# Review on Mammogram Segmentation methods

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***Abstract :*** This study has been undertaken to investigate the determinants of stock returns in Karachi Stock Exchange (KSE) using two assets pricing models the classical Capital Asset Pricing Model and Arbitrage Pricing Theory model. To test the CAPM market return is used and macroeconomic variables are used to test the APT. The macroeconomic variables include inflation, oil prices, interest rate and exchange rate. For the very purpose monthly time series data has been arranged from Jan 2010 to Dec 2014. The analytical framework contains**.**

***IndexTerms* - Mammogram, Segmentation, Pectoral Muscle, Thresholding, Edge Detedction**

## I. INTRODUCTION

Breast cancer is the most common cancer in women and is the leading cause of cancer-related death among women aged 15-54 [1]. Since breast cancer is a progressive disease, evolving through stages of cellular dedifferentiation and growth, the time at which breast cancer is detected is crucial. The earlier breast cancer is detected, the higher is the chance of survival [2-3]. Visual interpretation of mammogram is a fatiguing and time-consuming task because of the small size of the microcalcifications (ranging from 0.1 mm to 0.7 mm) and the low contrast of the image. This applies particularly to the mass screening where a radiologist must examine a high number of mammograms in a day which increase a significant can number of errors which is very dangerous both in positive and negative cases. In fully automatic CAD (Computer Aided Detection) systems, these lesions are detected, segmented and this ROI is given as an input to the classification scheme to identify the type of abnormality or a type of cancer. Hence accurate segmentation of the suspicious lesions is a major step in CAD system. [4]. Figure 1 shows the malignant and benign masses.

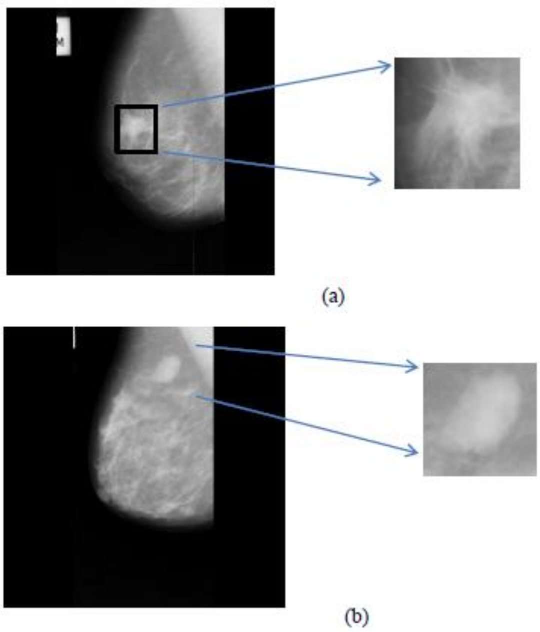


Figure 1 (a) Malignant Mass (b) Benign Mass

## II. PREPROCESSING

Digital mammograms are medical images that are difficult to be interpreted Hence pre-processing techniques are necessary, in order to remove the noise during scanning and to enhance the quality of the image. It also includes unrelated and surplus parts in the back ground of the mammogram. It is the very first step to be carried out before any further processing which makes segmentation results more accurate. Hence this step can be divided into three steps.

1. Removing high frequency noise
2. Removing scanning effects and labels.
3. Removing Pectoral Muscles

There are several methods proposed for mammographic-image preprocessing. Gamma correction method was proposed by Baeg et.al in 2000 [5] for mammographic enhancement. They have used texture-features and classified 150 biopsy-proven masses into benign and malignant classes which resulted in an area under Receiver Operating Characteristic (ROC) curve of 0.91. Gamma correction is not complex however the effects are localized and not global. Recently [6]. Indra Kanta Maitra et.al in 2012 proposed a method in which contrast enhancement is done by using the contrast limited adaptive histogram equalization (CLAHE) technique. To remove pectoral muscle, the rectangle is defined to isolate the pectoral muscle from the region of interest (ROI) and finally the pectoral muscle is suppresses using modified seeded region growing (SRG) algorithm. Yufeng Zheng (2010) et.al. [7] has used another technique in which a digital mammogram is down-sampled, quantized, remove noise and enhanced. Nonlinear diffusion is utilized for suppressing noise. Hussein ZR (20090 uses Median filtering, open morphological operation and contrast enhancement are used to reduce noise and image enhancement in [8]. Recenty R.Poongothai et al (2012) has proposed [9] a method for pectoral muscle removal as follows. An intensity value is taken using histogram function. The edge between pectoral region and breast region is detected using Fuzzy Connected Component Labeling. The raster scan method is used for fixing the pectoral removal area in the original image. Ali Cherif Chaabani et al. (2010) proposed automatic thresholding (Otsu‟s) and connected component labeling algorithm. Identifying the pectoral muscle has been done using Hough transform and active contour [10]. Javad Nagi et al. (2010) [11] proposed algorithm which uses morphological preprocessing and seeded region growing (SRG) to remove digitization noises, suppress radiopaque artifacts and remove the pectoral muscle.

## III. SEGMENTATION

Segmentation is a most important step in cancer detection. Image segmentation is use to extract the region of interest (lesion) from the mammogram image. As there are several tissues present in mammogram so it becomes a challenging task to isolate the lesion from it. Performance of feature extraction techniques mainly depends on the segmentation accuracy which will in turn assist radiologists in diagnosing the affected or suspicious area and classify the tumor. For this perfection needed in segmentation therefore many times scientist go for manual or semi-automated segmentation. There have been various approaches proposed for segmenting the breast profile region There Some of the broad techniques used are thresholding, region growing, boundary detection etc. All these methods are discussed in the following sections.

**3.1 Thresholding Techniques** Thresholding is utilized to segment an image by setting all pixels whose intensity values are above a threshold to a foreground value and all the remaining pixels to a background value. Global thresholding [12-14] is one of the common techniques for image segmentation. Histogram is used to get the global distribution of intensities. The peaks, valleys and curvatures of the histogram are analyzed to find the threshold value. As masses usually have greater intensity than the surrounding tissue hence a global threshold can be used separate the masses from the background tissues. It is not very accurate method because there is usually a certain amount of overlap between the breast region and background. Hence finding a perfect threshold in every case is very difficult and many times results in the misclassification of some mass region as breast region and vice versa. However Global thresholding has good results when used as a primary step of some other segmentation techniques. Another problem with global thresholding is that changes in illumination across the mammogram may cause some parts to be brighter and some parts darker in ways that have nothing to do with the objects in the mammogram. Remedy for such uneven illumination can be by determining thresholds locally. Which means, instead of using a single global threshold, the threshold itself is allowed to smoothly vary across the image. Local thresholding is comparatively better than global thresholding. The threshold is obtained locally for each pixel based on the intensity values of its neighbor pixels [15]. Li et al. [25] has used local adaptive thresholding to segment mammographic image into parts belonging to same classes and an adaptive clustering to improve the results. Matsubara et al. [16] developed an adaptive thresholding technique that uses histogram based analysis to divide mammogram image into three categories based on the density of the tissue. ROIs containing suspicious masses are detected using multiple threshold values based on the category of the mammographic image. Dominguez et al. [17] performed segmentation of regions via converting image into binary image by using multiple threshold levels. For images in the study, with grey values in the range [0, 1], 30 levels with step size of 0.025 were adequate to segment all mammographic images. Varela et al. [18] segmented suspicious regions using an adaptive threshold level. The images were previously enhanced with an iris filter. Li et al. [19] has proposed adaptive gray-level thresholding to obtain an initial segmentation of ROI. This was followed by a multiresolution Markov random field modelbased method.

**3.2 Region-Based Techniques** The region based segmentation is partitioning of an image into similar areas of connected pixels through the application of some similarity criteria. Markov random field (MRF) is one of the segmentation methods in iterative pixel classification category. It is a statistical method and powerful modeling tool [19]. Székely et al. [20] uses "coarse" segmentation. In this the feature vector is calculated and given to a set of decision trees that classifies the image segment. Results provided by the coarse segmentation is given to ―fine" segmentation which uses MRF technique to improve the preliminary result. After this they used a combination of three different segmentation methods: a modification of the radial gradient index method, the Bézier histogram method and dual binarization to segment a mass from the image. Region growing and region clustering techniques are also based on pixel classification. Region growing is a technique based on a controlled growing of some initial pixels (seeds). A seed pixel is chosen manually or automatically by developing some logic based on appropriate criteria. After completion of growing process, all the pixels are grouped into regions. 26 Zheng et al. [21] used an adaptive topographic region growing algorithm to define initial boundary contour of the mass region and then applied an active contour algorithm to modify the final mass boundary contour. Region clustering searches the region directly without initial seed pixel . The global segmentation approach proposed by Bick et al. [13] used thresholding techniques, region growing and morphological filtering. For noise reduction, mammograms were filtered and texture features were extracted A histogram is then constructed for all pixels whose local range was minimal. This histogram was then used to classify pixels as belonging to either the breast or non-breast regions. Region growing is then used to label the different regions, while morphological filtering is used to eliminate irregularities along the breast contour and contour tracing extracts the breast contour. Pappas [22] has proposed a K-means clustering algorithm to separate the pixels into clusters based on their intensity and their relative location. Sahiner et al. [23] also used K-means clustering algorithm. It was then followed by object selection to detect initial mass shape within the ROI. The ROI is extracted based on the location of the biopsied mass identified by a eligible radiologist. Preliminary mass shape detection is followed by an active contour segmentation method to refine the boundaries of the segmented mass. Ojala et al. [24] described an active contour method for smoothing breast contours in mammograms and given a comparison a with two other methods, called B Spline approximation and Fourier smoothing. Li et al. [25] proposed a method of an adaptive clustering to improve the result obtained from the localized adaptive thresholding. The drawback of these region based method is it is time consuming and noise or variation of intensity may result in holes or over segmentation.

**3.3 Edge Detection Techniques** Edge detection algorithms are based on the gray level discontinuities. Basis for edge detection are gradients or derivatives that measure the rate of change in the gray level. Prewitt operator, Sobel operator, Roberts operator and Laplacian of Gaussian (LoG) operator are used for general edge detection. Fauci et al. [26] developed an edge-based segmentation algorithm. It uses iterative procedure, a ROI Hunter algorithm for selecting ROIs. The algorithm is based on the search 27 of relative intensity maximum inside the square windows that form the mammographic image. Petrick [27] proposed use of Laplacian of Gaussian filter along with density weighted contrast enhancement (DWCE). DWCE method enhances the structures within the mammogram image so that the edge detection algorithm is able to detect the boundaries of the objects. Zou et al. [28] used gradient vector flow field (GVF) which is a parametric deformable contour model. After the enhancement of mammogram images with adaptive histogram equalization, the GVF field component with the larger entropy is used to extract the ROI. One of the recent approaches to segmentation of the breast contour was presented by Semmlow et al. [29]. He used a spatial filter and Sobel edge detector to locate the breast boundary on xero-mammograms. Abdel-Mottaleb et al. [30] proposed a system of masking images with different thresholds to find the breast edge. An interesting methodology was described by Lou et al. [31]. It is based on the assumption that the trace of intensity values from the breast region to the air-background is a monotonic decreasing function. This technique first searches for an initial boundary using a clustered image. For each initial boundary point a corresponding point is estimated with an extrapolation method. By using a refinement process, a contour point is derived from the extrapolated point, after that by linking all the boundary points, the breast shape is defined.

**3.4 Other Techniques** Li et al. [32] proposed a finite generalized Gaussian mixture (FGGM) distribution which is a statistical method for enhanced segmentation and extraction of ROI. They used FGGM distribution to model mammographic pixel images together with a model selection procedure based on the two information theoretic criteria to determine the optimal number of image regions. Finally, they applied a contextual Bayesian relaxation labeling (CBRL) technique to perform the selection of the suspected masses. Ball and Bruce [33] segmented suspicious masses in polar domain. They used adaptive level set segmentation method (ALSSM) to adaptively adjust the border threshold at each angle in order to provide high-quality segmentation results. They extended their work in [34] where they used spiculation segmentation with level sets (SSLS) to detect and segment 28 spiculated masses. In conjunction with level set segmentation they used Dixon and Taylor line operator (DTLO) and a generalized version of DTLO (GDTLO). Hassanien et al. [35] developed an algorithm for segmenting speculated masses based on pulse coupled neural networks (PCNN) in conjunction with fuzzy set theory. The method, as explained by Chandrasekhar et al. [104], involves modelling the nonbreast region (background) of a mammogram as a polynomial and subtracting it from the original mammogram. An initial threshold is used to approximate the breast area. This region contains the full breast region, a small portion of the breast contour, and the non-breast region, included in the region being modeled. This modeled background is then subtracted from the original mammogram, providing a difference image which, when thresholded, results in a binary mammogram. A connected components algorithm is then used to identify and merge related regions, followed by morphological operations to smooth irregularities to yield a labeled binary mammogram representing the breast/non-breast association. . One of the inherent limitations of these methods is the fact that very few of them preserve the skin or nipple in profile. Despite the numerous techniques that have been proposed in pursuit of an adequate segmentation method in the field of digital mammography there is still no exact solution to this complex problem. The complexity of mammograms comes from inherent blurring caused by round anatomical feature shapes in the direction of X-ray beam and superimposed boundaries resulting from overlapping features in the path of each X-ray beam .

## IV. CONCLUSION:

Here we can conclude that due of the diversity of breast masses and overlap of breast tissue in the 2D projected images as well as the limited testing datasets, it is very difficult to compare the performance and robustness of these segmentation methods as well as to find out which one is always superior to the other segmentation algorithms in different image databases.

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