CHAPTER 3
LITERATURE SURVEY ON TUMOR DETECTION FROM MAMMOGRAM

3.1 INTRODUCTION

Mammography is a specific type of imaging system used to examine the breast as mentioned by Tang et al (2009) and radiology information available online (2010). Wang and Karayiannis (1998) claim that, one of the difficulties with mammography is that mammograms generally have low contrast. This makes it difficult for the radiologists to interpret the results. CAD is used to aid radiologists in their interpretation of mammograms. CAD systems improve the detection rate of tumor in its early stages.

In this chapter, the existing techniques for image enhancement, image segmentation and image classification for the detection of tumor from mammogram are analyzed.

3.2 IMAGE ENHANCEMENT

Methods in this category are motivated by the fact that tumors are tend to be brighter than their surroundings as given by Tang et al (2009). The basic idea here is to employ image enhancement methods to improve the contrast of tumor regions. Image enhancement techniques have been proposed to improve the quality and readability of mammograms. The image
enhancement methods are classified into two types: direct and indirect contrast enhancements as given by Tang et al (2009).

### 3.2.1 Direct contrast enhancement methods

In direct contrast enhancement methods, a contrast measure is first defined and enhancement is performed by directly manipulating the contrast as given by Sun and Tang (2003).

Dhawan et al (1986) provided a direct contrast enhancement technique for mammographic images in which a neighborhood consisting of a square region of pixels centered on a given pixel, called the center of the neighborhood and a larger square annulus called the surround were extracted around each pixel. A local contrast for each pixel using the average intensities of the center and the surround regions was defined. The contrast value for each pixel was transformed to a new enhanced contrast value using contrast enhancement function and then, the obtained enhanced contrast value was combined with the original image value to produce a new pixel value of the enhanced image. The limitation of this method is as the spatial as well as the gray value resolution (only 6-bit) is low, cancer regions of low contrast cannot be found.

Cheng and Xu (2002) presented an adaptive fuzzy logic contrast enhancement method for mammographic images. The method was based on the maximum fuzzy entropy principle. It transformed the image to a fuzzy domain and then, a local measure of contrast, called fuzzy entropy in the fuzzy domain, was computed. The contrast was enhanced using both global and local information. Finally, the enhanced image was obtained using defuzzification, by which the enhanced mammogram was transformed back to the spatial domain from the fuzzy domain.
Jiang et al (2005) proposed a method, in which a structure tensor operator was produced and then applied to each pixel of the mammographic image, which resulted in an eigen image. The eigen image was combined with a fuzzy image, which was obtained by a fuzzy transform from the original image to enhance the contrast.

The limitation of the above two techniques is that it is not easy to determine the suitable membership functions and rules.

### 3.2.2 Indirect contrast enhancement methods

An indirect contrast enhancement method includes unsharp masking, histogram equalization and multiscale wavelet enhancement as discussed by Tang et al (2009).

Laine et al (1994) provided a method using multiscale wavelet enhancement for mammographic image enhancement. In this the authors investigated mammographic image enhancement over complete multi scale representation. An image needed to be enhanced was decomposed into a multi scale representation and the coefficients in each sub band of the multi scale representation were modified using a nonlinear mapping. Three multi scale representations were investigated, including the dyadic wavelet transform, the \( \varphi \)-transform and the hexagonal transform. From the results it is identified that wavelet based image processing algorithms could play an important role in improving the performance of digital mammography. The drawback of this method is that the parameters in the nonlinear mapping at each scale are global, which are not optimal.

Kim et al (1997) proposed an adaptive image enhancement method based on the first derivative and local statistics. In this method, film artifacts that could be misread as cancer were removed and the important features of
the mammographic image were enhanced by adding the adaptively weighted gradient images.

Ferrari et al (2001) developed a method for the analysis of asymmetry in mammograms using directional filtering with Gabor wavelets. In their method, the breast boundary was detected first and all artifacts outside the breast were removed. Then, the pectoral muscle was detected and removed. The fibro glandular disk was segmented and the resulting image was decomposed using a bank of Gabor filters at 12 orientations and four scales. The Karhunen–Loève transform was employed to select the principal components of the filters’ responses. Rose diagrams were computed from the phase images and subsequently analyzed to detect the presence of asymmetry as characterized by variations in oriented textural patterns. The Gabor-filter-based method gives quantitative measures of the differences in the directional distribution of the fibro glandular tissue.

Heinlein et al (2003) proposed an algorithm for feature enhancement in mammograms using discrete wavelet decompositions called integrated wavelets. The integrated wavelet transform allows more flexible and adaptive discretization of scales than the dyadic wavelet transform.

Scharcanski and Jung (2006) presented a wavelet-based method to perform noise reduction and image enhancement, which combined noise equalization, wavelet shrinkage and scale-space analysis. Different from other wavelet-based methods, this method used two detail images (horizontal and vertical) instead of three detail images (horizontal, vertical and diagonal). The wavelet shrinkage step was mainly used to preserve edges that were persistent over several scales and to remove residual noise.

Gharekhan et al (2010) studied the spectral features of the polarized fluorescence spectra of normal and cancerous human breast tissues through
continuous wavelet transform, which identifies the distinguishing features between the tissue types. After pinpointing these features they studied the autocorrelation property of the wavelet coefficients of the fluorescence spectra, which was found to differentiate normal and malignant tissues with high sensitivity. The intensity difference of parallel and perpendicularly polarized fluorescence spectra was subjected to investigation, since the same was relatively free from the diffusive background.

From the above literature review DWT is selected as one of the image enhancement methods in this research. The advantages of wavelet enhancement methods relate to the observation that mammograms contain features with varying scale characteristics as given by Pisano et al (2007); calcifications are mostly contained at small scales, whereas larger objects such as masses are mostly contained in coarse scales as described by Sakellaropoulos et al (2003). Thus, different features can be selected and enhanced at different scales.

### 3.3 IMAGE SEGMENTATION

Segmentation subdivides an image into its constituent regions (or) objects. Image segmentation algorithms are based on one of the two basic properties of intensity values: discontinuity and similarity. In the first category the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into regions that are similar according to the set of predefined criteria. The techniques that are used to find the objects of interest are usually referred to as segmentation techniques which segment the foreground from background. The segmentation techniques are generally pixel-based or region-based as given by Li et al (1995), Timp and Karssemeijer (2004).
3.3.1  **Pixel-based approaches**

In the pixel-based approaches, features are extracted for each pixel and classified as suspicious or normal as described by Sampat et al (2005). The advantage of these approaches is their simplicity in implementation. Their limitation is that they often deal with large pattern spaces. Pixel-based methods are computationally intensive processes or limited to the detection of one tumor type as described by Li et al (1995).

Brzakovic et al (1990) developed a work in which the analysis of mammograms was performed in two stages. First the system identifies pixel groupings that may correspond to tumors. Next detected pixel groupings were subjected to classification. The essence of the first processing stage was multi resolution image processing based on fuzzy pyramid linking. The second stage employed a classification hierarchy to identify normal (or) tumor. The classification hierarchy was organized in such a way that, the simplest measurements were used at the top and the system steps through the hierarchy only when it cannot classify the detected pixel grouping with certainty. This work concentrates on recognition of two general classes of tumors: benign-non cancerous lesions and malignant-cancerous lesions. These classes of tumors were characterized by a variety of symptoms and in their work it was considered that malignant lesions were star shaped, round nodular-ill defined with translucent ring of dehydration. Benign lesions were round and well defined. The objective of the first processing stage of Automation of Mammogram Analysis was to identify possible tumors in mammograms. The heart of the process was fuzzy pyramid linking. Identification of possible tumors was a very difficult task due to the variations of gray level intensities in digitized mammograms. This approach first identified pixel grouping that had different intensity properties and then, decided if they were tumors. This task was accomplished using the following steps: 1) threshold to separate
object from background, 2) fuzzy pyramid linking to identify homogeneous regions, and 3) threshold to separate identified regions from the background. The initial assumption of the system was that a mammogram contains object of interest and a dark background. In order to increase efficiency, this approach first separated the background from the object using image threshold and assigned all pixels, whose intensity was lower than the threshold value to the background. Next, it analyzed the object (i.e. pixels $I(i, j) > 0$) using multi resolution image processing. The multi resolution image processing algorithm is an image segmentation algorithm that uses fuzzy pyramid linking. The algorithms used in this work employ local intensity mean and variance to identify regions that have statistically homogenous characteristics. This modification increases sensitivity of the algorithm to gradual intensity changes that appear frequently in mammograms. In order to meet the requirements of the pyramid structure and increase the processing speed, processing was performed locally on sub images (windows) whose size, $s \times s$, is power of two. These sub images cover the object of interest with overlap. Possible tumors, i.e. statistically homogeneous regions that differ from their surroundings were detected using fuzzy pyramid linking. In general, an image pyramid is a data structure in which the input image forms the base of the pyramid. Each subsequent level of the pyramid was formed by taking averages over regions of the level below such that each level was of a lower resolution than its predecessor.

Kegelmeyer et al (1994) presented a pixel-based approach in which Law’s texture features and a local oriented edge characteristics were extracted from Regions Of Interest (ROIs) and a binary decision tree classifier was employed to classify tumor from normal tissues.

Hatanaka et al (2001) described an approach that uses an adaptive threshold technique for detecting tumor. The partial loss masses were
identified by their similarity to a sector form model in the template matching process. To calculate the similarity, four features were applied: average pixel value; standard deviation of pixel values; standard correlation coefficient defined by the sector form model and concentration feature determined from the density gradient.

Sampat and Bovik (2003) presented an approach to detect tumor mass in digitized mammograms. The approach consisted of two steps. In the first step, a filter algorithm was used to enhance the features. In the second step, a filter was used to detect the spatial location with the enhanced features.

Kom et al (2007) proposed a tumor detection algorithm that first used a linear transformation filter algorithm to enhance the image; the enhanced image was subtracted from the original image to obtain a difference image. A local adaptive thresholding technique was developed to detect the mass in the difference image.

Eltonsy et al (2007) proposed a multiple concentric layers based algorithm to detect tumor in mammograms. The algorithm consists of two steps. First, the breast regions of screening mammograms were processed by segmentation and granulation techniques. Then, the suspicious focal areas were detected using knowledge based reasoning.

The primary advantage of using pixel-based methods is that one has a large number of samples to train a classifier. However, this class of methods also has inherent disadvantages. It does not take into account the spatial arrangement of the pixels, which is a very important factor to discriminate tumor from normal tissue. A different set of features would be required to describe different tumor types. It is computationally intensive and hence, most pixel based methods must sub sample images before detection.
3.3.2 Region based approaches

In region based approaches, regions of interest are first extracted by a segmentation technique and each region is classified based on its selected features. These approaches offer the advantages of providing information from the beginning on important diagnostic features for classification, such as the morphology and geometry of the extracted regions and having small pattern space and thus reduced processing time as described by Li et al (1995).

Davies and Dance (1989) proposed a method for detection of cancer. They first detected suspicious regions by a local threshold. Those regions were limited by size criteria and those with an irregular shape were deleted. A nearest neighbor cluster method was used to find significant groups. This method shows suspicious regions.

Lai et al (1989) presented a method for detecting breast tumor in mammograms. It relies on a combination of criteria including the shape, brightness contrast and uniform density of tumor areas. The method used modified median filtering to enhance mammogram images and template matching to detect breast tumors. In the template-matching step, suspicious areas were picked by threshold values and a percentile method was used to determine a threshold for each film.

The limitation of the methods presented above is that they concerned only with the localization of the suspicious areas and no attempt is made by them to further classify these areas.

Brzakovic and Neskovic (1990) described an approach to find tumors from mammograms. They looked for large masses; therefore they digitized a whole mammogram into a $256 \times 256$ pixel image. Their region-
based algorithm was especially adapted to tumors that extend over a relatively large area.

Lau and Bischof (1991) proposed procedures to compare the corresponding anatomical regions between the left and right breast images in terms of shape, texture and density. They also proposed a directional feature to quantify oriented patterns. However, alignment procedures encounter problems, such as the natural asymmetry of the breasts of a given subject, the lack of good corresponding points between the left and right breast images to perform matching and distortions inherent to mammographic imaging. The method was evaluated using ten pairs of mammograms where asymmetry was a significant factor in the radiologist’s diagnosis.

Dengler et al (1993) presented a method for the detection of cancer in mammograms. The proposed approach used a two-stage algorithm for spot detection and shape extraction. In the first stage a weighted difference of Gaussian filter was applied for the noise invariant and size specific detection of spots. A morphological filter reproduces the shape of the spots. The results of both filters were combined with a conditional thickening operation. The topology and the number of the spots were determined with the first filter and the shape by means of the second.

Li et al (1995) introduced a technique in which detection was performed in two steps: segmentation and classification. In segmentation, regions of interest were first extracted from the images by adaptive threshold. In the next stage a modified Markov Random Field (MRF) model based method was used. In classification, the MRF segmented regions were classified into suspicious and normal by a fuzzy binary decision tree based on a series of radiographic, density related features.
Tab et al (2001) proposed a multi resolution image segmentation algorithm for scalable object based wavelet coding applications. This algorithm was based on DWT and MMRF modeling. In order to optimize the segmentation of objects of interest in all scales of the wavelet pyramid, with scalability constraint multi resolution analysis was incorporated.

Caputo et al (2002) investigated a Markov Random Field (MRF) based approach for cancer detection. The use of MRF models for image segmentation is advantageous over other statistical methods due to its ability to characterize the spatial intensity distribution of an image.

Ouadfel and Batouche (2003) used Ants Colony System based Markov Random Field (ACS-MRF) for image segmentation. Here a colony of artificial ant searches for an optimal labeling of image pixels that maximizes MAP estimate. In this work the ACS-MRF algorithm was compared with Simulated Annealing (SA) and Genetic Algorithm (GA). These algorithms were compared using cerebral Magnetic Resonance (MR) images as the test image. Their results showed that the ACS-MRF segmentation algorithm performed well than other two algorithms.

Székely et al (2004) proposed a system for detecting tumor in mammographic images. Here the preprocessed image was first made to undergo coarse segmentation and then fine segmentation was carried out. During coarse segmentation texture features were calculated and the image was segmented using decision trees. The output was further segmented finely, using MMRF.

Bellotti et al (2006) proposed a completely automated CAD system for mass detection. The system included the following three steps. First, an edge-based segmentation algorithm was implemented to select the suspicious regions. Then, eight gray-tone independent texture features of the ROIs were
derived. Finally, a supervised two-layered feed forward neural network, which was trained with the gradient-descent learning rule, was employed to classify tumor from normal tissues.

Regentova et al (2007) combined wavelet transforms with hidden Markov trees in a maximum likelihood framework for cancer detection. They have made a separate category for the decomposition methods and used feature extraction techniques for the detection of tumor.

Prajna et al (2008) extended a method based on Gabor filters and phase portrait analysis to detect initial sites of tumor. The fractal dimension of each ROI was estimated using the circular average power spectrum technique. Analysis with a set of four features, including fractal dimension and three texture features known as entropy, sum entropy and inverse difference moment had been carried out.

Region based methods are used in this research. Region based detection takes into account the spatial information in contrast to pixel based methods. The features are directly correlated to important diagnostic information like the shape and margin of extracted regions.

3.4 CLASSIFICATION

In order to identify the tumor affected mammograms classification is needed. To achieve this geometrical and textural features are extracted from the region of interests based on the characteristics of tumor affected areas.

3.4.1 Neural network classifier based approaches

Zheng and Wei (1996) proposed a computationally efficient Mixed Feature based Neural Network (MFNN) for the detection of cancer in digitized mammograms. The MFNN employs features computed in both the
spatial and spectral domain and uses spectral entropy as a decision parameter. Back propagation with Kalman Filtering (KF) was employed in network training for evaluation of different features and related error analysis.

Dhawan et al (1996) used two categories of correlated gray level image structure features for classification of difficult to diagnose cases. The first category of features included second order histogram statistics based features representing the global texture and the wavelet decomposition based features representing the local texture of the area of interest. The second category of features represented the first order gray level histogram based statistics of the segmented regions and the size and the distance features of segmented region. Various features in each category were correlated with the biopsy examination results of difficult to diagnose cases for the selection of the set of features representing the complete gray level image structure information. The selection of the features was performed using the multivariate cluster analysis as well as a Genetic Algorithm (GA) based search method. The selected features were used for classification using back propagation neural network and parametric statistical classifiers. The back propagation neural network classifier yielded results using the set of features selected through the GA based search method for classification.

Hadjiiski et al (1999) designed a classifier combining an unsupervised and a supervised model. The unsupervised model was based on an Adaptive Resonance Theory (ART2) network, which clustered the masses into a number of separate classes. The classes were divided into two types: one containing only malignant tumor and the other containing a mix of malignant and benign. The malignant classes were classified by ART2. The mixed classes were the input to a supervised Linear Discriminant Classifier (LDA). In this way, some malignant masses were separated and classified by
ART2 and the less distinguishable benign and malignant masses were classified by LDA.

Lo et al (2002) dealt with a Multiple Circular Path Convolution Neural Network (MCPCNN) architecture specifically designed for the analysis of tumor and tumor like structures. First each suspected tumor area was divided into sectors. The defined mass features for each sector was computed independently. These sector features were used on the input layer and were coordinated by convolution kernels of different sizes that propagate signals to the second layer in the neural network systems. The convolution kernels were trained as required by presenting the training cases to the neural network.

Zhang et al (2004) proposed a system where a neural-genetic algorithm was used for feature selection and a neural network was used for classification. It also combined the computer-extracted statistical features from the mammogram with human extracted features for classifying different types of small size breast abnormalities.

Kinoshita et al (2007) proposed an unsupervised learning approach based on Kohonen Self Organizing Map (SOM). The SOM was trained using visual features related to breast density patterns. A set of features was computed for each mammogram, which include shape factors, texture, and moment features as well as angular projections and morphological features that were derived from segmented fibro glandular tissues.

Islam et al (2009) presented an algorithm, called Adaptive Merging and Growing Algorithm (AMGA), in designing Artificial Neural Networks (ANNs). This algorithm merges and adds hidden neurons during the training process of ANNs. The merge operation introduced in AMGA was a kind of a mixed mode operation, which prunes two neurons and adds one neuron. The
adaptive strategy merges or adds hidden neurons based on the learning ability of hidden neurons or the training progress of ANNs. In order to reduce the amount of retraining after modifying ANN architectures, AMGA prunes hidden neurons by merging correlated hidden neurons and adds hidden neurons by splitting existing hidden neurons.

Shukla et al (2009) presented a method to detect Breast Cancer using Soft Computing tools like Artificial Neural Networks (ANNs) and Neuro Fuzzy Systems. The feed-forward neural network was trained using three ANN algorithms; the Back propagation Neural network (BPN), the Radial Basis Function (RBF) and Adaptive Neuro Fuzzy Inference System (ANFIS). The performance was compared by the metrics like accuracy of diagnosis, training time, number of neurons and number of epochs.

3.4.2 SVM based approaches

El Naqa et al (2002) demonstrated that tumor can be identified by applying a Successive Enhancement Learning (SEL) procedure, where Support Vector Machine (SVM) training was adjusted iteratively by reincorporating misclassified samples.

Campanini et al (2004) presented an SVM-based featureless approach for tumor detection in digital mammograms. Instead of extracting features from ROIs, the authors used a multi resolution, over complete wavelet representation to codify the image with redundancy of information. Two SVM classifiers were used in this approach. The first SVM classifier was used to find the tumor and the second SVM classifier was used to reduce the number of false positives.

Timp et al (2007) presented an automated mass detection method to detect temporal changes in mammographic masses between two consecutive
screening rounds. Two kinds of temporal features, difference features and similarity features were designed to realize the interval change analysis. An SVM was employed as a classifier to detect the temporal changes in mammographic masses. The classification performance was evaluated with and without the use of temporal features.

BPN, RBF and SVM classifiers are used in this research due to their robustness and widely applicable characteristics.

In the literature review the methods that have explored the challenge of detection of breast cancer in mammograms are reviewed. In the following section the existing three techniques which have been used in the first three proposed approaches with modification are discussed.

The method presented by Cascio et al (2006), is selected for the approach 1 since this method provided a segmented output without loss of meaningful information. In this method the Region Of Interest (ROI) was obtained through a segmentation process, by means of a contour searching. In the classification step, feature extraction plays a fundamental role. After the features were computed for each ROI, they were used as inputs to a supervised neural network. The output neuron provides the probability that the ROI was pathological or not. The authors obtained a sensitivity of 82%.

The method developed by Domínguez and Nandi (2007) is selected for the approach 2 since it increased the signal-to-noise ratio of the lesions being detected and eliminated the false-positive findings. They had proposed an algorithm for enhancement of mammograms which had the objective of improving the segmentation of distinct structures in mammograms. The enhancement algorithm used wavelet decomposition and reconstruction, morphological operations and local scaling. After enhancement, the
segmentation of regions was performed and a set of features were computed from each of the segmented regions. A ranking system was used for classification.

The method provided by Zheng and Chan (2001) is selected for the approach, since this algorithm provided high sensitivity of 97.3%. They had adopted an artificial intelligent algorithm, which was a combination of techniques like fractal analysis, Multi Resolution Markov Random Field (MMRF) technique and binary decision tree. In fractal analysis, the Blankets method was used to find the roughness value of the surface. MMRF was used for segmentation. This segmentation process was initialized using a clustering algorithm called dogs-and-rabbits algorithm, which was an extension of K-means clustering algorithm. The major difference between the K-means clustering algorithm and the dogs-and-rabbits algorithm was that, the cluster centers were moved towards the data points in the later case. Here the concept of cliques and neighborhood systems were used.

In this chapter, methods used for tumor detection from mammogram are discussed. Mammography offers high quality images as described by Tang et al (2009) and radiology information (2010) and is currently the only widely accepted imaging method used for routine breast cancer screening. The techniques used in Computer Aided Detection (CAD) systems have a major impact on their performance. The challenge in breast cancer detection is that, although many techniques have been proposed so far, the recent studies show that, the performance of the commercial CAD systems still needs to be improved as given by Pisano et al (2005), Ciatto et al (2007) and Tang et al (2009). The development of new algorithms for CAD system of breast cancer detection is very important. The aim of this research is to develop an efficient system for breast cancer detection.