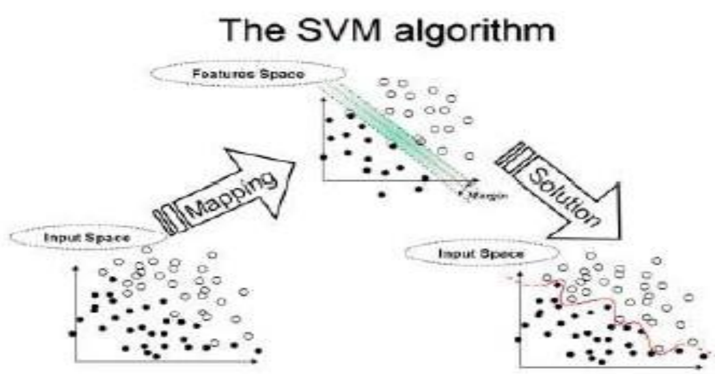


Figure 6.2 SVM Algorithm

The SVM finds an optimal hyper plane responsible for the largest separation of the two classes by solving the following optimization problem subject to the condition.

$Min\ w, b \quad \frac{1}{2}\ W^T W$

The quadratic optimization problem of (JJ) can be solved using a langrangian function

$$Lp(w, b, \alpha) = \frac{1}{2} W^T W - \sum_{i=1}^{m} \alpha i(yi(Wxi + b) - 1)$$

where αi is the constant known as langrage multipliers. The solution of (HH) for αi determines the parameters w and b of the optimal hyper plane. Thus a decision function for the binary classification is formulated as

$$f(x) = sgn(\sum_{i=1}^{m} yi\ \alpha i(x, xi) + b)$$

In any classification task only a few langrangian multipliers αi tend to be greater than zero and the corresponding training vectors are the closest to the optimal hyper plane and are called the support vectors. In nonlinear SVM, the training samples are mapped to a higher dimensional space with the help of a kernel function K (xi ,xj) instead of the inner product <xi , xj> . Some of the famous kernel functions are the polynomial kernels, radial basis function kernels, and sigmoid kernels.

6.2.1 PERFORMANCE MEASURE

ACCURACY

The obtained results are compared in terms of accuracy as shown in Table I. Accuracy gives the efficiency of the classification process. It is calculated using the equation (14).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Where,

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

CHAPTER 7

MATLAB SOFTWARE

7.1 INTRODUCTION

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. we can use MATLAB for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology.

MATLAB (**mat**rix **lab**oratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran. MATLAB is widely used proprietary software for performing numerical calculations. It comes with its own programming language, in which numerical algorithms can be implemented.

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems.

7.2 IMAGE PROCESSING TOOLBOX

Image Processing Toolbox supports a diverse set of image types, including high dynamic range, Gigapixel resolution, embedded ICC profile, and tomography. Graphical tools let you explore an image, examine a region of pixels, adjust the contrast, create contours or histograms, and manipulate regions of interest (ROIs). With toolbox algorithms you can restore degraded images, detect and measure features, analyze shapes and textures, and adjust color balance. The image processing toolbox allows such manipulations as:

(i) Direct visualization of images in MATLAB

(ii) Object grouping and data collection

(iii) Filtering and fast convolution

(iv) Fourier analysis of images

7.3 KEY FEATURES

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- 2-D and 3-D graphics functions for visualizing data
- Tools for building custom graphical user interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java, COM, and Microsoft® Excel

7.4 INTERFACING WITH OTHER LANGUAGES

MATLAB can call functions and subroutines written in the C programming language or Fortran. A wrapper function is created allowing MATLAB data types to be passed and returned. MATLAB libraries example XML or SQL support) are implemented as wrappers around Java or ActiveX libraries. Calling MATLAB from Java is more complicated, but can be done with a MATLAB toolbox[25] which is sold separately by MathWorks, or using an undocumented mechanism called JMI (Java-to-MATLAB Interface).

7.5 APPLICATIONS

There are many fields that use MATLAB software. Some of them are

(i) Data Exploration ,Acquisition ,Analyzing &Visualization

(ii) Analyzing of algorithmic designing and development

(iii) Mathematical functions

(iv) Computational functions

(ix) Image processing and filtering

7.6 ADVANTAGES OF MAT LAB

(i) Entrance time to start using MATLAB is low. After only a few hours of training, a new MATLAB user can start developing simulation tools.

(ii) Recent versions of the MATLAB compiler can compile to C, C++ and binary code, allowing the use of different optimization options for high-speed executables.

(iii)The open architecture allows for very rapid extension of the range of functionality of MATLAB by developing and sharing new toolboxes.

CHAPTER 8

SIMULATION RESULTS AND CONCLUSIONS

8.1 SIMULATION RESULTS

B-MODE AND ELASTOGRAPHY BENIGN IMAGE

The noise in the images is reduced using wavelet transform method and the images are segmented using level set method. The resulted images are shown in the Fig 8.1

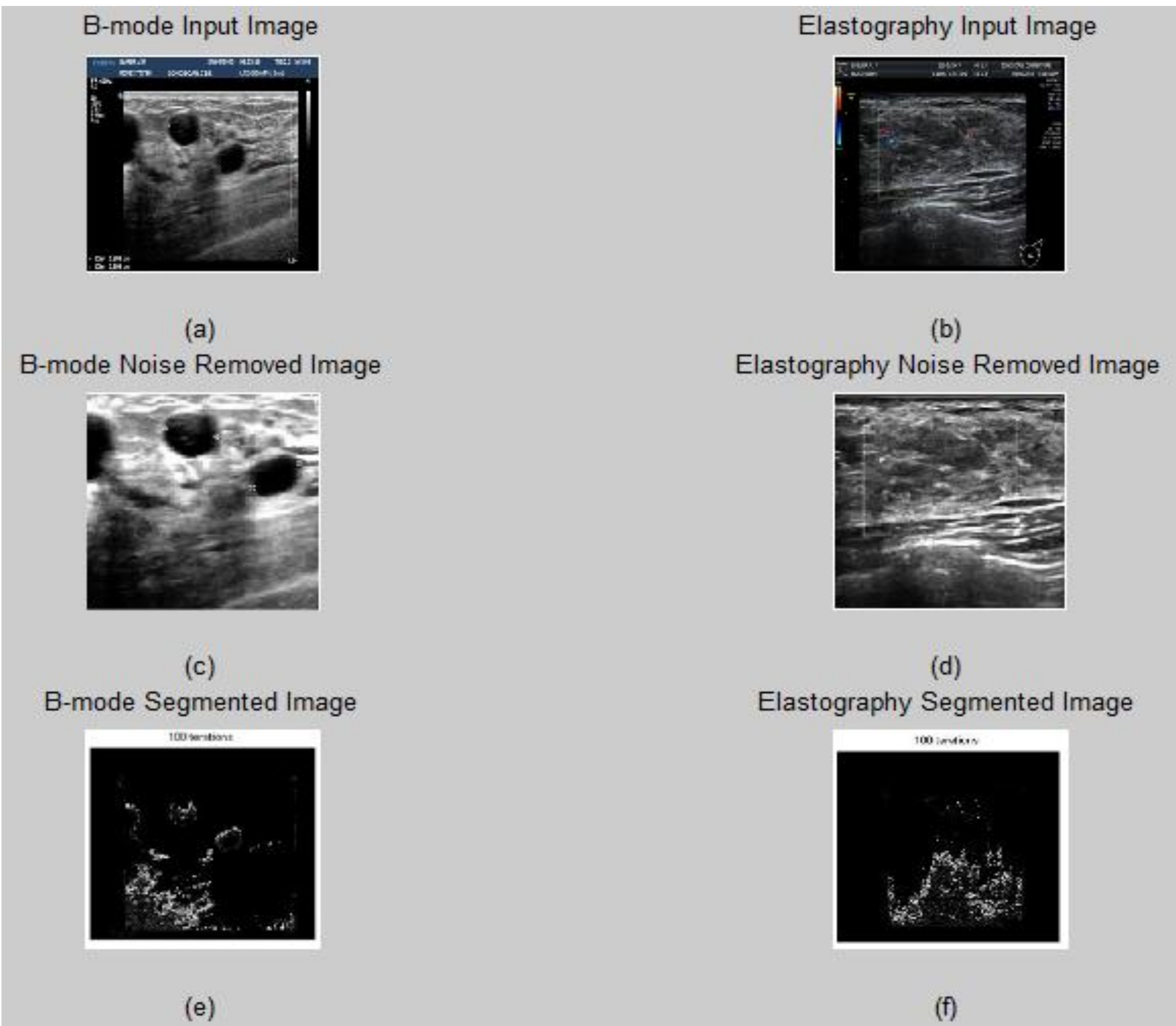


Fig 8.1 B-Mode and Elastography Benign Image

The input images of benign B mode and Elastography are shown in the fig 8.1 a and b. The noise removed images are shown in the fig 8.1 c and d. The segmented images are shown in the fig 8.1 e and f.

B-MODE AND ELASTOGRAPHY MALIGNANT IMAGE

The noise in the images is reduced using wavelet transform method and the images are segmented using level set method. The resulted images are shown in the Fig 8.2

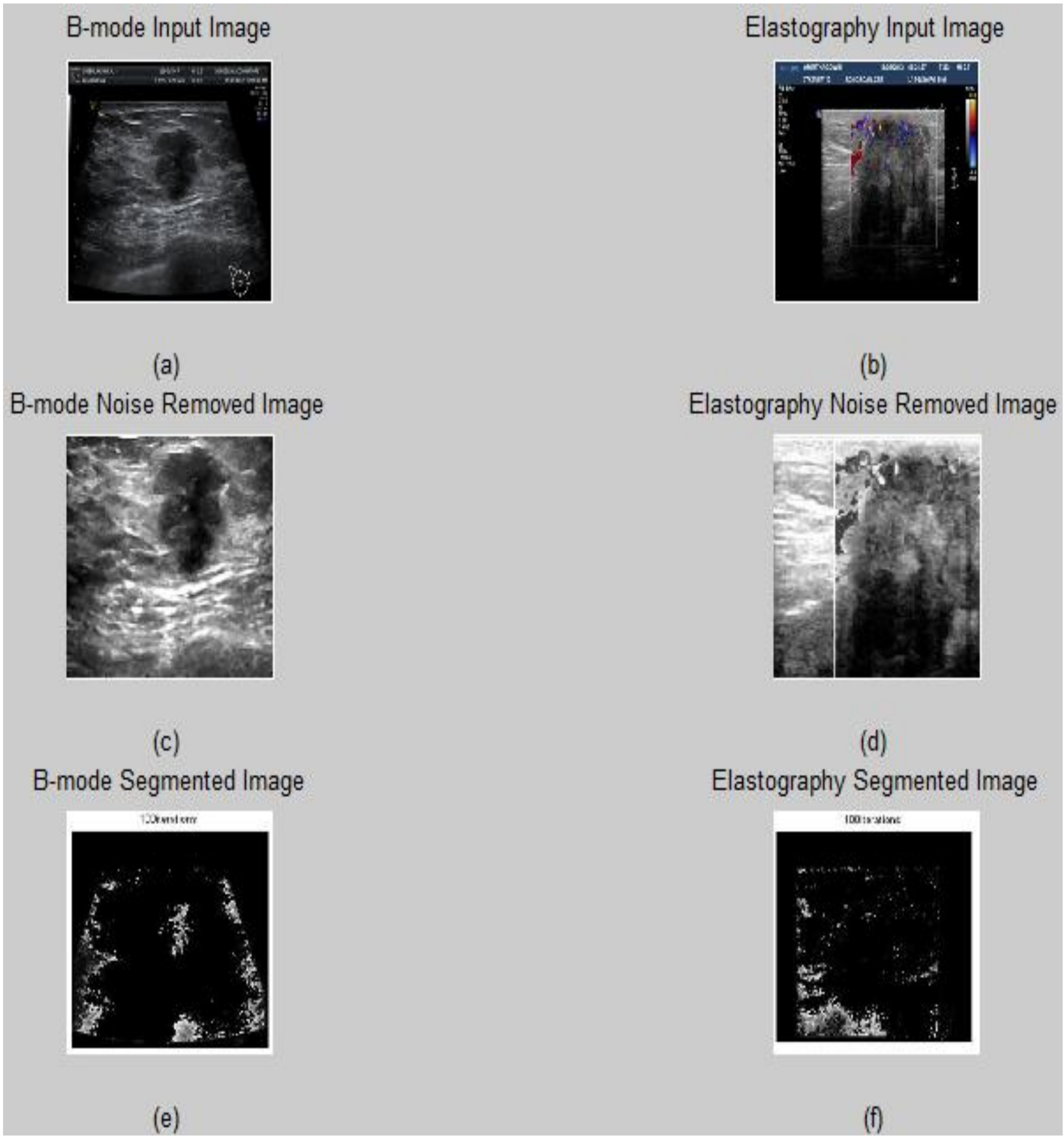


Fig 8.2 B-Mode and Elastography Malignant Image

The input images of malignant B mode and Elastography are shown in the fig 8.2 a and b. The noise removed images are shown in the fig 8.2 c and d. The segmented images are shown in the fig 8.2 e and f.

The following features in the TABLE 8.1 are extracted for the Benign and Malignant images for the classification of breast tumors.

Features	Benign	Malignant
Variance	360.8738	14402.143
Mean_value	7.484329	16.869217
Standard_deviation	0.971767	3.1153617
Avg_inner	490493	1105541
Avg_outer	38689	40194
Strain_difference	451.804	1065.347
Strain_ratio	7.428423	16.116284
Median_value	0	0
Avg_grad	2.614017	5.2221798
Intensity_var	360.8738	14402.143
Angularity	0	0
Orientation	6.296593	0.9461821
Undulation_final	25	20
Perimeterdiff	2	4.8284271
Solidity	0.004853	0.1129944
Width_height	1	1
Contour_diff	730.4931	393.89628
Edge_density	171312.2	342240.77
Texture_Feature	5.183262	5.2376841
Tamura_texture	245246.5	552770.5
Skewness	-1.30E-10	-2.426E-10
M0	0.022435	0.0073187
M1	1.42E-06	3.432E-06
M2	1.30E-06	8.924E-08
M3	4.43E-07	8.896E-09
Smoothness	0.545239	0.5452391
Uniformity	7.87E-08	6.506E-08

TABLE 8.1 FEATURE EXTRACTION

Various features are extracted for both benign and malignant images. This includes stress, strain, shape and texture features. Extracting more number of features will increase the system performance. The above table shows that there is significant difference between the benign and malignant images.

The accuracy measured for different reduction techniques using different classifiers are given in the TABLE 8.2

CLASSIFIER	REDUCTION TECHNIQUE	METHOD	ACCURACY (%)
BPN	PCA	B-MODE	95
		ELASTOGRAPHY	90
		COMBINED	95
	LDA	B-MODE	90
		ELASTOGRAPHY	95
		COMBINED	95
SVM	PCA	B-MODE	85
		ELASTOGRAPHY	85
		COMBINED	88
	LDA	B-MODE	80
		ELASTOGRAPHY	85
		COMBINED	88

TABLE 8.2 CLASSIFICATION OUTPUT

Different classifiers with various reduction techniques are compared with their accuracy values. By using BPN classifier and PCA reduction technique yields 95%, 90%, 95% accuracy for the B mode, Elastography and combined methods respectively. By using BPN classifier with the LDA reduction method yields 90%, 95%, 95% accuracy for the B mode, Elastography and combined methods respectively. By using SVM classifier with the PCA reduction technique yields 85%, 85%, 88% accuracy for the B mode, Elastography and combined methods respectively. And by using SVM classifier with the LDA reduction technique yields 80%, 85%, 88% accuracy for the B mode, Elastography and combined methods respectively.

Thus the Neural network classifier with BPN algorithm for the combined method yields better performance than the Elastography and B mode methods done alone.

8.2 CONCLUSION

The proposed method is to develop a quantitative method for breast cancer diagnosis based on Elastography and B-mode images in order to reduce unnecessary biopsies and also to evaluate the diagnostic performance of Elastography and B-mode sonography individually and combining them to yield a better performance. The noise in the Ultrasound B-mode and the Elastography images are reduced using wavelet transform method. Experimental results show that our proposed method yields significantly improved visual quality when compared to other filters. Further the image is segmented using level set active contour method. From the segmented image twenty eight Elastographic and B-mode features are selected such as stress, strain, shape and texture features. The texture features include Entropy, Uniformity, Mean and Median, Standard deviation, Smoothness, Tamura texture and Moments. The shape feature includes Edge density, Perimeter difference, Contour difference, Width-Height, Solidity. The strain feature includes Strain ratio, Strain difference, and Average gradient. And the other shape features include Intensity variation, Angularity, Orientation, Undulation, Spectral, Average inner, Average outer, Probability and Skewness features have been computed.

With the extracted features from the image, to improve the efficiency of the system feature reduction is performed using PCA and LDA methods. The feature values are normalized and reduced. The reduced data set is classified using the MLP neural network with BPN algorithm and also using SVM as benign or malignant and the results were compared. The reduction method PCA along with the neural network classifier yields the better result than the other methods. The accuracy of the classifiers has been calculated and compared so as to find the best suitable method for the breast cancer detection. It is concluded that sonoelastographic images and neural network analysis of features has the potential to increase the accuracy for the classification of benign and malignant breast tumors.

8.3 FUTURE WORK

PCA and LDA reduction methods were used in the proposed methods. In future GA can also be used for the feature reduction for the betterment of the proposed method. The neural network with different algorithms can be implemented to improve the accuracy. More images of Elastography and B mode can be included for the better results.

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LIST OF PUBLICATIONS

JOURNAL

- Published a paper titled "*An automated Breast Cancer Detection and Classification based on Ultrasound Elastrography and Echography Images: A survey"* in International Journal of Applied Engineering Research (IJAER) Volume 9, Number 21 (2014) Pp.4939-4946

CONFERENCES

- Presented a paper titled "*An automated Breast Cancer Detection and Classification based on Ultrasound Elastrography and Echography Images: A survey*" in International Conference on Pattern Recognition and Multimedia Signal Processing on 9th and 10th January 2015 held at Annamalai University, Annamalainagar.

- Presented a paper titled "*Breast Cancer Detection based on Combined Analysis of Elastrography and B-mode Image Features*" in Conference on Emerging Technologies and its Applications in Computers during 27th and 28th March 2015 held at PSG College of Technology, Coimbatore.