Chapter 1

Introduction

Computer aided diagnosis is an important tool used by radiologists for interpreting medical images. Image processing techniques can be employed on the mammograms for the detection of breast cancer at an early stage. A brief introduction to the research is presented in this chapter. Fundamentals of digital image processing; its history and different steps involved in image processing are mentioned. The state-of-the-art technology in the mammogram image analysis is also highlighted. This chapter gives the motivation and objective behind this research. The main contributions of the present research are also highlighted.
1.1 Digital Image Processing

Sight is the most powerful of the five senses – sight, hearing, touch, smell and taste – which humans use to perceive their environment. Human beings who are blessed with eyesight start acquiring the images around them immediately after their birth. Processing, analyzing and understanding of images then become almost a routine (CeT 1998). In fact, more than 99% of the activity of the human brain is involved in processing images from the visual cortex (Dou 2009).

Image processing is the science of manipulating a picture. It covers a large number of techniques which are present in numerous applications. These techniques can enhance or distort an image, highlight certain features of an image, create a new image from portions of other images, restore an image that has been degraded during or after the image acquisition, and so on (Cra 1997).

Oxford dictionary defines image as an optical appearance produced by light from an object reflected in a mirror or refracted through a lens (Oxf 2011). Image can be formed by other types of radiant energy and devices. However, optical images are most common and are most important. The light intensity is recorded at corresponding points on a plane to form an image. The simplest kind of the intensity or the brightness image is a black and white image (Cha 2009).

An image is a two dimensional function \( f(x, y) \), where \( x \) and \( y \) are spatial coordinates (Gon 2005). The amplitude of \( f(x, y) \) at any pair of coordinates \( (x, y) \) is called the intensity level or gray level of the image at that point. When \( x \), \( y \) and the amplitude \( f \) are finite discrete quantities, then it is called a digital image. Thus a digital image is an array of numbers each of which is called image elements, picture elements, pixels or pels. The field of digital image processing refers to processing digital images by means of a digital computer.

Before the advent of digital computers, machine processing of visual and other sensory images was a daunting task. During the 1970s and 1980s, the focus was on image representation using transforms and models, image filtering and restoration, still and video compression, and image reconstruction. Although mainframes were
originally used, affordable minicomputers became popular. This progress in computer hardware as well as in image acquisition and display devices enabled image-processing research groups to emerge around the world. Since the mid-50s, powerful workstations and personal computers have made desktop or even laptop image-processing research and technology possible. Later, with advances in computing, memory, and image-sensing technology, techniques developed for image enhancement, still and moving image compression, and image understanding gave this field a solid base of practical applications (CeT 1998).

More recently, technology has tremendously extended the possibilities for visual observation. Photography makes it possible to record images objectively, preserving scenes for later, repeated, and perhaps more careful, examination. Telescopes and microscopes greatly extend the human visual range, permitting the visualization of objects of vastly differing scales. Technology can even compensate for inherent limitations of the human eye. The human eye is receptive to only a very narrow range of frequencies within the electromagnetic spectrum (Fig. 1.1)

![Electromagnetic spectrum](image)

**Fig 1.1** Electromagnetic spectrum arranged according to energy per photon
Nowadays, there are sensors capable of detecting electromagnetic radiation outside this narrow range of “visible” frequencies, ranging from γ-rays and x-rays, through ultraviolet and infrared, to radio waves. Today, there is almost no area of technical endeavor that is not impacted in some way or other by digital image processing (Dou 2009).

1.2 History of Digital Image Processing

The history of digital images is quite young. First of the digital images appeared in the earlier 1920s (Gon 2005). The first application was in the newspaper industry, when pictures were sent by submarine cable between London and New York. The introduction of Bartlane cable picture transmission system, in the early 1920s, helped to reduce the time taken to transmit across the Atlantic from more than a week to less than 3 hours. These pictures initially had only 5 distinct gray levels, but increased to 15 gray levels by the 1929.

As digital computers were not involved for the creation, these examples cannot be considered as part of digital image processing. The first computers to carry out meaningful image processing tasks appeared in the early 1960s. Since then there was no looking back (Gon 2005).

In 1964, pictures of the moon was transmitted by Ranger 7, which were the first images taken by the U.S spacecraft (Cra 1997). Over the years, NASA had plenty of images to process. The Ranger spacecraft provided hundreds of images of the lunar surface. The Surveyor 7 spacecraft returned 21,038 television images of its landing site on the moon. The Mariner 4, launched in 1964, returned 22 digital images of Mars. The Viking missions started in 1975 and they provided over 100,000 images of Mars. The Voyager mission, in 1977, launched two spacecraft that returned a wide range of imagery of the outer planets: Saturn, Uranus, Neptune, and Jupiter.

In late 1960s and early 1970s in parallel with space applications, image processing techniques were used in medical imaging, remote earth resources and astronomy. From the 1960s until the present, the field of image processing has grown
vigorously. They have a broad range of applications in interpreting images in industry, medicine biological sciences, and physics. The typical problems in machine perception includes automatic character recognition, industrial machine vision for product assembly and inspection, military recognizance, automatic processing of fingerprints, screening of X-rays and blood samples and machine processing of aerial and satellite imagery for weather prediction and environmental assessment (Gon 2005).

1.3 Steps in Digital Image Processing

In all the applications of image processing, *image acquisition* is the first step. Numerous electromagnetic and some ultrasonic sensing devices are frequently arranged in the form of a 2-D array. The response of each sensor is proportional to the light energy falling onto the surface of the sensor. Generally image acquisition stage involves preprocessing like scaling (Gon 2005).

The simplest and most appealing areas of digital image processing are the *image enhancement*. This is a subjective approach. The goal is to process the image so that the result is more suitable than the original image for a specific application. The word specific is important because the methods for enhancing one kind of images may not be suitable for another kind, eg. X-ray images and space craft images.

*Image restoration* attempts to reconstruct or recover an image that has been degraded by using an a priori knowledge of degradation phenomenon and is based on mathematical and probabilistic models of image degradation. This includes deblurring of images degraded by the limitations of a sensor or its environment, noise filtering, and correction of geometric distortion or nonlinearities due to sensors (Jai 1989).

*Image analysis* techniques require extraction of certain features that aid in the identification of the object. *Segmentation* techniques are used to isolate the desired object from the scene so that measurements can be made on it subsequently. *Segmentation* partitions the image into its constituent parts or objects. The level to which the subdivision is carried depends on the problem being solved. *Representation*
and description almost follow the output of a segmentation stage, which is usually raw pixel data, constituting the boundary of the region, i.e. a set of pixels separating one region from another or all the points in it. In either case, converting data to a suitable form for computer processing is necessary. Description is also called feature selection. It deals with extorting the attributes that result in some quantitative information of interest or is basic for differentiating one class of object from another.

Recognition is a process that assigns a label to an object, based on its descriptors.

1.4 Medical image processing

The advent of medical imaging is one of the milestones in the progress of medical science. Medical imaging systems detect different physical signals arising from a patient and produce images. It serves as a beneficial tool for the medical practitioners during diagnosis of ailments.

An imaging modality is an imaging system which uses a particular technique for producing the image. Some of these modalities use ionizing radiation, radiation with sufficient energy to ionize atoms and molecules within the body and others use non-ionizing radiation. Ionizing radiation in medical imaging comprises x-rays and γ-rays, both of which need to be used prudently to avoid serious damage to the body and to its genetic material. Non-ionizing radiation like, ultrasound and radio frequency waves, on the other hand, does not have the potential to damage the body directly and the risks associated with its use are considered to be very low.

The application of image processing techniques to medical imaging has made the results accurate and reliable. In many cases it is possible to eliminate the necessity for invasive surgery, thus avoiding trauma to the patient as well as inevitable element of risk. One of the early applications of image processing in the medical field is the enhancement of conventional radiograms. When converted to digital form, it is possible to remove noise element from x-ray images thereby enhancing their contrast. This aids interpretation and removes blurring caused by unwanted movement of the
patient. This form of representation also enables the physicians to measure the extent of tumors and other significant features accurately.

In medical imaging, the perfect diagnosis and/or assessment of a disease depends on both image acquisition and image interpretation. The advances in medical quality compliance regulations, image detector systems and computer technology have tremendously increased the role and contribution of radiology to medical diagnosis. For example, a major contributor to the improvement in medical imaging has been cross-sectional imaging (e.g., X-ray computed tomography (CT) and Magnetic Resonance Imaging (MRI)), which depends greatly on computer power and data storage capabilities, and produces many three-dimensional (3-D), high-quality images for interpretation.

The image interpretation process, however, has only recently begun to benefit from computer technology. Most interpretations of medical images are performed by radiologists; however, image interpretation by humans is limited due to the nonsystematic search patterns of humans, the presence of structure and noise (camouflaging normal anatomical background) in the image, and the presentation of complex disease states requiring the integration of vast amounts of image data and clinical information.

Computer Aided Diagnosis (CAD), defined as a diagnosis made by a radiologist who uses the output from a computerized analysis of medical images as a “second opinion” in detecting lesions, assessing extent of disease, and making diagnostic decisions, is expected to improve the interpretation component of medical imaging. With CAD, the final diagnosis is made by the radiologist. Computerized image analysis has been applied mainly to medical imaging techniques such as X-ray, sonography, and Magnetic Resonance Imaging (Gig 2001).

X-ray imaging is a transmission-based technique in which X-rays from a source pass through the patient and are detected either by film or an ionization chamber on the opposite side of the body.

Breast cancer is one of the common cancer forms affecting women worldwide. Each year, more than 180,000 new cases of invasive breast cancer are diagnosed and more than 40,000 women die from the disease (Nas 2001). Early detection is the only
hope for reducing the burden of decease due to breast cancer. Clinical data show that women diagnosed with early-stage breast cancers are less likely to die of the disease than those diagnosed with more advanced stages of breast cancer.

X-ray mammography has been able to detect cancer at an earlier stage, reducing disease specific mortality. Mammograms are particularly difficult to interpret for women with dense breast tissue, as dense tissues interfere with the identification of abnormalities associated with tumors. Screening mammograms produces a large number of mammograms which are generally normal ones. Thus there is a chance that radiologists, who have a huge case load, make mistake while taking decision.

The major categories of error are due to poor radiographic technique, absence of radiographic criteria of cancer, obvious oversight by the radiologist and lack of recognition of subtle radiographic sign (Mar 1979). To cater to this problem, different image processing techniques are applied for the Computer Aided Diagnosis in digital mammogram, which help the radiologists in taking decisions.

1.5 Literature survey

In mammography, the contrast between the soft tissues of the breast is intrinsically small making the interpretation of a mammogram difficult. Also, a relatively small change in the mammographic structure can indicate the presence of a malignant breast tumor.

Polokowski et.al. (Pol 1997) developed a new model-based vision (MBV) algorithm to find out regions of interest (ROI’s) corresponding to masses in digitized mammograms and to classify the masses as malignant/benign.

Sameti et. al (Sam 2009) introduced a stepwise discriminant analysis with six features to distinguish between the normal and abnormal regions. The best linear classification function resulted in a 72% average classification.

A dense to sparse microcalcification clusters grouping method based on distance independent of size, shape and orientation of real clusters was proposed by Mao et. al. (Mao 1998).
J. Tang *et al* (Tan 2009) proposed a new image enhancement technology based on a multiscale contrast measure in the wavelet domain for radiologists, for screening the mammograms. Peng *et al* (Pen 2009) employed a Stochastic Resonance (SR) noise based detection algorithm to enhance the detection of microcalcifications in mammograms.

The left–right (bilateral) asymmetry in mammograms was analyzed based on the detection of linear directional components by using a multiresolution representation based on Gabor wavelets. This gave an average classification accuracy of 74.4% (Fer 2001).

Faye *et al* (Fay 2009) decomposed mammogram images using Daubechies 3 wavelet function and the corresponding coefficients extracted were used to differentiate between normal and abnormal mammograms and to classify the abnormal ones into benign or malignant tumors with an average classification accuracy of 98%.

The gradient-based features and texture measures based on gray-level co-occurrence matrices (GCMs) were used for the classification of mammographic masses as benign or malignant by Mudigonda *et al*. (Mud 2000). Their method produced a benign versus malignant classification of 82.1%, with an area Az of 0.85 under the receiver operating characteristics (ROC) curve.

Context features that represent suspiciousness of normal tissue were developed for the detection of malignant masses in mammograms (Hup 2009). The Free response receiver operating characteristic (FROC) curves were computed for feature sets including context features and a feature set without context. Results show that the mean sensitivity in the interval of 0.05–0.5 false positives/image increased more than 6% when context features were added.

Detailed literature reviews on appropriate fields are presented from chapter 3 onwards.

1.6 Objective of the research

The objective of this research work is
• To classify mammograms into normal and abnormal. Abnormalities include masses and microcalcifications which are benign and malignant.

• After classification, mammograms with microcalcifications are considered. The region containing microcalcifications in the mammograms are identified.

Fractal based methods are employed in the present work.

1.7 Motivation

Breast cancer is one of the leading causes of mortality among women. At present, India reports around 100,000 cases of breast cancer annually. According to a study by International Agency for Research on Cancer (IARC), a branch of World Health Organization (WHO), there will be approximately 250,000 new cases of breast cancer in India by 2015 (Bre 2011). In the United States, one in eight women is affected by breast cancer, which kills more women than any cancer except lung cancer (ACS 2008). But early detection of breast cancer can help in reducing the mortality rate by 30%.

The breast parenchymal and ductal patterns are highly self similar, which is the basic property of fractals. Therefore; fractal analysis can be applied in mammograms.

1.8 Contribution of the thesis

The main contributions of this research include:

• The development of a new fractal feature which gave high classification accuracy for the efficient classification of mammogram into normal and abnormal and its subclasses.

• The development of a new fast fractal based mammogram modeling method with improved detection score, for the identification of microcalcifications, which are early indication of breast cancer.
1.9 Organization of the Thesis

Chapter 2 deals with the description and the imaging modalities for the detection of breast cancer. The different classes of mammograms like masses, microcalcifications etc are also presented in this chapter.

Chapter 3 is dedicated to the description of fractals. The fundamental properties and mathematical background are detailed here.

Chapter 4 presents the classification method based on fractal features. The basic property of fractal dimension was used for the classification. The three different fractal dimension estimation methods like the differential box counting method, blanket method and triangular prism surface area method are discussed. The six fractal features derived from these methods and the distance measures used to differentiate between the different classes of mammograms are also presented in this chapter.

Chapter 5 deals with the extension of fractal image modeling for the detection of microcalcifications. Here the self similarity property of fractals is exploited. The time taken for the fractal image coding is too large and four methods based on mean and variance, entropy, mass center and shade – non shade blocks were introduced. This considerably reduced the encoding time as well as increased the microcalcification detection accuracy.

The summary and conclusions based on the present work are given in Chapter 6. A brief description on the future prospects and possibility of the continuation of the present work are also included in this chapter.