

## NEW COMPUTER AIDED DETECTION METHOD FOR THE EFFECTIVE DETECTION OF BREAST CANCER

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### ABSTRACT

Analyzing mammogram images is the most challenging task for radiologists in detecting breast cancer. Computer Aided Detection (CAD) plays major role in detecting such disease. Preprocessing, segmentation and detection are the processes involved in CAD. In this study, we have designed a CAD by improving the processes for the effective detection for breast cancer. Selective median filter has been used for noise reduction, Modified Local Range Modification (MLRM) is used for the enhancement, Cloud Model Based Region Growing Segmentation (CMBRGS) is used for effective segmentation of suspected area and rank based method is used for detection of cancer. This CAD method has been tested for over 40 mammogram images and found the detection accuracy of 98.8%.

**Keywords:** Mammogram, Breast Cancer, CAD, Selective Median Filter, MLRM, Segmentation

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### 1. INTRODUCTION

Breast cancer is a major public health problem in the world and the most common form of cancer among women worldwide. It currently accounts for more than 30% of cancer incidence and a significant % of cancer mortality in both developing and developed countries. Successful treatment relies on early detection (Padayachee *et al.*, 2007). Digital mammography is one of the most reliable method involves in the detection and diagnosis of breast pathological disorders (Papadopoulos *et al.*, 2008). Analyzing mammogram images is the most challenging task in medical image processing. Computer Aided Detection (CAD) tool is the aid for the radiologists in analyzing such images for the effective detection and diagnosis of the disease. Such a CAD tool consists of Preprocessing, Segmentation and detection processes (Papadopoulos *et al.*, 2008). Dense regions in digital mammogram images are usually noisy and have low contrast and their visual screening is difficult (Scharcanski and Jung, 2006). Contrast enhancement is

the most sensitive imaging technique for breast cancer detection. Global and local histogram equalization techniques had been proposed by (Cheng *et al.*, 2006). ACM active contour model (Precioso *et al.*, 2005), spatial constraint to a fuzzy cluster (Liew *et al.*, 2003), Markov Random Field (MRF) (Deng and Clausi, 2005) had been proposed for the preprocessing. Image is modeled as a set of spatial patterns to incorporate the spatial information implied by each pattern into the object function of Fuzzy C Means (FCM) clustering, in (Xia *et al.*, 2007), presented a new method of dissimilarity between a spatial pattern and a cluster, which reflects not only the distance in feature space, location of the pattern of the lattice. Feature extraction is used to find an appropriate measure to characterize the homogeneity of each region inside an image (Xia *et al.*, 2007). The contrast in mammograms is very low and the boundary between normal tissue and tumors is unclear, the traditional segmentation methods might not work well (Cheng *et al.*, 2006). Image enhancement algorithm has been utilized for the improvement of contrast features and

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the suppression of noise (Papadopoulos *et al.*, 2008). Contrast Limited Adaptive Histogram Equalization (CLAHE) based on local parameters was proposed by (Pizer *et al.*, 1987), region based approach for the enhancement of Regions of Interest (ROI) has been proposed by (Morrow *et al.*, 1992). Non linear gray level re-scaling method has been used for enhancement (Scharcanski and Jung, 2006) and filtering signal dependent noise on digitized mammographic phantom images using a direct contrast modification method was proposed by (Adel *et al.*, 2008). Automated interpretations of microcalcifications and masses are very difficult since the ROI's are usually of low contrast, especially in the age of young women (Cheng and Xu, 2002). So, Mammographic feature enhancement (cluster detection and enhancement) will be essential and critical for automated mammogram analysis. It is performed by emphasizing image features and suppressing noises so that the image quality can be greatly improved and be useful for breast cancer diagnosis. In this study we have discussed about the MLRM for noise removal and contrast enhancement and CMBRGS for cluster detection and segmentation.

## 2. MATERIALS AND METHODS

The database of mammograms used in this work is known as Mammographic Image Analysis Society (MIAS) Mini Mammographic Database. The example image used in this study is mdb75 and it is shown as original image in results section. The entire method presented in this study was implemented in MATLAB 7.0 and makes extensive use of the Image Processing Toolbox. The methodology used consists of three main stages. First is the pre-processing stage and it consists of noise removal and enhancement. Second is the segmentation stage and the third is detection stage.

### 2.1. CAD

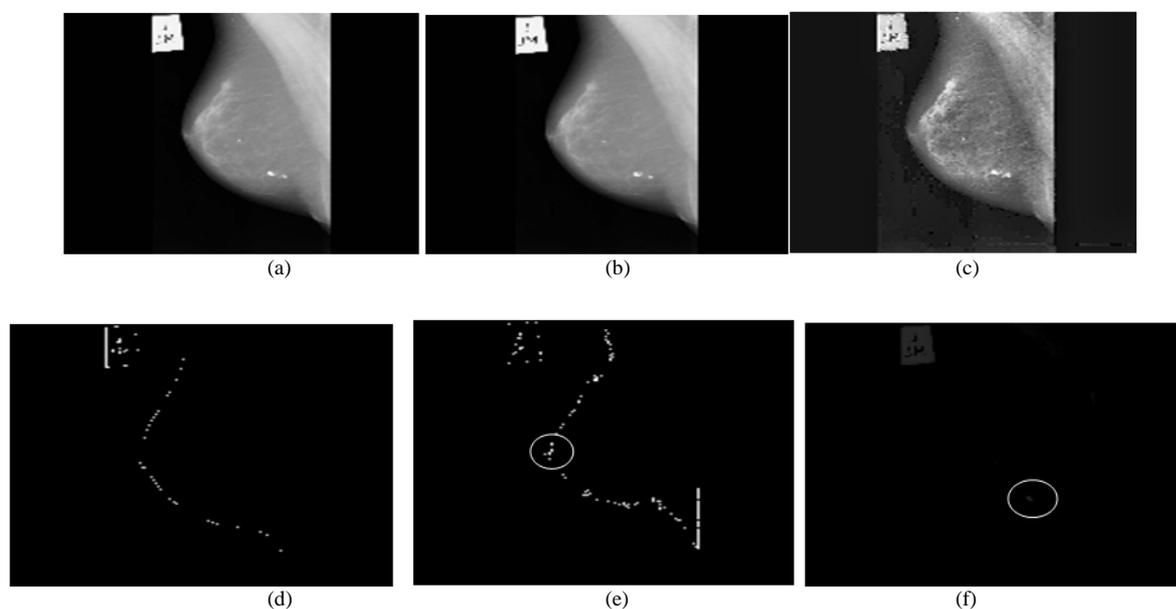
**Preprocessing:** The basic need for pre-processing in mammography is to remove the noise and to increase the contrast, especially for dense breasts. There are two possible approaches to enhancing mammographic features are to increase the contrast of suspicious areas and to remove background noise. **Noise removal:** A selective median filter is used remove the background noise (Yang *et al.*, 2005) and the resulted image is shown as selective median filtered image in **Fig. 1**. **Contrast enhancement:** MLRM algorithm is used and it processes same as that of LRM (Papadopoulos *et al.*, 2008) but with two changes. The first is maximum and minimum

pixel values of non-overlapping 48×48 pixel sized blocks are computed during first pass instead of 51×51 in LRM. And the second is estimation of regional maximum and minimum values based on the interpolation of eight surrounding grid points instead of four in LRM removes the noise and enhances the contrast better. **Edge detection:** process involves in finding asymmetry between the breasts. This can be achieved by detecting the nipple position and with respect to the position both the breast are compared to find the asymmetry. And it is a traditional method for image segmentation (Cheng *et al.*, 2006). There are many methods exists like Roberts, Sobal, Prewitt, Laplacian of Gaussian. Edge detected image can be easily segmented for observing region of interest. Here a hybrid model of edge detection is used (Abdel-Mottaleb *et al.*, 1996). We have combined the MLRM contrast enhancement method with Laplacian of Gaussian (LoG) edge detection method for the segmentation of Region of Interest (ROI) and nipple position as shown in the results. **Segmentation:** Cloud Model and Region Growing Segmentation is used. Uncertainty is widely existed in the subjective world. In all kinds of uncertainty, randomness and fuzziness are the most important and fundamental. Cloud model is an effective tool of uncertain transition between qualitative concepts and their quantitative expressions, can express the relationship between randomness and fuzziness (Kun *et al.*, 2006). It is in accord with the process of human thinking. It is a simple and effective way to simulate the uncertainty by mean of knowledge representation which provides a basis for the automation of both logic and image thinking with uncertainty. We suppose that  $U$  is a quantitative domain represented by accurate numerical value,  $U = \{x\}$ ;  $C$  is a qualitative concept under  $U$ . If the element  $x \in U$  and  $x$  is a random implement of  $C$ , the certainty degree of  $x$  to  $C$ ,  $\mu(x) \in [0, 1]$  is a random number with stable tendency (Deyi and Changyu, 2004):

$$\mu : U \rightarrow [0,1] \quad \forall x \in U \quad x \rightarrow \mu(x) \quad (1)$$

From Equation 1 the distribution of  $x$  in  $U$  is called cloud. And each  $x$  is called a cloud drop.

Cloud model has three numerical characteristics, Expected value ( $E_x$ ), Entropy ( $E_n$ ) and hyper-Entropy ( $H_e$ ), which are used to reflect the features of the concept (Kai *et al.*, 2006). Forward Cloud Generator (CG) generates the cloud with the help of given numerical characteristics ( $E_x$ ,  $E_n$  and  $H_e$ ) and  $CG^{-1}$  (backward Cloud Generator) generates the numerical characteristics from the cloud drop.



**Fig. 1.** Results of the mammogram image (75) taken from MIAS database (a) Original Image (b) Selective Median Filtered Image (c) MLRM Output (d) Edge Detected Image (e) Nipple Detected Image (f) CMBRGS Output

**Table 1.** Average ROC values of CAD techniques

Main Techniques involved in Breast Cancer Detection (CAD)	Detection accuracy (%)
Entropic Thresholding (ET) (Dominguez and Nandi, 2008)	86.0
Wavelet and Neural Network (WNN) (Yang <i>et al.</i> , 2005)	88.0
Bilateral Image Subtraction (BIS) (Retico <i>et al.</i> , 2006)	95.0
Tree Structured Wavelet Transform filter with Neural Network (TSWTNN) (Zhang <i>et al.</i> , 2002)	97.0
Proposed Method (GMBRGS)	98.8

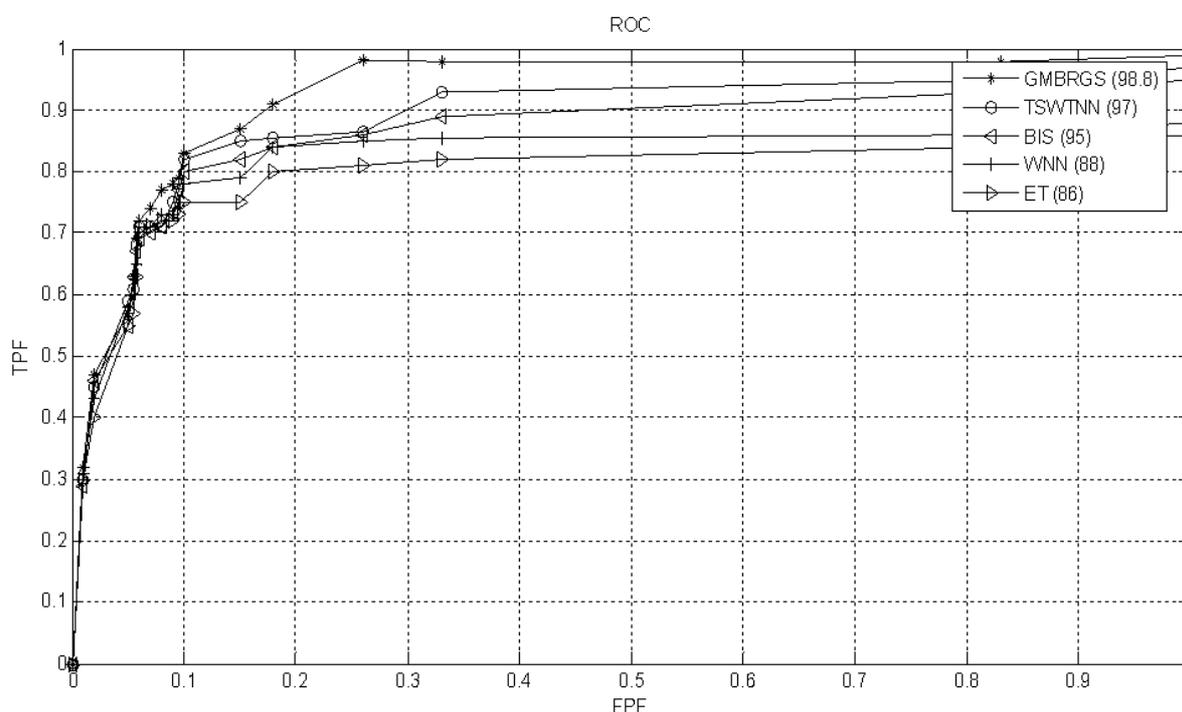
From the point of view of cognitive science, concept is the basic cognitive element. It is corresponding to a quantitative data space and is the nature form of thinking about the object formed in the minds of human. In order to make use of the abstract concept to observe and analyze region, we must in some way to express the region into concepts. From the Cloud Model theory, we know that it's a concept express model. It reflects the homogeneity, fuzziness and randomness of a region. So, we use  $CG^{-1}$  to extract the concept of the region around the seed, it can get the concept's connotation and extension, which is used here as the segmentation threshold. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity and texture. Adjacent regions are significantly different with respect to the same characteristics result as segmented image in **Fig. 1**. Detection of microcalcification and mass: were done based on the ranking system in (Dominguez and Nandi, 2008).

### 3. RESULTS

The proposed CAD detects the cancer in an effective way and the resulted images are given in **Fig. 1**. (a) is the original mammogram, (b) is the selective median filtered image and the image clarity has been improved, (c) is the MLRM enhanced output of mdb 75, (d) is the edge detected image with clear edges of breast area and this is very useful in detecting nipple position, (e) is the nipple detected image and the detected nipple has been circled and (f) is the segmented image with circled segmented area. This image has been tested already and found that it is a fatty breast with malignancy.

### 4. DISCUSSION

Further, the Receiver Operating Characteristics (ROC) analysis has been done for this CAD method.



**Fig. 2.** ROC of the proposed method

We have tested over 40 sample images and the performance of the proposed technique has been evaluated by calculating True Positive Fraction/sensitivity (TPF) and False Positive Fraction/specificity (FPF). The ROC curve in **Fig. 2** gives the relationship between TPF and FPF. The average ROC values of proposed method has been compared with the existing techniques and tabulated in **Table 1**. The result of the proposed method we found was good in detecting the cancer (malignancy) with the accuracy of 98.8%, which is efficient than the other existing methods and this has also been validated by expert radiologists.

## 5. CONCLUSION

This new CAD method will provide good support to the radiologist in detecting the breast cancer. The selective median filtering and small modification in the LRM technique (MLRM) reduces the noise and enhances the mammogram image better. Then the new edge detection method and CMBRGS technique has been used to correctly segment the cluster. Both performs well on mammogram image and we have detected the nipple position and the exact position of

cancer with high image quality. ROC analysis has been done for this proposed method and we found the detection accuracy of 98.8%, which is better compared to the existing detection methods. In future, we have plans to implement this new CAD method in Field Programmable Gate Array (FPGA).

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