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A REVIEW ON PREPROCESSING AND SEGMENTATION TECHNIQUES FOR THE DETECTION OF MICRO-CALCIFICATIONS IN MAMMOGRAMS

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Abstract: Mammography is a popular method for the detection of breast cancer and removal of primary tumor. To monitor and control breast cancer breast cancer segmentation is required. Many researchers worked in this area and it is still a challenging problem. In this paper we present different techniques used for preprocessing of a mammogram and various segmentation algorithms to detect the occurrence of micro-calcifications in digital mammograms from mini-MIAS database. The images of mammograms are noisy and of low contrast and is divided into various regions. We introduce a simple approach from enhancement of mammogram to preprocessing and then followed by segmentation of cancerous region.

I. INTRODUCTION

Breast cancer is a leading cause of death among all cancer diseases for middle-aged and older women. In U.S. Breast cancer death rates are higher than that of any other cancers for women. Mammography is a well-known method for detection of breast tumors. Early detection and removal of the primary tumor is an essential and effective method to enhance survival rate and reduce mortality for the radiologists. Early and efficient detection is most effective way to reduce morality, and currently a screening program based on mammography is considered one the best and popular approach for the detection of breast cancer. Mammography is a low-dose X-ray produced that visualize the internal structure of breast on a mammogram. On average, mammography will detect about 80-90 percent of breast cancers in women without symptoms. The first digital mammography system received U.S. Food and Drug Administration (FDA) approval in year 2000. It has been proposed that a computer-aided diagnostic (CAD) system be used as a second reader to assist the radiologist, leaving the final decision to the human. CAD systems are very helpful for radiologists to study mammograms. CAD can increase the diagnostic accuracy and efficiency with high reproducibility. The abnormalities in mammograms can be divided into two types: (1) micro-calcifications or (2) masses. Calcifications are tiny mineral deposits or calcium within the breast tissue. They look like small white spots on a mammogram. The calcifications may be of different types and may differ in distribution. A mass is usually something a little more substantial and clearer than a lesion. Specifically, a mass has volume and occupies space. On a mammogram, it tends to be denser in the middle than towards the edges. Masses may also have different shapes and margins, may differ in size, location, and orientation, and may have different backgrounds. If the mass appears more like a lobule than a purely round or oval shape, then it is somewhat more suspicious for breast cancer. Masses with irregular shapes are highly suspicious for breast cancer. There is another type of breast cancer known as speculated lesions. Spiculated lesions have a central tumor mass that is surrounded by a radiating pattern of linear spicules. Most spiculated lesions are malignant. The first step in mammography is the selecting the image from the database. The two databases can be used: mini-MIAS database and DDSM database. The next step is preprocessing of mammographic image which is used for noise removal and enhancement of image. After that the region of interest is detected by using segmentation and clustering of various parts of the mammogram.

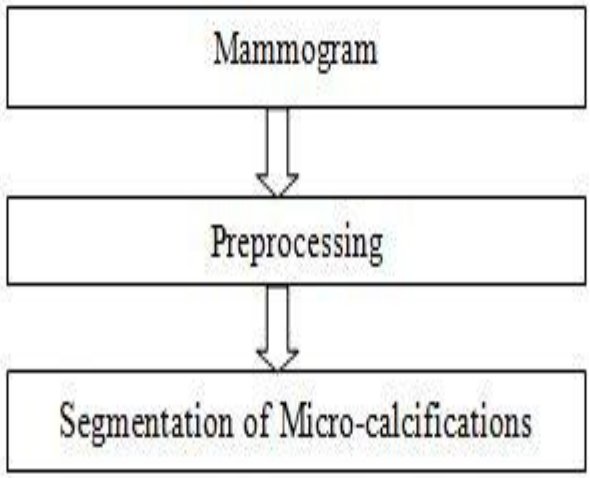


Fig.1 Block diagram of the proposed mammographic micro-calcifications detection scheme

II. LITERATURE REVIEW

In mammograms there are two main views: The first is MLO view that is Medio-lateral Oblique view and other is CC view that is Cranio-caudal view. The MLO view is used in preprocessing step because it presents the whole view of mammogram whereas some information may be lost in CC view [8]. It is important to enhance the mammographic image to remove noise and other artifacts in preprocessing step. Mario and Mislav [1] presented an approach for the detection of breast skin line and segmentation of pectoral muscle form mammogram for further detection of cancer. Abdelali et al. [2] detect the boundaries of different breast regions and segmenting into different mammographic densities using k-means clustering algorithm that is useful for risk assessment and evaluation of density changes. Pectoral muscle will increase the false positives in computer aided detection (CAD) of breast cancer. For this reason, pectoral muscle is has to be identified and removed using various thresholding techniques and regression analysis by Chen-Chung Liu et al. [3] . The pectoral muscle is extracted using positional characteristics and then to combine the Otsu thresholding technique and mathematical morphological processing to find the border of pectoral muscle. Multiple Regression Analysis (MRA) is applied on rough border for further segmentation. The automated identification of pectoral muscle is proposed by R.J. Ferrari et al. based upon a multiresolution technique using Gabor wavelets [4]. Straight line representation is done by hough transformations. A method for automated identification of the end points with a supervised learning algorithm, a two step procedure to detect the muscle contour followed with the delineation of the contour using a shortest path technique by Ines Domingues and Jaime S. Cardoso [5]. The contrast level adaptive histogram equalization (CLAHE) technique described by Indra Kanta Maitra and Sanjay Nag [6]. This technique describes the isolation of pectoral muscle from the ROI and finally suppression of pectoral muscle using seeded based region growing (SBRG) algorithm. Anuj Kumar Singh and Bhupendra Gupta presented an approach for segmentation of a mammogram by using simple technique such as averaging and thresholding [7]. The max-mean and least variance methods are used for tumor detection. The pectoral muscle is first estimated by a straight line and this estimation is then refined using iterative cliff detection to delineate the pectoral margin more accurately in an approach presented by Sze Man Kwock et al. [8]. The work of Aminah Abdul, Wan Eny, Arshmah, Rozi Mahmud, Siti Salmah and Abdul Kadir indicates that the Segmentation of mammogram is done by using two methods: Region based segmentation and boundary based segmentation [9]. Region growing method is used to extract the various regions based on intensity of pixels by selecting the seed point of a particular region. In Boundary based techniques, segmentation is achieved by locating its boundary using image gradient.

III. PREPROCESSING

Preprocessing steps are very important in order to limit the search for abnormalities without undue influence from background of the mammogram. On images obtained directly from the digital mammography devices preprocessing is important. To limit the region of search for suspicious detection, the breast region must be initially segmented from the image as the figure shows. Mammographic preprocessing can also reduce the effects of image noise, blood vessels and grandular tissues, which lead to many FPs in the suspicious region detection stage.

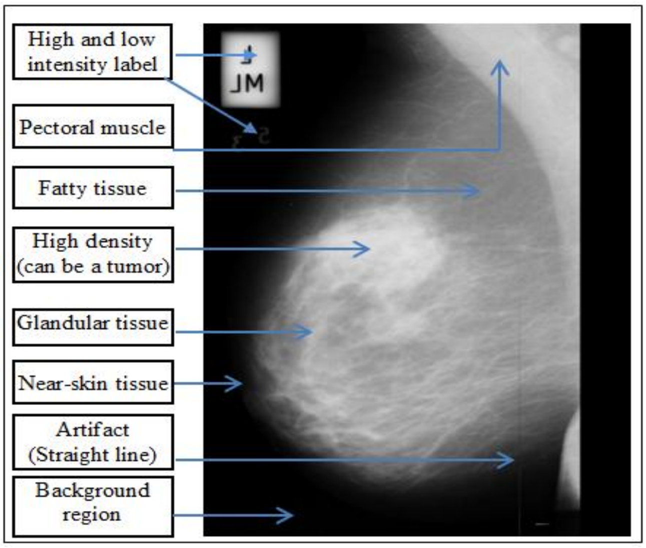


Fig. 2 The different components in the mammogram image.

Pectoral Muscle Detection: The pectoral muscle is visible as a triangular region of high density at upper left corner of the image. Its presence poses additional source of complexity in automated analysis. The texture of pectoral muscle may also be similar to the abnormalities and may cause false positive results. Removal of pectoral muscle is also one of the important step of preprocessing in CAD applications. The main problem in pectoral muscle detection is its low visibility in certain types of breasts, mainly higher density breasts.

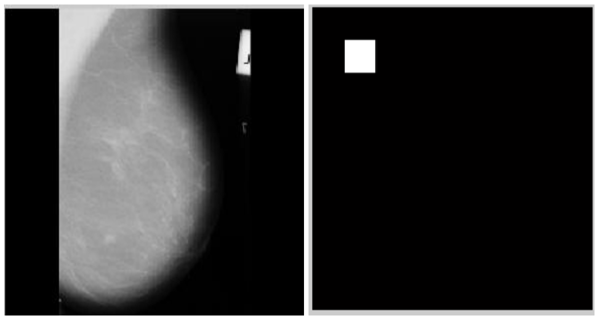
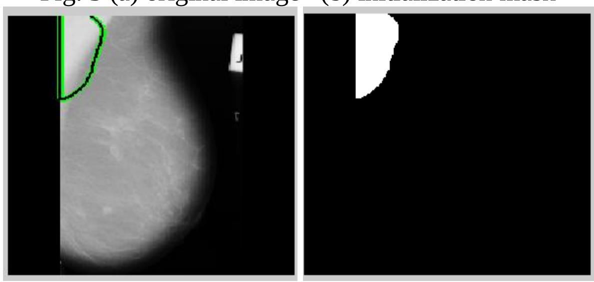


Fig. 3 (a) original image (b) initialization mask



(c) pectoral muscle identification (d) segmentation of pectoral muscle region.

IV. SEGMENTATION

Breast segmentation consists of breast border contour extraction, pectoral muscle extraction, nipple identification etcetera techniques can be broadly classified as into five main classes threshold based, Cluster based, Edge based, Region based, Watershed based segmentation. Segmentation plays an important role in image analysis. The goal of segmentation is to isolate the regions of interest depending on the problem and its characteristics. Many applications of image analysis need to obtain the regions of interest before the analysis can start. Therefore, the need of an efficient segmentation method has always been there. A gray level image consists of two main features, namely region and edge. Segmentation algorithms for gray images are generally based on two basic properties of image 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 and second category are based on partitioning image into regions that is similar according to a set of predefined criteria. The main cluster based techniques in segmentation are K-means clustering algorithm and Fuzzy C-means algorithm. There are several methods for segmenting images based on two fundamental properties of the pixel values: One of them is "discontinuity" that uses the discontinuities between gray-level regions to detect isolated points, edges and contours within an image. The other is "similarity" that uses decision criteria to separate an image into different group based on the similarity of the pixel levels. Clustering is one of the methods of second category. Clustering algorithms attempt to separate a dataset into distinct regions of membership.

Thresholding Based segmentation: A thresholding parameter *d* is used to separate pixels of cancer region from normal region.

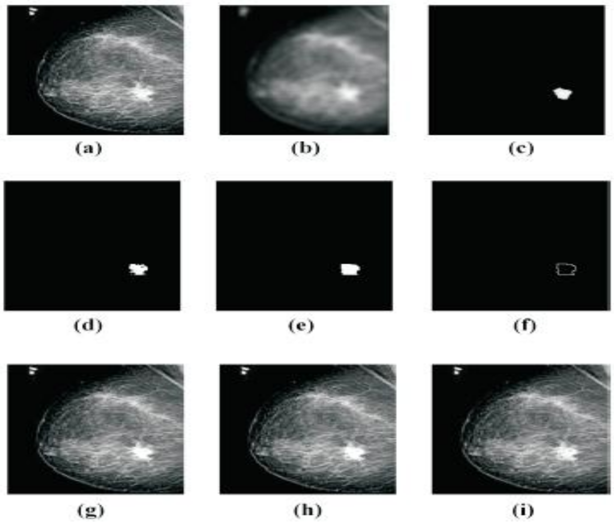


Fig. 4 Thresholding Based Segmentation

Fuzzy C-means Clustering: Fuzzy C-Means clustering (FCM) consider each cluster as a fuzzy set. Computational steps of FCM algorithm are: choosing the number of classes and the initial value for the means, classify the image by defining membership value for each class and assigning the pixels to the class corresponding to the closest mean, Re-computing the means of the class and at last, if the change in any of the means is more than some pre-defined small positive value, then stopping, else reclassifying the image based on membership functions and iterating the algorithm.

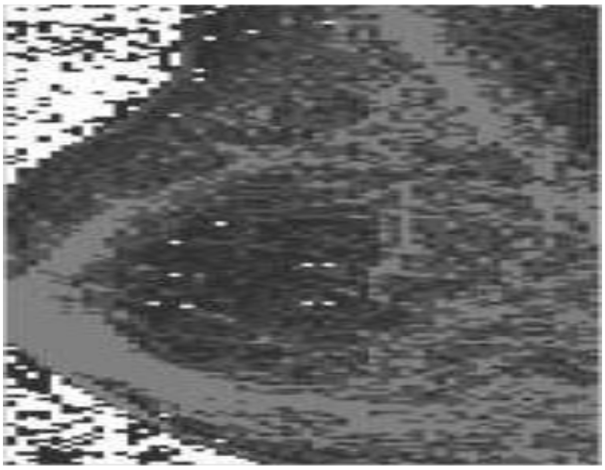


Fig. 5 Segmentation results using FCM clustering.

K-means Clustering: K-Means clustering generate a specific number of disjoints and flat (non-hierarchical) clusters. It is well suited to generate globular clusters. The K-Means method is numerical, unsupervised, non-deterministic and iterative. Some of disadvantages in K-Means algorithm are difficult in comparing quality of the clusters produced (e.g. for different initial partitions or values of K affect outcome), Fixed number of clusters can make it difficult to predict what K should be, does not work well with non-globular clusters. Different initial partitions can result in different final clusters

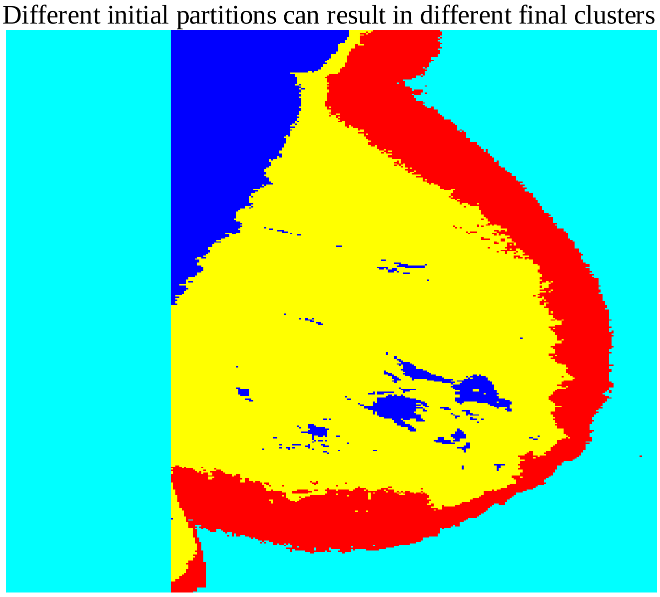


Fig. 6 Segmentation of image into different clusters using K-means clustering

V. CONCLUSION

In this work, we presented a review of various preprocessing techniques for the detection of boundary of breast tissue region in mammograms and further segmentation of image into different regions called clusters. This research can be helpful for classification of micro-calcifications as malignant or benign. The segmentation of a mammogram into its various regions can help in further detection and diagnosis of micro-calcifications. The future work of this research is to automatically classify breast density to fatty, fatty-grandular or dense-grandular tissues.

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