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Detection of Microcalcifications in Digital Mammogram

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***Abstract*- Breast cancer is currently one of the leading causes of deaths among women worldwide. In order to reduce mortality of the women early detection is important, because an early diagnosis is more likely to be successful in the early stage of the disease. In this paper an efficient technique is proposed for early detection of tumors is carried out in two methods. The first uses the decomposition property of wavelet transform and is subjected to statistical analysis.**

The statistical analysis involves by finding skewness and kurtosis on the spatial coordinates of the decomposed image. This statistical analysis removes the complexity of edge detection techniques. And this becomes a pure numerical approach of finding the tumor.

In the second method the input image may be classified in to benign and malignant based on the shape of the boundary by using Hough Transform.

A CAD system becomes a part of routine clinical work for the detection of breast cancer in mammograms at many screening sites and hospitals. These systems act only as a second reader and final decision is made by the radiologist.

Keywords- Mammogram,Tumors

I. INTRODUCTION

Cancer is the term used for a group of diseases in which the cells in the body grow and divide in an uncontrolled manner to produce abnormal cells. In INDIA the death rate of one in eight women has been reported. In Norway, new cases registered per every year are 2100 and the deaths per year may be 800.According to WHO's international agency for research on cancer in Lyon ,France , every year more than one million women are affected with breast cancer around the world. Each year it is estimated that nearly 200000 women will diagnose with breast cancer and more than 40000 will die of it [4]. Male breast cancer is a rare condition, accounting for only about 1% of all breast cancers. The American Cancer Society estimates that in 2010, about 1,970 new cases of breast cancer in men would be diagnosed and that breast cancer would cause approximately 390 deaths in men (in comparison, almost 40,000 women die of breast cancer each year). Breast cancer is 100 times more common in women than in men. Most cases of male breast cancer are detected in men between the ages of 60 and 70, although the condition can develop in men of any age. For detecting Breast cancer a high quality image is required. Mammograms are X-ray images of breast, which help radiologist in detecting the cancer at early stages [12]. Small calcium deposits which occur in the breast tissue are called micro calcifications are assumed to be early symptoms of cancer, but these micro calcifications are very small in size, i.e.1mm diameter so it is very difficult to detect even for an experienced radiologist. In order to increase the diagnostic efficiency, several computer aided techniques can be used to locate and classify possible Lesions. This is helpful in giving a second opinion to the radiologist, in the diagnosis

II. LITERATURE REVIEW

To detect the boundary of cancer tumors in a digital mammograms the edge based segmentation techniques [2] of first and second order provides an effective segmentation to detect the boundary profiles. Detecting edge of image significantly reduces the amount of data and filters out insignificant information, while preserving the important structural properties in an image. Edge detectors are a collection of very important local image pre-processing methods.

A. Sobel Operator:

The Sobel operator performs a 2-D spatial gradient measurement on an image [2]. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and y-direction (rows). A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The actual Sobel masks are shown below:

Gx =

-1	0	+1
-2	0	+2
-1	0	+1

Gy =

+1	+2	+1
0	0	0
-1	-2	-1

Figure: 1.1.Mask of Sobel Operator

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B. Prewitt Operator

The Prewitt edge detector is a also much better operator. This operator having a 3x3 masks deals better with the effect of noise. The Prewitt edge detection masks are one of the oldest and best understood methods of detecting edges in mages. Basically, there are two masks, one for detecting image derivatives in X and one for detecting image derivatives in Y. This Prewitt operator is obtained by setting c = 1.

G_x =

-1	0	1
-1	0	1
-1	0	1

G_y =

1	1	1
0	0	0
-1	-1	-1

Figure. 1.2. Masks of Prewitt operator

C. Robert Operator

The Robinson edge detector is similar to the Sobel edge detector. The Robinsons row, column and corner masks are shown below. It is symmetrical by the axis. The maximum value is found in the edge magnitude and the edge direction is defined by the maximum value found by the edge magnitude.

Limitations: Edge-based methods center around contour detection: their weakness in connecting together broken contour lines make them, too, prone to failure in the presence of blurring**.** presence of blurring**.**

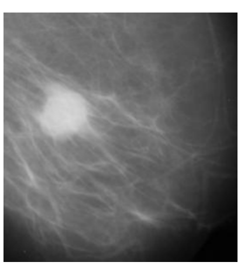


Fig. 2.1. 512× 512 original mammogram

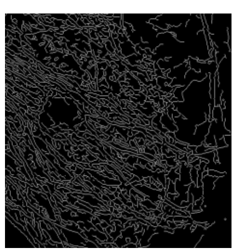


Fig. 2.2. Image after Canny operation

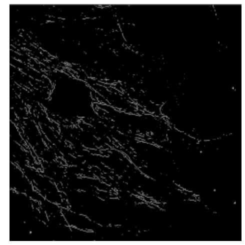


Fig.2.3. Image after Sobel operation

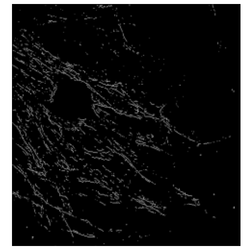


Fig.2. 4. Image after Robert operation

Breast tissue Classification using statistical feature extraction of mammograms given by **Sheshadri H.S Kandaswamy** In this an attempt is made to classify the breast tissue based on the intensity level of histogram of mammogram. The statistical features extracted are mean, standard deviation, entropy extracted. Based on the values of these features breast tissue may be classified. This classification may be useful for the radiologist to detect the normal breast from the cancer affected breast with visual inspection.

A Novel image segmentation technique for detection of breast cancer [2] given by **LSS Reddy, C.Nagaraju .**In this an attempt is made for early detection of breast cancer with effective boundary, which is carried in two steps.

In the first step the mammogram input image is applied to Gaussian filter for noise removal later NN classifier is used which classifies cancerous part as ‘1’and noncancerous part as ‘0’.

In the second step effective boundary detected by using morphological operator. This resembles the erosion followed by dilation.

Limitations: Visual inspection only possible and Gaussian filter not effective for noise removal.

III. PROPOSED SYSTEM

In this paper the tumor can be detected by using. Flowchart for the proposed technique is given in Fig.3

The digitized mammogram is preprocessed by Gaussian Low pass filter. At this stage the noise is removed, and it is introduced due to image acquire and image transmission.

Segmentation subdivides an image into its constituent regions or objects that have similar features

i) Review of Wavelet Transform

The Discrete wavelet Transform (DWT) of image signals produces a non redundant image representation, which provides better spatial and spectral localization of image formation [13]. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal is passed through two complementary filters and emerges as two signals, approximation and details. This is called decomposition.

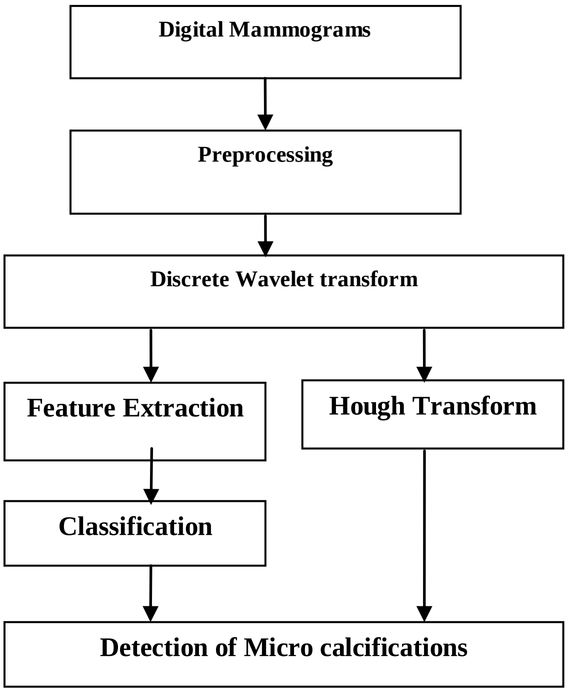


Fig.3.: Block Diagram representation of Proposed Method

Fig.4 Shows bank of filters iterated for the 2D-DWT.An image can be decomposed in to a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL, HH. The next level of wavelet transform is applied to the low frequency sub band image LL only.

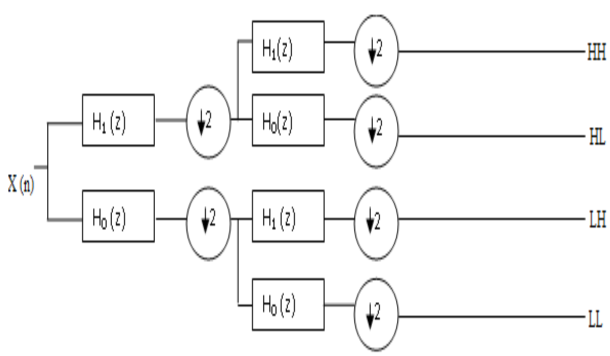


Fig.4 Bank of filters iterated for the 2D-DWT

The decomposition of the image in to different resolution levels which are sensitive to different frequency bands. By choosing an appropriate wavelet with aright resolution level, tumors can be detected effectively in digital mammograms .Experimental results show that the daubechies wavelet achieves the best detecting result [34].

Here the detection is carried out in two steps. First, the detail-image is divided into same square region size, i.e. n x n pixels. Second, Skewness and Kurtosis values may be calculated from the square regions.

ii) Feature Extraction

The histogram can give a general idea of the shape but two numerical measures of shape will give more precise evaluation, they are

Skewness: It gives the amount and direction of skew.

Kurtosis: It tells about how tall & sharps the central peak

A statistical test based on skewness and kurtosis is effective in finding regions with asymmetrical and heavier tailed distributions.

If a region contains micro calcifications the symmetry of the distribution of detail image coefficients is destroyed [3]. The detail image is first divided in to overlapping square regions, i.e, N * N pixels in which statistical parameters such as skewness & kurtosis are estimated. A Region with high positive skewness & kurtosis is marked as a region of Interest (ROI).

a) Skewness: *Skewness* is a measure of the asymmetry of a histogram. A distribution is said to be symmetric if it looks the same to the left and right of the centre point. If longer tails occurs to right the distribution is said to be skewed to right, while if the tails occurs to the left it is said to be skewed to the left.

Skewness can be defined as the ratio of the third cumulate K_3 and the third power of the square root of the second cumulate.

$$\gamma_1 = \frac{\boldsymbol{K_3}}{\boldsymbol{K_2}^{3/2}}$$

$$K_2 = \sum \frac{(\boldsymbol{x}-\boldsymbol{M})^2}{\boldsymbol{n}} \qquad K_3 = \sum \frac{(\boldsymbol{x}-\boldsymbol{M})^3}{\boldsymbol{n}}$$

Where

γ_1 = Skewness M = Mean

K_2 = Variance n= sample size K_3= third moment

-- Positive skewness indicates a long right tail

-- Negative skewness indicates a long left tail

-- Zero skewness indicates symmetry around the mean

b) **Kurtosis:** Measure of the degree of peakedness of a distribution. In some cases a distribution may have its values concentrated near the mean so the distribution has large peak. In other cases the distribution may be relatively flat. It gives about the central peak is high & sharp or short & broad.

Kurtosis is more commonly defined as the fourth cumulate divided by the square of the variance of the probability distribution,

$$\gamma_2 = \frac{K_4}{{K_2}^2}$$

Excess kurtosis = γ_2 - 3

The kurtosis for the normal distribution is 3

Positive excess kurtosis indicates flatness (long, fat tails)

Negative excess kurtosis indicates peakedness

iii) Classification

The detection problem is posed as hypotheses given by

$$\Gamma(x) = \begin{cases} 0 & \gamma_1 < T_1 \text{ or } \gamma_2 < T_2 \\ 1 & \gamma_1 > T_1 \text{ and } \gamma_2 > T_2 \end{cases}$$

Where

T1 and T2 are Skewness & Kurtosis threshold values respectively.

Value '0' signs there are no micro calcifications in the regions.

Value '1' signs there is micro calcifications in the regions

iv) Results Proposed (method-1):

Fig.5 shows the simulation results of two sample test images which gave a suitable results based on detection and location of microcalcification. Skewness and kurtosis analysis of various suspected regions are shown in Fig.6

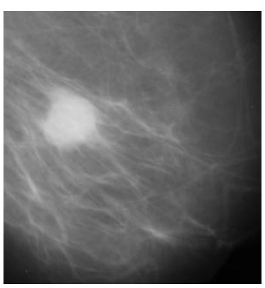


Fig.5.1. Input image with microcalcification

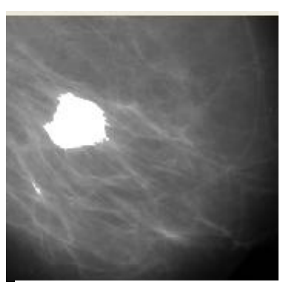


Fig.5.2. Output image with microcalcification

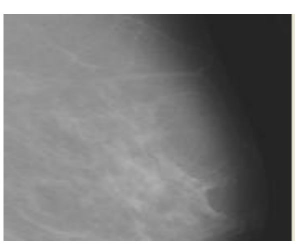


Fig 5.3.Input image without micro calcification

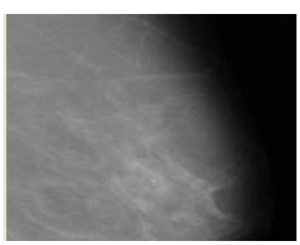
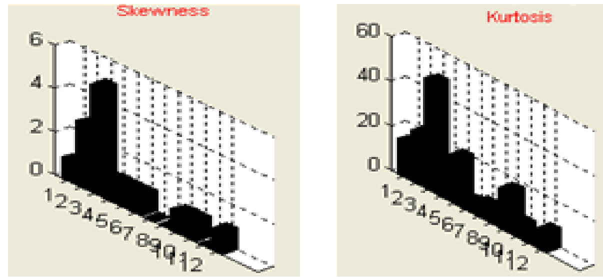
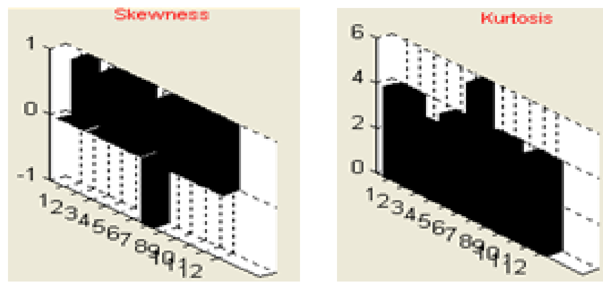


Fig.5.4.Output image without micro calcification



(a)



(b)

Fig.6.Skewness and Kurtosis measurement for (a) Abnormal ROI (b) Normal ROI

The table 1 shows the difference in skewness and kurtosis values between normal and malignant images with which classifying those become easier Detection efficiency improved using Hough transform for another classification

S.No	Skewness		Kurtosis	
	Normal	Malignant	Normal	Malignant
1	1	5	11	49
2	1	5	9	68
3	1	6	6	59
4	1	3	7	31
5	1	4	6	32
6	2	3	11	26
7	2	3	10	31

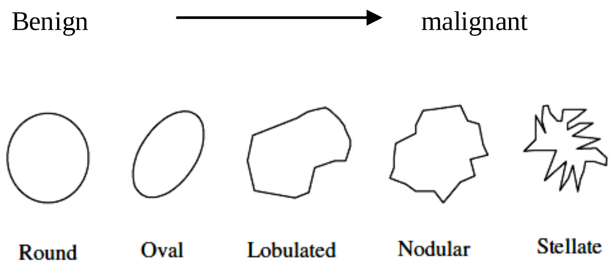
Table 1.Comparision of skewness and kurtosis values

• *Hough Transform* (method-2)

Masses could be classified as benign and malignant based on their shape Benign images has boundary with smooth, soft and circular in shape but for malignant images rough, irregular and star shaped boundaries.

Figure.7 shown below we can easily understand the shape of the suspected area and the nature of the cancer. It starts at round shape as benign and ends at stellate shape as malignant [14].

Figure.7: A flow chart showing the stages involved in the diagnosis of abnormalities [14, 15].



Hough transforms uses for detecting natural shapes like line and circles.
Circles may be detected by finding origin and radius

Equation for circle

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

v) Results Proposed method-2

Fig.8 shows the simulation results of two sample test images which gave suitable results based on detection and location of micro calcification and various suspected regions are shown in Fig

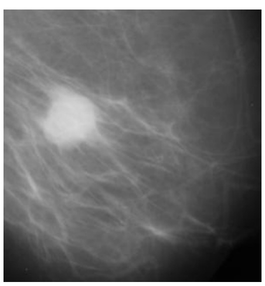


Fig. 8.1. Input image with microcalcification

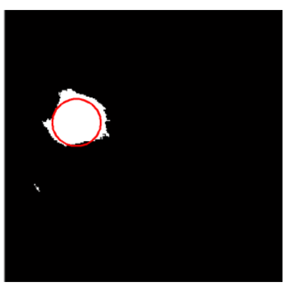


Fig.8.2. Output image with microcalcification

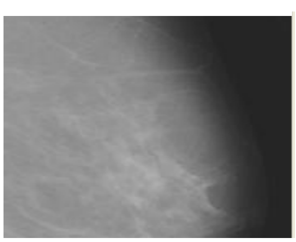


Fig. 8.3. Input image without microcalcification

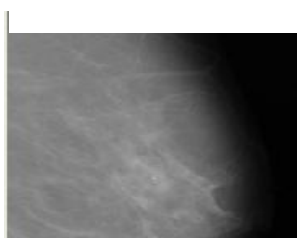


Fig.8.4. Output image without microcalcification

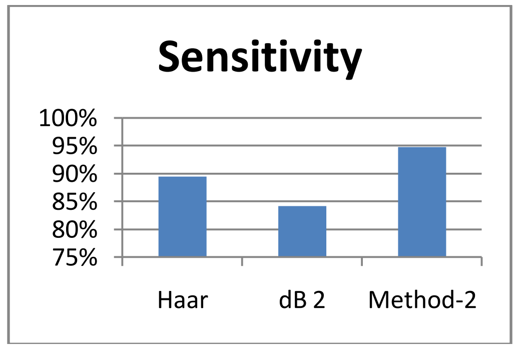
vi) Performance Analysis

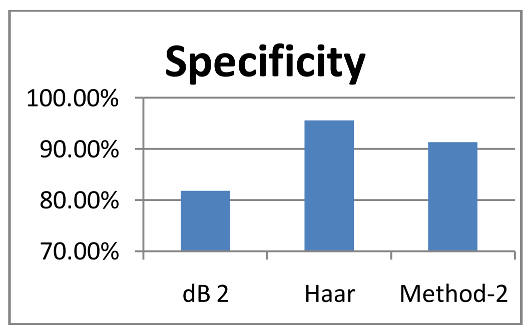
1. Sensitivity $= \frac{TP}{TP+FN} \times 100$
2. Specificity $= \frac{TN}{FP+TN} \times 100$
3. Accuracy $= \frac{TP+TN}{FP+FN+TP+TN} \times 100$
4. MCC =

$$\frac{(TP.TN - FP.FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \times 100$$

Where

TP = Predicts malignant as malignant
TN = Predicts Benign as Benign
FP = Predicts Benign as malignant
FN = Predicts malignant as Benign





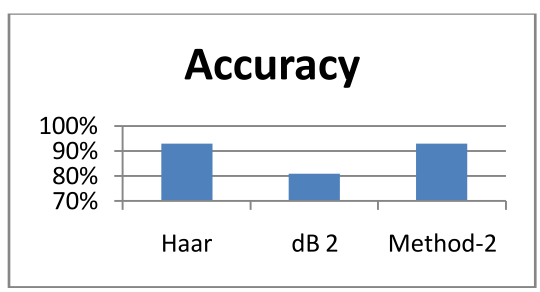


Fig.9.Performance analysis for various methods

IV. CONCLUSION & FUTURE WORK

The proposed method detects the micro calcifications successfully in digital mammograms. From the experimental results the proposed approach has higher classification accuracy than the ordinary techniques.

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