



Comparative analysis of different techniques for breast cancer detection in Mammograms

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ABSTRACT

Segmentation of images is one amongst the primitive and most vital stages of processing in images and plays a very crucial role in analyzing medical mammogram images but images of mammogram have moderate level of distinction and are disrupted with sturdy speckle noise. Owing to the effects, mammogram images segmentation is extremely difficult and conventional segmentation techniques may not leads to result satisfaction. Due to high noise, low distinction, and alternative imaging artifacts, region boundaries in mammogram images often do not adjust to the assumptions of many image processing algorithms. This paper addresses the potencies and weaknesses of the existing techniques of carcinoma detection in mammograms. The paper provides new aspects of research for researchers.

Keywords: Mammogram images, breast cancer, image segmentation, MICO technique.

1. INTRODUCTION

Every 1/8 deaths across world is suffering with tumor. Tumor here means cancer, Cancer is the 2nd major destruction in countries like United States and the 3rd major in developing countries. About five lakhs sixty two thousand three hundred forty Americans in 2009, died of cancer, more than 1500 people a day. In 2009 approximately fourteen lakh seventy nine thousand three hundred fifty new cancer cases were detected. In the US, cancer is the 2nd most regular reason behind death and accounts for nearly 1/4 deaths [10].

Mammography is the basic technique to detect the breast cancer. According to this technique the radiation goes into the breast and shows internal parts of the body. After the completion of this technique, their result will be shown in X-Ray film sheet. The aim of this technique is to find the tumor in the very initial stage when recovery is possible. No screening tool is 100% effective. Good quality mammograms can find 85-90% of cancers. Segmentation is the most challenging task due to the healthy tissues and artifacts in the mammograms. Many types of algorithms have been proposed in literature for early detection of the cancer in breast in mammograms [3].

1.1 SEGMENTATION

The primary objective of segmentation is to alter the illustration of the image into meaningful image that is more appropriate and simple to analyze. Background objects are sharper in mammogram images. The preparation point is needed in order to make segmentation results more accurate and improvement in quality of images. A method based on variance thresholding is used to perform the segmentation. As if, threshold is more of the variance, then the block is considered as a background region otherwise, it is considered as a part of the foreground. The gray scale variance for a block of size 8×8 is defined as:

$$V(x) = \frac{1}{8^2} \sum_{p=0}^{8-1} \sum_{q=0}^{8-1} (I(1,1) - M(1,1))^2 \quad (1)$$

$$M(x) = \frac{1}{8^2} \sum_{r=1}^8 \sum_{s=1}^8 J(r, s) \quad (2)$$

Where variance for block x is denoted by V(x), mean gray- level value for the block x is denoted by M(x), I (p, q) and J (r, s) are the gray-scale value for pixel (p, q) and (r, s) respectively in block k [11].

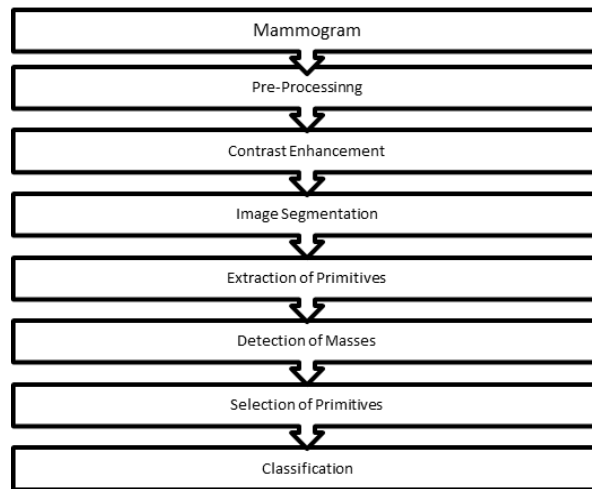


Figure 1: Mammogram Analysis Steps [3]

1.2 MULTIPLICATIVE INTRINSIC COMPONENT OPTIMIZATION (MICO)

This method provides a new energy minimization technique to estimate and correct the bias field and segment the mammogram images simultaneously. It optimizes two multiplicative intrinsic components of images in mammogram, the bias field and the true image. Bias field deals with intensity inhomogeneities present in the image space and the true image defines a physical property of the tissue [8].

i) MR images decomposition into multiplicative intrinsic components:

MR images formation has been generally accepted as that MR image I can be modelled as:

$$I(x) = b(x)j(x)+n(x) \quad (3)$$

Where intensity of image observed is denoted by I(x) at voxel x, true image is shown by J(x), Bias field i.e. b(x) explains the inhomogeneity in intensity in the observed image, and additive noise is denoted as n(x) with zero-mean.

The bias field b is assumed to be smoothly varying and the true image J characterizes a physical property of the tissues being imaged [1].

ii) Illustration of multiplicative intrinsic components:

The bias field b(x) and therefore the true image j(x) are represented as

$$b(x) = W^T G(x) \quad (4)$$

Where W^T is the inverse operator performed on optimal coefficients used for bias field estimation and G(x) could be column vector valued function used to represent the premises functions.

$$j(x) = \sum_{i=1}^N c_i u_i(x) \quad (5)$$

Where constant function is represented by c_i for x in the ith tissue and membership function is represented by u_i to represent N tissues. So to find out the multiplicative intrinsic components b and J of an observed image I following energy is minimized [1]

$$F(b, j) = \int |I(x) - b(x)J(x)|^2 dx \quad (6)$$

The expression of energy F allows us to derive an effective energy minimization scheme [8]

The image segmentation and denoising methods are broadly categorized as:

A. Methods based on Region:

Thresholding & region growing methods.

B. Spatial Methods of Filtering:

It includes linear and non-linear filters.

C. Filtering methods of Domain Transform:

- i) Morphological operators and microcalcifications are used.
- ii) GABOR wavelet is used.

D. Methods of Clustering:

K-Means and FCM methods are used.

E. Methods of Classification:

ANFIS and SVM classifiers are used.

In this paper the work done by different researchers and scholars is to assist in the problem of image segmentation has been reviewed along with their advantages and drawbacks.

2. LITERATURE REVIEW

A critical review of the studied literature is summarized in table I.

Table 1: Comparison of Different Papers Reviewed

Researcher	Paper Reference	Used Methods	Advantages	Drawbacks
Ragupathy, U. S., & Saranya, T. (2012)	[17]	Extraction of features are from RoI. ANFIS is used for classifier construction. GABOR Wavelet method is used.	Sensitivity of images increases by 4% with architectural distortion.	Mass and sensitivity of images needs to be improved.
Digambar A Kulkarni, Vijaylaxmi K Kochari (2016)	[13]	K-Means Clustering algorithm.SVM for classifier construction.	K-Means is simple. Good accuracy of classifier.	It is difficult to analyze k-value and there is dissimilarity in final clusters due to early different partitions.
Kontos, K, & Maragoudakis, M. (2013, September)	[2]	Extraction of image segmentation is done by The Statistical Region Merging (SMR) algorithm.	Accuracy is improved when identify tissues of tumor.	Class imbalance. Genetic selection feature method needs precision improvement.
Al-Bayati, M., & El-Zaart, A. (2013)	[15]	1.Otsu Method 2.Valley 3.Neighbourhood Valley	Intensity and variance method are good in desolation from intensity background of micro calcifications.	T = 190 is unable to detect the tumor in Otsu Method; Details of object is also not clear.
D. Selvathi and A. Aarthi Poornila(2017)	[14]	Unsupervised Deep Learning technique is used.	Digitization in noise is removed.	Decrease the adequate performance of the technique in

			Accuracy is upto 98.5% in classifying images. It also helps to find more accuracy in smaller masses.	detecting the cancer.
Gowri, D. S., & Amudha, T. (2014, March)	[4]	Image enhancement techniques like smoothing, filtering, denoising, and histogram equalization were used.	Histogram equalization (HE) is best method to improve contrast of digital images.	Contrast enhancement is the major problem in processing the image.
N. Singh, A.G. Mohapatra Rath, B. N., & G.K. Kanungo (2012)	[16]	Clustering Algorithm i.e. K-Means FUZZY Algorithm i.e. C-Means	1. Low implementation cost. 2. Detect early breast cancer	Give unsatisfactory and noisy images. K-Means tends to run faster than FCM
K. Kashyap, M. Bajpai & P.Khanna (September) (2015)	[5]	FCM Algorithm is used.	1. Sharp edges are obtained. 2. Improvement in accuracy of segmentation of images.	This method does not classify the benign and malignant masses.
Angayarkanni. N, Kumar. D and Arunachalam. G(2016)	[11]	Enhancement of images should be done by segmentation, Binarization etc.	Best performance in terms of sensitivity, specificity and classification accuracy is 99.66%	No final decision is given so there is a concern of cancerous changes in images.
R. Guzmán-Cabrera et.al(2012)	[10]	Microcalcification are used to distinguish it from background tissue and Morphological operators are used to distinguish masses.	Gray level value segmentation and extraction of regions is successful.	It is not the best option to identify suspicious regions along with non-relevant regions.
Mane, S. A., & Kulhalli, K. V. (2015)	[7]	Features are extracted from Gabor Wavelet. SVM is used as a Classifier.	1.Maximizes the accuracy 2. Cost of computation is decreased.	Doctors are responsible for final medical image.
Dheeba, J., Singh, N. A., & Selvi, S. T. (2014)	[18] [21]	Artificial neural networks (ANN) method is used.	This is the highly complex method with non-linear systems	It is difficult to decide on hidden layers and neurons range in each layer.
El Atlas, N., El Aroussi, M., & Wahbi, M. (2014, November)	[18]	SOM method was used.	Robustness increased.	Increase the time of iterations in self-organizing map.
Mohamed, H., Mabrouk, M. S., & Sharawy, A. (2014)	[22]	1. Enhancement technique 2.Histogram Equalization 3.Otsu's technique	1. Removal of noise. 2. Removal of background.	Multi-class problems dealing in SVMs.

3. CONCLUSIONS

We have studied the various methods for breast cancer detection and have found that there are several advantages and disadvantages of existing methods. As concluded from the above literature survey inaccuracy in the size of cancer and larger computational time to detect cancer are two major limitations of existing methods. We can work on these methods to improve detection accuracy and computational time.

4. ACKNOWLEDGEMENT

The scholars are grateful to all the researchers for their important approaches.

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