LITERATURE SURVEY

2.1 Introduction

Breast cancer is one of the major causes of death among Women and it takes years to develop. Although breast cancer can be fatal, people have the highest chance of survival if cancer could be detected at the early stages. Our study involves a literature research on diagnostic techniques used for breast cancer which is being discussed in this chapter.

This chapter discusses the state of the art related to the proposed work on the analysis of soft tissue patterns for early detection of breast cancer. The topics related are classified under four sections: The first section describes related works on detection of breast cancer, the second section on preprocessing for both mammogram and ultrasound, as we have finally fused the information retrieved from these two modalities. The third section focuses on methods related to detection of abnormalities in breast using the modalities, mammogram and ultrasound. Fourth section describes the work carried out on different fusion techniques to fuse features retrieved from different modalities. Finally, we have highlighted the limitations of existing work which shows us the path to carry out research by considering limitations in the existing methods.

2.2 Automated Detection of Breast Cancer

Majority of automated abnormality detection systems usually involve three steps: noise removal, filtering or feature extraction and decision analysis which results in a binary outcome which says either yes or no (abnormality present or not present). The first two steps may be considered as pre-processing. Reviews of important work in preprocessing, image processing, and statistical methods relevant to calcification and mass detection will be discussed in later sections. The
purpose of preprocessing is to enhance the image, which may be achieved by either increasing contrast or by removing background tissue or suppressing noise.

Most of the Contrast enhancement techniques include local or global area thresholding, density-weighted contrast enhancement and segmentation. For noise removal, often non-linear methods are applied. Ginger and Davis have used median filtering, edge preserving smoothing, half neighborhood and directional smoothing methods for noise removal [52, 34]. The main task of pre-processing is to locate the breast region relative to the off-breast image area (background). Once the breast region is located and pre-processed, various image processing and statistical methods are applied to detect the abnormality.

A wide variety research has been devoted to automated detection of breast cancer. These approaches include use of wavelet transforms, watershed transforms, and clustering analysis [113, 74, 15, 129, 10, 150]. Due to characteristic similarity of the surrounding tissue with actual mass, the mass detection methods concentrate on extracting features that may differentiate the mass. These features may include asymmetry measures between breasts, local textural changes, or radiating density patterns. Hence, the approaches used for mass detection include directional wavelet analysis, rubber band straightening transforms, a variety of texture analysis methods and clustering analysis [55, 121, 110].

2.3 Preprocessing

Biomedical images are often affected and corrupted by various types of noise and artifacts where any image pattern or signal other than that of interest could be termed as artifact. This section gives an insight of several works carried out to detect and to remove these noise and artifacts in mammograms and breast ultrasound images.

2.3.1 Preprocessing and Segmentation in Mammogram

Preprocessing and segmentation in digital mammogram includes two stages: Breast contour identification and Pectoral muscle segmentation. The pectoral
muscle represents a predominant density region in most MLO views of mammograms, and can affect the results of image processing. The literature related to this is discussed here.

J. Suckling et al. [71] segmented mammograms into four major components: background, pectoral muscle, fibro-glandular region and adipose region, using multiple, linked self-organizing neural networks. Karssemeijer [100] used Hough transform to detect the pectoral edge. This method assumes that pectoral edge is approximately a straight line oriented in a certain direction. Gradient magnitude and orientation, length of projected line, and corresponding pectoral area were taken into account to select the correct peak in Hough space.

Ferrari et al. [116] segmented mammograms into skin-air boundary, fibro-glandular tissue, and pectoral muscle, based on the Hough transform. Georgsson [41] extracted pectoral muscle by region growing. Fei Maa, introduced two image segmentation methods based on graph theory in conjunction with active contours to segment the pectoral muscle in screening mammograms. One method is based on adaptive pyramids (AP) and the other is based on minimum spanning trees (MST). Both algorithms correctly identify components of the image belonging to the pectoral muscle in most cases, but the components found have ragged edges and tend not to include the extreme edge of the pectoral muscle. Major problem would be in those situations where the abnormalities are located in the pectoral-breast boundary, as its neighborhood will have very different grey-level values.

While considerable research and progress have been made in the area of image segmentation, the robustness and generality of the algorithms have not been established. Furthermore, image segmentation itself is an ill-posed problem.

2.3.2 Preprocessing and Segmentation in Breast Ultrasound

Ultrasound image segmentation is strongly influenced by the quality of data. There are some characteristic artifacts which make the segmentation task complicated such as: attenuation, speckle, shadows, and signal dropout due to the orientation dependence of acquisition that can result in missing boundaries.
However, there have been recent advances in transducer design, spatial/temporal resolution, digital systems, portability, etc., which means: the quality of information from an ultrasound device has significantly improved [125]. This has led to increased use of ultrasound in not only its traditional area of application, diagnosis (and CAD), but also emerging areas such as image-guided interventions and therapy. Thus, there is currently a re-emergence of interest in understanding image processing tasks, image segmentation, applied to ultrasound data.

Mishra et al. [1] proposed an active contour solution where the optimization was performed using a genetic algorithm. In the first image, low pass filtering and morphological operations were used to define an initial estimate of the contour. A nonlinear mapping of intensity gradient was used in energy functional which is minimized. The final contour was used to initialize contour finding in the next time frame. Manual delineations were done on 20 frames by two experts. The area correlation was found to be 0.92. This was a preliminary evaluation from which strong conclusions cannot be drawn.

Mignotte and Meunier [91] chose to use a statistical external energy in a discrete active contour for the segmentation of short axis images, arguing that this was well-suited in ultrasound images with significant noise and missing boundaries. A shifted Rayleigh distribution was used to model gray levels statistics. The multi-scale optimization strategy of Heitz et al. [42] was adapted to perform the energy minimization. The same optimization strategy was used for a maximum-likelihood (ML) region segmentation to extract a crude endocardial initial contour for the snake algorithm.

Mignotte et al. [91] proposed a boundary estimation algorithm, posed in a Bayesian framework where prior information was modeled using deformable templates. This was a fully automatic unsupervised (i.e., no learning) approach. The estimation problem was formulated as a Maximum A Posteriori (MAP) optimization solved by means of a genetic algorithm. The template was defined by a circle along with a set of admissible affine global, non affine global and local transformations. Illustrative results on simulated data and on a series of short axis
images (50 frames) were shown. A comparison to manual delineations by two experts was also presented. The region-based segmentation method of Boukerroui et al. [30] follows a similar (Bayesian) methodological approach.

Abdul Kadir [9] presented the application of Snake for the segmentation of masses on breast ultrasound images. The boundaries of masses identified may be used in classification of cancers or noncancerous masses. They have attempted to segment masses on breast ultrasound images using Balloon Snake by combining mathematical optimization conception together with computer technology. The accuracy of segmentation results was 95.53%.

Yan and Toshihiro [149] proposed segmentation scheme using Fuzzy C-Means (FCM) clustering incorporating both intensity and texture information of images is proposed to extract breast lesions in ultrasound images. The proposed spatial FCM is more tolerant to noise than the conventional one. Based on the speckle texture and image intensity, it copes with speckle noise and fuzziness of boundaries in ultrasound images.

The low-level segmentation techniques are known to be fast and simple, but these methods simply analyze an image by reducing the amount of data to be processed. This problem can result in loss of important information. Moreover, low-level segmentation techniques may incorrectly identify region or boundary of an object due to distraction of noise in an image. The boundary of abnormality should be identified accurately so that all important information required by the radiologist from the object such as shape, margin, and area can be determined. For the image to be interpreted accurately, the image must be segmented accurately into regions that correspond to objects or parts of an object. The iterative algorithm namely active contours were proven to be the effective high level techniques in line and edge detection, image segmentation, shape modeling, and motion tracking as claimed through research carried out by Kass [80].
2.4 Detection of Abnormalities in Breast

Some of the important signs of breast cancer, radiologists normally look for: spiculated masses, micro-calcifications, architectural distortions and bilateral asymmetry. Many techniques have been developed to detect masses and micro-calcifications automatically. In literature, various methods have been proposed and available for detection of AD and spiculated masses in mammograms and breast ultrasound.

2.4.1 Detection of Abnormalities in Mammograms

The literatures relevant for the detection of abnormalities in mammograms are highlighted here. Matsubara [94] used morphology and concentration index to detect architectural distortion. Sampat and Whitman [131] employed filtering in the Radon transform domain to enhance mammograms. They have used radial spiculation filters to detect spiculated lesions. The algorithm was tested on 45 cases exhibiting speculated masses and on 45 cases with the presence of architectural distortion. A sensitivity of 80% was obtained with 14 false positives per image in the detection of architectural distortion, and 91% with 12 false positives per image in the detection of spiculated masses.

Tourassi [141] used fractal dimension to differentiate between normal and architectural distortion patterns in mammograms. It was tested on dataset containing 112 ROIs with architectural distortion patterns. An area under the receiver operating characteristics (ROC) curve of Az = 0.89 was obtained. It was observed that average fractal dimension of ROIs exhibiting architectural distortion was lower than that of ROIs with normal patterns.

Rangayyan and Ayres [119] applied Gabor filters to characterize oriented texture patterns and detect architectural distortion. The methods were tested with one set of 19 cases of architectural distortion and 41 normal mammograms, and another set of 37 cases of architectural distortion. FROC analysis shows the sensitivity of 0.79 at 8.4 false positives per image. Spiculation levels of breast mass boundaries are a primary sign of malignancy on mammography. Luan Jiang [88], developed
an automated computerized method to detect speculation levels. A quantitative spiculation index is computed to assess the degree of spiculation. The method achieved an overall classification accuracy of 66.4%, with 54.3% sensitivity and 78.3% specificity. There are also a number of studies on the performance of commercial CAD system in the detection of architectural distortion.

Burhenne et al. [22] obtained a sensitivity of 75% of a commercial CAD system in the detection of architectural distortion. Evans et al. [40] reported that a commercial CAD system correctly identified 17 of 20 cases of architectural distortion. We focused on the detection of Spiculated Mass and AD for a number of reasons. Spiculated Mass carries a much higher risk of malignancy than calcifications or other types of masses. About 81% of Spiculated Mass and 48-60% of AD is malignant [83].

Mudigonda et al. [103] presented a mass detection method that performs segmentation of objects based on intensity contours and texture flow-field analysis. Their study included 43 masses and 13 normal cases from the Mini-MIAS database with the performance of 81% and average of 2.2 FPs per image. Julia E. E. de Oliveira [77] proposed a method to classify spiculated mass and micro-calcification using Haar wavelet transform and SVM. A result of 89.6% of accuracy was achieved by them.

Arnau Oliver and Xavier [19] tried to distinguish true spiculated mass from normal breast parenchyma based on local binary patterns and SVM classifiers. They used a set of 1792 suspicious regions of interest extracted from the DDSM database and achieved 90% sensitivity. Leonardo de Oliveira Martins [86] used K-means algorithm and SVM classifiers to detect masses in digital mammograms. Using shape and texture descriptors they classified the masses and obtained the accuracy of 85%. Artificial Neural Networks were used by Mohammed J. Islam and Majid Ahmadi [98] to automatically classify the masses. They used seven features to classify the ROI’s and achieved 90.01% sensitivity.
Eltonsy et al. [37] developed a method to detect masses and architectural distortion by locating points surrounded by concentric layers of image activity. The technique was evaluated on 80 images including 13 masses, 38 images with masses and architectural distortion, and 29 images with only architectural distortion. Overall sensitivity of 91.3% with 9.1 false positives per image was obtained. Mohd Khuzi et al. and R Besar [2] developed an automated system for assisting the analysis of digital mammograms by extracting the textural features of ROIs by using gray level co-occurrence matrices (GLCM). Results were analyzed plotting ROC curve, where area under ROC rated 0.8 – 0.9 with AZ= 0.84. M.

Arfan Jaffar and Bilal Ahmed [89] have done some experiments for tumor detection in digital mammogram images by extracting eight different multi domain features using SVM and MLP classifiers achieving accuracy of 85% and 84% respectively. SVM classifiers are used by Guo and Shao [56] along with Hausdorff fractal dimension to detect AD which classified 72.5% of correct answers. S. Baeg and N. Kehtarnavaz [124] worked on mammograms to detect architectural distortions by considering the denseness texture feature. They evaluated their method by plotting ROC and the area under the curve was 0.90.

It is estimated that 12-45% of cancers missed in mammographic screening are AD [57]. The detection sensitivity of the current computer systems for Spiculated Mass and AD is low and there is a pressing need for improvements in their detection.

2.4.2 Detection of Abnormalities in Breast Ultrasound

An ultrasonographic image consists of different values of gray-level intensity, and different tissues have markedly different texture. Benign lesions are classically described as regular masses with homogenous internal echoes, but malignant lesions are described as masses with fuzzy border and heterogeneous internal echoes.
Cheng and Itoh [25] proposed a novel method for automated detection of breast tumors in three dimensional ultrasonic images using fuzzy reasoning. 10 cases of malignant and 10 cases of benign tumors are successfully extracted by the proposed method. Horsch [63] presented a method which involved thresholding a preprocessed image that has enhanced mass structures. Madabhushi and Metaxas [92] combined intensity, texture information, and empirical domain knowledge used by radiologists with a deformable shape model in an attempt to limit the effects of shadowing and false positives. Their method requires training but in small database. They show that their method is independent of number of training samples, and also good reproducibility with respect to parameters, and gives a true positive area of 74.7%.

Yuji Ikedo and Daisuke [152] proposed a scheme for mass detection in whole breast ultrasound images using bilateral subtraction technique based on a comparison of average gray values of a mass candidate region and a region with the same position and same size as the candidate region in contra lateral breast. The sensitivity was 83% (5/6) with 13.8 (165/12) false positives per breast before applying the proposed reduction method. By applying the method, false positives were reduced to 4.5 (54/12) per breast without removing a true positive region.

Dar and Chang [31] in their research used morphology operation, histogram equalization, and fractal analysis for classifying ultrasound images. The fractal analysis is applied to obtain the fractal texture features to classify the test cases of masses into benign and malignant. The accuracy rate was up to 88.80%. Yuji and Takako [153] proposed a computerized classification scheme to recognize breast parenchyma patterns in whole breast ultrasound (US) images. They employed Canonical discriminant analysis with stepwise feature selection for the classification of parenchymal patterns. The classification scheme resulted in accuracy of 83.3% (10/12 cases) in mottled pattern cases.

Ruey-Feng and Wen-Jie [121] worked on segmenting tumors in ultrasound images using newly developed level set method at first, and then six morphologic features are used to distinguish the benign and malignant cases. In the experiment,
the accuracy of SVM with shape information for classifying malignancies was 90.95% (191/210) and the sensitivity was seen to be 88.89% (80/90).

### 2.5 Classification of Breast Abnormalities

The features extracted which represents the abnormalities in the breast are large while describing the subject’s task performance. However there may be difficulties using all this information clinically without performing some kind of classification. There are many statistical approaches which are studied and used for classification. Artificial Neural Network (ANN) techniques have been receiving increased attention, both in general and medical applications. More traditional neural network technique by Hlena Grip, et al, which adapts to large input data, is Back Propagation Neural Network (BPNN) [61]. The BPNN structure consists of multiple output nodes, each representing a class which is representative of tasks under consideration. The output node with highest output signal determines the prediction of the input vector. The resilient back propagation (BP) algorithm is appropriate when using sigmoid transfer function.

A method to classify breast abnormalities for early detection of breast cancer using Support Vector Machine (SVM) is proposed by Y. Ireneus and Selvi [148]. SVM’s are well known learning machines for two-class classification problems. It is an appropriate implementation of the structural risk minimization (SRM) principle and creates a classifier. For any pattern classification, SVMs have good generalization performance without domain knowledge of the problems. The SVM classifier is trained based on subjects mammographic and ultrasound images which are collected relative to the presentation of a particular problem.

### 2.6 Fusion

Various medical modalities are used in all phases of cancer detection. Information extracted from these modalities reveals morphological, metabolic and functional information of tissues. Integrating this information in a meaningful way assists in clinical decision making.
Studies showing the advantages of dual modality and feature level fusion have appeared in literature. Gian Luca et al. [51] have proposed a serial scheme on well-known benchmark face datasets and fingerprint dataset which combines two serially matchers at which performance of the serial model is higher than parallel. Brunelli and Falavigna [115] have experimented using tanh method for normalization and weighted geometric average for fusion of voice and face biometrics. Hierarchical combination scheme is also used by them for a multimodal identification system. Kittler et al. [69] has used various fusion techniques on face and voice biometrics. He has experimented on sum, product, minimum, median, and maximum rules and have found that the sum rule outperformed others. He finally concluded that the sum rule is not significantly affected by the probability estimation errors and this explains its superiority.

Hassan and A. S. Mohamed [60] presented a study of multimodal palm veins and signature identification by extracting the features of both modalities using morphological operations and Scale Invariant Features Transform (SIFT) algorithm. They have used simple sum rule to achieve feature level fusion for both modalities. They have applied discrete cosine transform (DCT) algorithm to reduce the feature vectors dimensionalities of feature extraction techniques. Finally they have stated that SIFT algorithm is more accurate and does not need more preprocessing steps to identify people. Han-ling and Fan [59] proposed a hybrid optimization algorithm to deal with multimodal (CT and MRI) medical images. They used mutual information as a similarity measure and proved that subvoxel accuracy can be achieved for an efficient image registration and can avoid getting into local optimum. Andrzej Krol and Ioana [17] have investigated an approach for co-registration of PET images with MR images in image fusion level. They proved that it is an alternative to surgical breast biopsy.

Francis and Thomas [46] worked on fusion of data from mammography, ultrasound and non invasive infrared imaging modalities to improve early
diagnosis. They concluded that data fusion helps in early detection of breast cancer.

2.7 Other Related Works

Literature reveals that there has taken place extensive research in the field of breast cancer detection. This involves areas which include methodologies incorporated in detection of abnormalities in mammograms and ultrasound, method in classification of breast abnormalities and also techniques to fuse the information retrieved from different modalities. Discussion on some of the works which also are referential to similar areas are included in this section.

Annie and Daniel [18] worked on Simultaneous capturing of ultrasound (US) and magnetic resonance (MR) images by fusing information obtained from both modalities. They proposed an MR-compatible US system where MR images are acquired in a known orientation with respect to US imaging plane and concurrent real-time imaging can be achieved. Tests were performed to quantify radio frequency (RF) noise introduced in MR and US images, with the US system used in conjunction with MRI scanner of different field strengths (0.5 T and 3 T). Simultaneous imaging was performed on a dual modality breast phantom in the 0.5 T open bore and 3 T close bore MRI systems to aid needle-guided breast biopsy. The results indicated that simultaneous US and MR imaging are feasible with properly-designed shielding, resulting in negligible broadband noise and minimal periodic RF noise in both modalities. They also concluded that US can be used for real time display of the needle trajectory, while MRI can be used to confirm needle placement.

H.S. Sheshadri & A. Kandaswamy [58] proposed a Computer Aided Design (CAD) system for early detection of breast cancer. They employed a simple thresholding method and used filters for clear identification of micro-calcifications. The method was applied on mini-MIAS (Mammogram Image Analysis Society, UK) database. The overall performance (OP) rate was about 78 percent, with area under ROC plot (Az) as 0.78.
Yujun Guo and Jasjit [154] have given a complete review on Breast image registration. They say that image registration plays a critical role in breast imaging. It provides an aid to better visualization of lesions on bilateral or temporal X-ray mammograms, or in the fusion of different modalities acquired using different principles of physics. The challenging task according to them is image registration where breast tissues are non-rigid, inhomogeneous, anisotropic and temporally changing. Methods were classified according to the modalities involved in the registration process. Intra-modality registration techniques focus on X-ray mammogram registration, while inter-modality techniques covered the registration of X-ray with other modality.

Ryohei and Yoshikazu [123] have developed a computerized scheme for detecting early-stage micro-calcification clusters in mammograms. They first developed a novel filter bank based on the concept of the Hessian matrix for classifying nodular structures and linear structures. Filter bank was developed with three important features: it allowed enhancement of nodular component, it allowed enhancement of nodular and linear component and its sub images can be used to reconstruct the original image.

Saskia and Peter [132] determined the thickness of dense tissue mapping to a pixel by using a physical model of image acquisition. This model is based on the assumption that the breast is composed of two types of tissue, fat and parenchyma. The correlation between MRI and mammography volumes was 0.94 on a per image basis and 0.97 on a per patient basis. Using the dense tissue volumes from MRI data as the gold standard, the average relative error of the volume estimates was 13.6%.

2.8 Limitations of Existing Work

From the state-of-art it is clear that even though several methodologies have been proposed in different phases of detection of abnormalities in breast there are some limitations in the existing work. We have summarized these limitations as follows.
• Algorithms identified the components of image belonging to the pectoral muscle but in most of the cases components found have ragged the edges and tend not to include the extreme edge of the pectoral muscle. Overall accuracy rate is from 85 to 90.

• Detection of abnormalities in Mammograms and Ultrasound: The detection sensitivity of the current computer systems for Spiculated Mass and AD is low. Accurate and robust detection remains a technical challenge because the spiculated patterns are often subtle and varied in appearance. Due to lack of ground truth spiculation levels in the data set, assessing the performance of a method is also difficult. Detection sensitivity is low due to low spatial resolution of ultrasound images. Spiculation feature is not addressed.

• Features retrieved from one modality are not sufficient to detect the abnormalities of breast cancer in early stages. Unimodal systems may not provide any complementary information for improved therapy. Some of the authors according to literature have worked on data level and image level fusion, but feature level fusion is not addressed by any of the authors for breast cancer detection. Image level fusion needs separate hardware set up (imaging system).

2.9 Analysis and Scope for Research

Most of the researchers, as discussed in literature, have been working in mammographic image analysis in many directions. The use of selected shape-based features was proposed in order to classify benign and malignant lesions [70, 84]. The computerized analysis was divided into four steps: 1) digitization of mammograms and enhancement of images, 2) detection and localization of suspicious areas, 3) extraction of features for every segmented mass, and 4) analysis of the features using several techniques. It has been observed in a great number of malignant diagnosed mammograms, that the main indicator used to issue a diagnosis was the shape of mass from mammograms and ultrasound. Though some other features were considered the work was carried out on single modality and the performance is low.
Although radiographic breast imaging and screening has allowed for more accurate diagnosis of breast disease at earlier stages of development, 10-30% of malignant cases are not detected for various reasons such as technical problems in the imaging procedure, abnormalities that are not observable, and abnormalities that are misinterpreted [72]. According to evidences between 5-20% of mammograms with abnormalities currently detected also show signs in the previous mammogram when viewed in retrospect, which may be considered as false negative (FN) errors [72, 90]. Nearly 65-80% of breast biopsies result in benign diagnosis, which may be considered as false positive (FP) biopsies [72]. Thus the cost of the FN misinterpretation is enormous. The diagnosis errors discussed above form the foundation for our work presented here. That is, we believe that computer aided decision methods can improve both the FP and the FN diagnosis rates.

There are important distinctions between detection and classification of suspected abnormalities. The detection process always precedes classification and may be implemented by some automated method or by a radiologist through conventional methods. Once the abnormality is detected, it must be classified using some means, which may be achieved by human assessment, pathology analysis, with automated methods, or some combination of the three. The work we are presenting here may be considered as the groundwork for an overall automated detection and classification system for early detection of breast cancer. This system may be considered as a complement to the radiologist's assessment as it provides a probabilistic figure of merit relating to the degree of malignancy.

As we have discussed in previous sections, structural features can be extracted from mammograms and functional features can be extracted from breast ultrasound images. Thus, it is meaningful and advantageous to combine the features retrieved from these two modalities to improve the detection performance. The main goal of this work is to extract distinguishable, discriminating and complementary features from two modalities (mammogram and breast ultrasound) and to fuse them to help in early detection of breast cancer.
2.10 Summary

The overall discussion includes a precise description of different methodologies involved in understanding and detection of breast cancer in an early stage, and to classify the different abnormalities of breast. The fusion methods that are involved in integrating the information extracted from different modalities are also discussed.

We have seen several preprocessing and segmentation methods to extract the ROI. Some of these algorithms are threshold based, and Hough transformation based where we find that the edges are ragged and tends not to include the extreme edge of the pectoral muscle.

The feature extraction procedure forms the basis for classification. Existing works have been carried out to extract features from single modality. Classification techniques are broadly discussed under neural network based classification procedures for classification. Finally fusion methods are discussed where fusion can be done in data level, feature level or classification level.

In total this chapter gives a detailed description of techniques involved in detection of breast cancer and also analysis of research is presented with possibility of further research which have been taken by us as presented in this thesis.