International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 07, July-2021

# Design of Mass Detection Algorithm using Hyper Analytical Wavelet Transform in Digital Mammography

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***Abstract*: Breast Cancer Diagnosis and Prognosis are two Medical applications that pose a great challenge to the researchers in Radiology and Computer Science. Digital Mammography plays a vital role for classifying tumors in breast cancer diagnosis. Wavelet transformation is one of the most effective mathematical tool for analyzing the mammograms. The proposed Mass Detection technique for detection of breast cancer using digital image processing and by using threshold CLAHE which can enhance the image, de-noise image the based on wavelet transformation. The result of this technique is ensured by the ability of different wavelet transform coefficients and filtering this coefficients will separate the unnecessary noise and give useful image. These coefficients are then calculated with 2D –Discrete wavelet transformation for different components and to compare 2D-DWT and Hyper Analytical wavelet transformation by using geometric feature extraction with Gabor filter for texture feature extraction in Segmentation. Feature Texture Analysis and automatic ROI(Region of Interest)using threshold OTSU algorithm for calculating texture measure of mammograms and mass density calculation based on texture measures and to calculate mass density based on the above features. Application of fuzzy c-means clustering the mass density based on distribution of pixels and to perform Circular transformation in detection of mass shape like round, oval, lobular and irregular shapes and to train Neuro- Fuzzy Classifier with mass features in comparison withedge detection algorithm and detect the tumors in an image..**

## 1.1 INTRODUCTION

The advancement in biomedical imaging has opened new doors towards. recognition of breast cancerby providing quantitative image substitutes. Various imaging modalities and their refinements have encompassed for the utilization of wavelets leading to methods for quantitatively analyze structural and functional deformalities in the breast image assessment methods there are based on adaptable computational techniques. The proposed Mass Detection technique for detection of breast cancer using digital image processing and by using threshold CLAHE which can enhance the image, image de-noises image the based on wavelet transformation. The result of this technique is ensured by the ability of different wavelet transform coefficients and filtering this coefficients will separate the unnecessary noise and give useful image calculate with 2D –Discrete wavelet transform for different components and to compare 2D-DWT and Hyper Analytical wavelettransform by using geometric feature extraction with Gabor filter for texture feature extraction in Segmentation Feature Texture Analysis and automatic ROI(Region of Interest)using threshold OTSU algorithm for calculating texture measure of mammograms and mass density calculation based on texture measures and to calculate mass density based on the above features. Application of fuzzy c-means clustering the mass density based on distribution of pixels and to perform Circular transformation in detection of mass shape, round ,oval ,lobular and irregular shape and to train neuro fuzzy classifier with mass features in comparison with edge detection algorithm and detect the tumors in an image.

## PROCESSIN MAMMOGRAM IMAGEANALYSIS

Digital mammograms are very useful in detecting micro-calcifications to diagnose breast cancer at an earlystage. Image Processing Technique such as contrast image enhancement, noise removal, segmentation, feature extraction, shape analysis can be done using digital mammograms.

### Wavelet Analysis of Mammogram Images

The given mammogram image is decomposed into multi-resolution hierarchy of localized information at different spatial frequencies. Multi-scale wavelet representation suggests a mathematical coherent basis not only for existing multi-grid techniques but also for exploiting non-linear systems. Multi resolution wavelet analysis provides a natural hierarchy in which the embedded programme provides an interactive paradigm for accomplishing scale-space feature analysis.

### Key Features of Wavelet Analysis of Mammogram

The generalized wavelet transformation algorithms proposed by Ebrahim Jelvehfard, Shradhananda,[3],[5] based on 2D-DWT has poor directionality, shift variance, absence of phase information which is serious drawbacks to make reliable or appropriate tool for the radiologist. The above existing drawbacks of the proposed of novel contribution in Hyper Wavelet transformation (HWT) increases better shift variance, good directionality enhancement and also maintains linear combination of coefficients details of four 2D –DWT sub bands which leads to the development of a reliable tool and help in critical decision making for the Radiologist in Breast cancer Diagnosis.

### 1.2.3. Hyper Analytical Transformation

The proposed Mass detection algorithm usingHyper Analytical Transformation follows:

International Journal of Engineering Research & Technology (IJERT)
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Vol. 10 Issue 07, July-2021

Fig. 1.1 Flowchart for Mass Detection

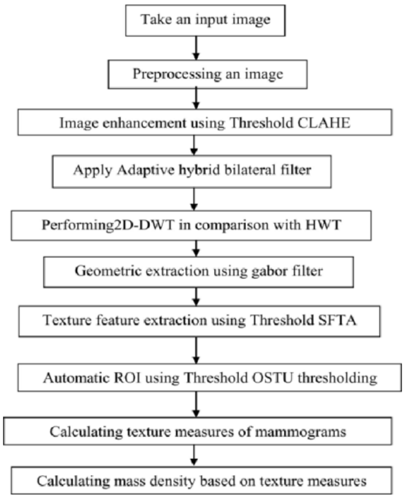
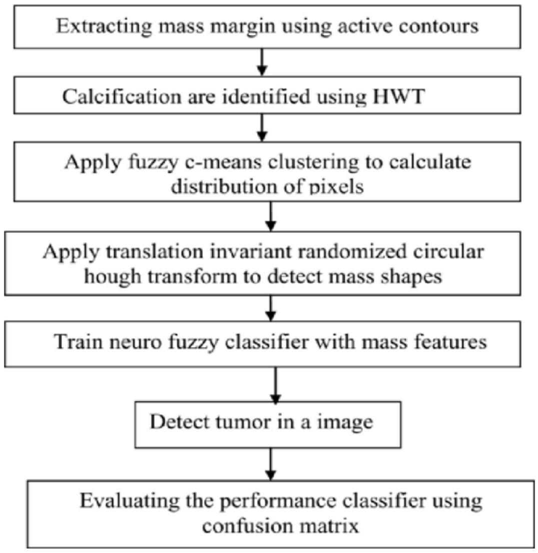



Fig. 1.2 Flowchart Calcification




## IMAGE PREPROCESSING

### Enhancement of Mammogram Image

Millions of pictures ranging from biomedical images to the image natural surroundings and activitiesenrich our daily visual experience. It is essential to increase dynamic features in the image to provide qualification images. Image adjustment is usually achieved by contrast enhancement using image histogram measures.

Mainly, image enhancement includes intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, etc. The task of mammogram enhancement is to sharpen the edges or boundaries of ROIs, or to increase the contrast between ROIs and background [1] [Balakumaran] et al. It is well-known that if a region differs in luminance from its surroundings by less than 2%, it is indistinguishable to human eye. Although micro calcifications are brighter than their surroundings, the contrast for some micro calcifications in a dense breast is quite low that cannot be detected by human eyes. The aim of contrast enhancement is to increase the contrast of microcalcifications over the threshold and help identify the minute microcalcifications.

The first step in the study of mammogram images image enhancement is denoising the image. The denoising technique should not affect or destroy information content in the image. The removal of background noise while preserving edge information of suspicious area in mammograms is the intended objective.

Various enhancement techniques viz., histogram equalization neigh-borhood based contrast enhancement algorithm, selective Median Filtering enhancement method based on multi scale analysis have been done enhancement of contrast of mammogram images.

### Contrast enhancement by using THRESHOLD CLAHE algorithm

The contrast-limited adaptive histogram equalization (CLAHE) produces images in which the noise content of an image is not enhanced, but in which sufficient contrast is provided for the visualization of structures within the image. Images processed with CLAHE have a more natural appearance and facilitate the comparison of different areas of an image. However,the reduced contrast enhancement of CLAHE may hinderthe ability of an observer to detect the presence of somesignificant gray-scale contrast.

Threshold CLAHE operates on small regions in the image, called ***tiles***, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image.

### Proposed Threshold CLAHE Algorithm

Threshold CLAHE method helps in increase ofglobal contrast of a image compared with histogramequalization method, The CLAHE method being anadaptive algorithm, works for multi resolution images **Objective:** Threshold CLAHE technique is applied onoriginal input mammogram to enhance the contrast.

**Algorithm:**

Step 1: Threshold CLAHE technique is applied on originalinput mammogram to improve the contrast.

Step2: Hyper analytical wavelet transform (HWT) is applied on the output obtained in the first step, then the segmentation at various scales (multi- resolution) to detect micro-calcifications and otherabnormalities.

Step 3: The proposed nonlinear complex diffusion based unsharp masking and crispening method is appliedon the enhanced mammogram

Step 4: The proposed modified threshold CLAHE basedimage segmentation is applied on mammograms obtained in step 3.

Threshold calculation Maxval = Maximum values

Num_bins = Number of histogram binsmu_t = Qumulative threshold value

Effectiveness metric of mammogram calculated by Em = maxval/(sum(p.*((1:num_bins).^2)') - mu_t^2);

So Effectiveness metric maybe used but for large scale processing of mammograms computational complexity may increase.

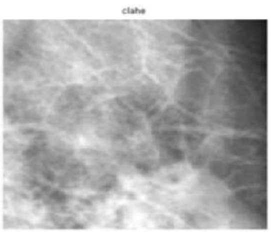


Figure: 1.3 Results Threshold CLAHE Algorithm

## Noise Modeling

The goal of denoising the image is to use appropriate techniques of refining the images so that the resultant image would have a better visual quality free from aberrations and noises.

## Noise Sources

Noise modeling in images is affected by capturing devices through data transmission media, image quantization and discrete source of radiation. The characteristics of noise depends on its source.

## Noise Removal based on wavelet transform

Wavelet transform plays an important role in biomedical image processing. Wavelets first introduced in medical imaging research in 1991in a journal paper describes an application of wavelet transforms for noise reduction in MRI images. A special issue of IEEE Transactions in Medical imaging, provides a large collection of most recent research work on wavelets in medical image processing.

## Proposed Noise Removal Algorithm:

1. Read the mammogram
2. By using preprocessing technique resize the image
3. Enhancing the image using Threshold CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm and compared with Histogram equalization and their performance.
4. Apply Mean and Median filters on the image for the removal of digitization noise to acquire the filtered image. Apply Adaptive hybrid Bilateral Filter to obtain the filtered image

## Calculating features of image

It is challenging process for researchers to eliminate noise from the noisy image to get the original image because it introduces artifacts (blurring ringing effect staircase effect and checkerboard effect) in the images.

It is very important to identify the noise present in the image to select appropriate denoising algorithm. If the image is corrupted with salt and pepper noise the filtering methods perform better. The wavelet based approach is useful if the image corrupted with Gaussian noise. So the denoising algorithm is application dependent. The image denoising algorithms can be broadly classified into spatial domain filtering methods and Transform domain filtering methods.

Traditional Smoothing Filters such as Mean, Median Filters are normally employed on spatial domain. Various enhancement techniques, viz., histogram equalization, neighborhood based contrast enhancement algorithm, selective Median filtering enhancement method based on multi scale analysis etc. may be used for enhancing the contrast of mammogram images. Mammographic image utilizes a narrow range of gray levels, without a well-defined histogram structure. Thus the conventional histogram equalization techniques may not be suitable in enhancing the mammogram images.

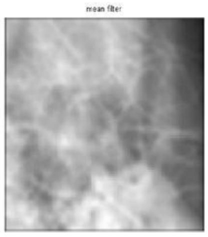
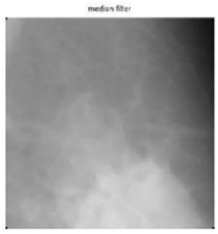


Figure: 1.4 Mean Filter



Median Filter

| | Standard deviation Sigma=5 | | Standard deviation Sigma=10 | | Standard deviation Sigma=15 | | Standard deviation Sigma=20 | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | MSE | PSNR | MSE | PSNR | MSE | PSNR | MSE |
| Noisy image | 24.89 | 7.69 | 25.66 | 7.36 | 25.98 | 7.13 | 26.39 | 7.01 |
| DWT | 26.36 | 6.99 | 26.74 | 6.63 | 26.83 | 6.22 | 27.06 | 6.03 |
| HWT | 27.36 | 5.19 | 27.43 | 4.97 | 27.52 | 4.86 | 27.96 | 4.63 |

The wavelet transformations are characterized by two features the Mother wavelet MW and primary resolution PR number iterations. An appealing particularity of the 2D is the inter scale dependency of the wavelet coefficients. The main advantage of the implementation of 2D DWT is its flexibility as it inherits from ID DWT, Daubechies, Symmlet or Coiflet family.

## Adaptive hybrid bilateral filter

The main advantage of the classical bilateral filtering method is that it considers both the spatial locality and neighboring points with similar amplitudes at the same time which make it can better preserving the image edges and textures than the conventional linear filtering algorithms.

We propose the Adaptive hybrid bilateral filter that smoothes the pictures by conserving the edges, suggests a nonlinear combination of close image values. Although bilateral filtering may be a nonlinear technique it's non-iterative, 'local' and straightforward. The nonlinearity arises attributes to the nonlinear relationship of picture element values of a picture. Our proposed bilateral filters comprise of 2 element filters: a domain filter and a variety filter. Domain filter element refers to the normal low-pass filter that provide average values of the image. The implementation of the domain filter utilizes a Gaussian blur kernel for filter weights. This adaptive quality is illustrated within the figures below. Bilateral filter is the resultant product of the domain and vary filters, which ends in an averaging of image pixels supported specially and measures closeness. This is often the central plan underlying the bilateral filtering interpolation technique.

Later we apply smoothing process to the pixels that are a unit in shut geometric proximity having similar contents. Thus, it can be assumed to safe the average over shut pixels. However, this central plan breaks down at the 'edges' of a picture. During this context, 'edges' ask those points on a picture wherever there are unit discontinuities or sharp contrasts between pixels content and its immediate neigh bur. The bilateral filter accounts for the sides by weight pixels supported their

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 07, July-2021

photometrical similarity additionally to geometricproximity.

**Proposed Adaptive Hybrid Bilateral Filter**

Step1:pre-compute Gaussian distance Exp (-(x^2+y^2)/2*sigma_d^2)

Step2: Apply Bilateral Filter having threshold as max.limit.

Step3: Extract the local Region

Step4: Compute Gaussian intensity weight H=exp (-(I-(A (ii, j) ^ 2/2*Sigma_r^2)

Step5: Calculate filter Response

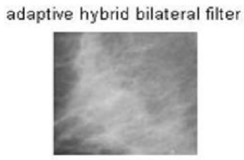



**Figure: 1.5 results of Adaptive hybrid Bilateral Filter**

**Performance criteria**

The Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are the two metrics used to compare image processing (denoising) quality. The MSE represents the cumulative squared error between the denoised and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the higher is value of the PSNR. The Mean Square Error (MSE) is calculated by using the followingequation 1.1,

$$MSE = \sum_{m=1,n=1}^{M,N} \frac{\left|I_0(m,n) - I_i(m,n)\right|^2}{M.N} \quad (1.1)$$

Where $I_i$ is input, noise free image $I_o$ is the output image may be noisy or denoised and M, N are the number of rows and columns of the image respectively.

Then, the Peak Signal to Noise Ratio (PSNR) isbeing computed using the following equation 1.2

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right) \quad (1.2)$$

Where, $R$ is the maximum fluctuation in the inputimage data type. For example, if the input image has a double-precision floating-point data type, then $R$ is 1. Ifit has an 8-bit unsigned integer data type, $R$ is 255, and so on.

Root mean square error is computed to measure the image enhancement Application.

$$RMSE = \sqrt{\sum_{m=1,n=1}^{M,N} \frac{\left|I_0(m,n) - I_i(m,n)\right|^2}{M.N}} \quad (1.3)$$

Equivalent number of looks computed to measure the image enhancement Application.

$$ENL = \frac{(NMV)^2}{(NSD)^2} \quad (1.4)$$

Table 1.1 Performance of Mean, Median, AdaptiveHybrid Bilateral Filters

| | Mean filter | Median filter | Adaptive hybrid bilateral filter |
|---|---|---|---|
| MSE | 20.5 | 18.2 | 16.3 |
| PSNR | 55 | 58 | 60 |
| RMSE | 7.75 | 1.0833 | 0.2039 |
| Enl | 0.0033 | 0.0021 | 1.198 |

Adaptive Bilateral smoothes pictures whereas conserving edges suggests nonlinear combination of close image values. Our proposed bilateral filter comprises of two element filters, a dominant filter and avariety filter.

Bilateral Filter is the product of domain and a varietyfilter**.**

It is observed that using Adaptive Bilateral filter which increases the PSNR value and decreases the MSE

.ENL equivalent number of looks one of the good approach estimating speckle noise levels, is to measure ENL over uniform image region. Larger value of ENL corresponds to better suppression of speckle. The valueof ENL also depends on the size of tested region.

**2D –DWT based thresholding**

The wavelet transformations are characterized by two features the Mother wavelet MW and primary resolution PR number iterations. An appealing particularity of the 2D is the inter scale dependency of the wavelet coefficients. The main advantage of the implementation of 2D DWT is its flexibility as it inheritsfrom ID DWT, Daubechies, Symmlet or Coiflet family.

Discrete wavelet transform (DWT) for an image as a 2-D signal can be derived from 1-D wavelet trans- form. The easiest way to get the 2-D scale and wavelet function is multiplying two 1-D functions. The 2-D scale function is achieved by multiplying two scale functions as below

$\emptyset(x, y) = \emptyset(x)\,\emptyset(y)$2-D

wavelet functions are accomplished by multi-plying two wavelet functions or scale and wavelet func-tions.

The implementation of an analysis filter bank for a single level 2-D DWT is shown in figure. This struc- ture produces three detailed sub-images (HL, HL, HH) corresponding to three different directional-orientations (Horizontal, Vertical and Diagonal) and a lower resolu-tion sub-image LL. The filter bank structure can be iter-ated in a similar manner on the LL channel to provide multilevel decomposition.

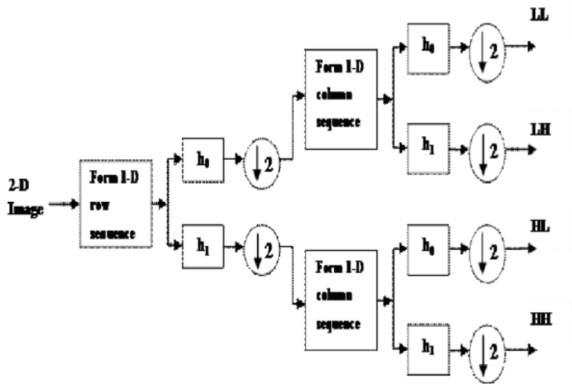



Figure: 1.6 Single level analysis filter bank for 2-DDWT

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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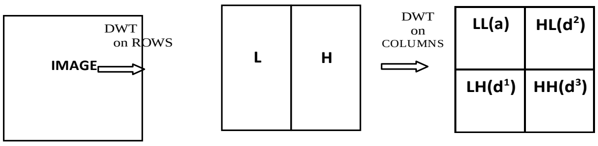



**Figure: 1.7 Block Diagram of DWT (a) OriginalImage (b) Output image after the 1-D applied on Rowinput (c) Output image after the second 1-D applied on column input**

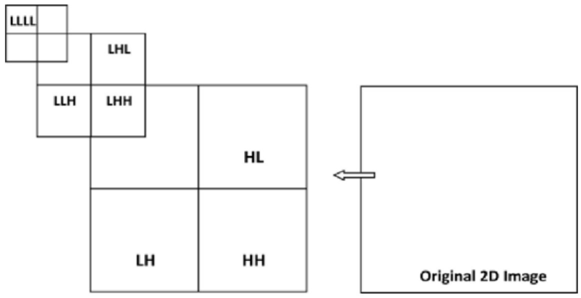



**Figure: 1.8 Multilevel decomposition hierarchyof an image with 2-D DWT**

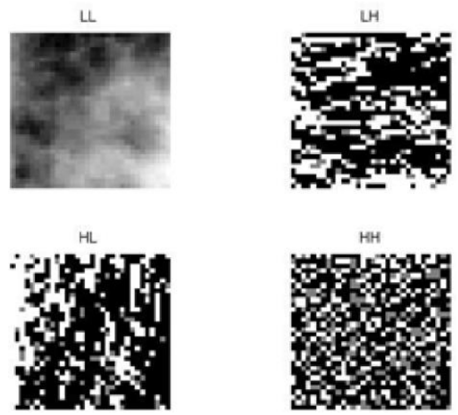



**Figure: 1.9 Results illustrating 2D DWT waveletdecomposition**

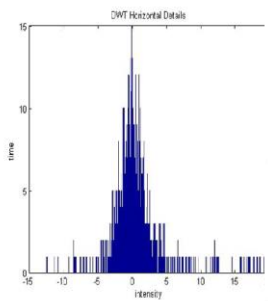



**Figure: 1.10 2D-DWT horizontal details**

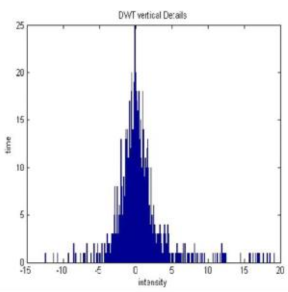



**Figure: 1.11 2D-DWT vertical details**

The main disadvantage of 2D DWT are the poor directional selectivity and shift sensitivity. Separable filtering along the rows and columns of the image produces four images at each level. The LH and HL band pass sub-images can select mainly horizontal and vertical edges respectively but the HH sub-image components from diagonal features of either orientation.

### Hyper Analytical Wavelet Transform

These can be overcome by introducing one of the following analytical wavelet transform called Hyper analytic wavelet transform.

The Merits of Hyper Analytical Wavelet transformation mentioned in Section 4.3.2.3.With the assumption of ideal high – pass filter, the spectra of wavelet coefficients $d_1$, $d_2$, $d_3$, and $d_3$, belonging to the sub – band HH, denoted by $F\{DWT_{HH}\{\delta(x,y)\}\}$, $F\{DWT_{HH}\{H_x\{\delta(x,y)\}\}\}$, $F\{DWT_{HH}\{H_y\{\delta(x,y)\}\}\}$ and $F\{DWT_{HH}\{H_y\{H_x\{\delta(x,y)\}\}\}\}$, are evolved. These spectral coefficients have two perfect orientations, corresponding to the two diagonals $\pm\frac{\pi}{4}$. These directions are the result of the fact that 2D DWT cannot separate these two orientations.

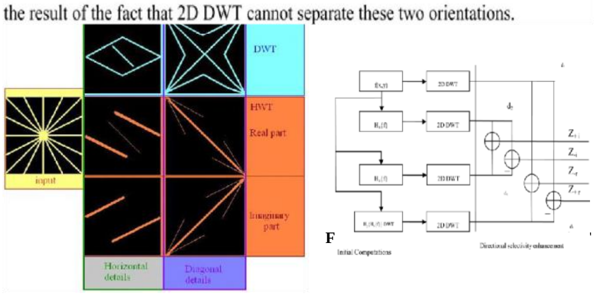



**Figure : 1.12 The absolute values of the spectra of horizontal and diagonaldetail sub images obtained after the first iterations of 2D DWT and HWT.In the HWT case, the real and imaginary parts of complex coefficients are separated**

After the linear combinations, we can observe that the spectra of the coefficients so obtained, for example, $Z_{R-}$ and $Z_{R+}$, $F\{HH_{Z_{R-}}\}(f_x,f_y)$ and $F\{HH_{Z_{R+}}\}(f_x,f_y)$, have only one preferential direction, namely the second diagonal, respectively the first one. In conclusion, by using the HWT these directions can be separated. The same strategy can be used to enhance the directional selectivity in the other two sub–bands: LH and HL, obtaining the preferential orientations at $\pm Tan^{-1}(2)$ and $\pm Tan^{-1}\left(\frac{1}{2}\right)$. A comparison of the directional selectivity of the 2D DWT and HWT, implemented as proposed in figure 4.4. Here, a special input image is considered to conduct simulation. Its spectrum is oriented in the following directions: 0, $\pm Tan^{-1}\left(\frac{1}{2}\right)$, $\pm\frac{\pi}{4}$, $\pm Tan^{-1}(2)$ and $\pi$.

From Fig 1.1.3

$$Z_{R+} = detailcoefficients(DWT\{f(x,y)\} - DWT\{H_x\{H_y\{f(x,y)\}\}\})$$

$$Z_{R-} = detailcoefficients(DWT\{f(x,y)\} + DWT\{H_x\{H_y\{f(x,y)\}\}\})$$

$$Z_{I+} = detailcoefficients(DWT\{H_x\{f(x,y)\}\} + DWT\{H_y\{f(x,y)\}\})$$

$$Z_{I-} = detailcoefficients(DWT\{H_x\{f(x,y)\}\} - DWT\{H_y\{f(x,y)\}\}) \quad \ldots(1.5)$$

$$Z_R = Z_{R+} + jZ_{R-}$$

$$Z_I = Z_{I+} + jZ_{I-} \quad \ldots(1.6)$$

The coefficients of $Z_{R+}$ and $Z_{I+}$ are oriented only in the positive directions such as, $Tan^{-1}\left(\frac{1}{2}\right)$, $\frac{\pi}{4}$ and $Tan^{-1}(2)$ for horizontal($\pm 26.56^0$), diagonal($\pm 45^0$) and vertical($\pm 63.44^0$)l details respectively, and The coefficients of $Z_{R-}$ and $Z_{I-}$ are oriented only in the negative directions such as, $Tan^{-1}\left(\frac{1}{2}\right)$, $\frac{\pi}{4}$ and $Tan^{-1}(2)$ for horizontal, diagonal and vertical details respectively. The preferred directions of HWT are summarized

| Coefficients Sub-bands | $Z_R+$ | $Z_R-$ | $Z_I+$ | $Z_I-$ |
|---|---|---|---|---|
| LH (horizontal) | $Tan^{-1}\left(\frac{1}{2}\right)$ | $-Tan^{-1}\left(\frac{1}{2}\right)$ | $Tan^{-1}\left(\frac{1}{2}\right)$ | $-Tan^{-1}\left(\frac{1}{2}\right)$ |
| HL (vertical) | $Tan^{-1}(2)$ | $-Tan^{-1}(2)$ | $Tan^{-1}(2)$ | $-Tan^{-1}(2)$ |
| HH (diagonal) | $\frac{\pi}{4}$ | $-\frac{\pi}{4}$ | $\frac{\pi}{4}$ | $-\frac{\pi}{4}$ |

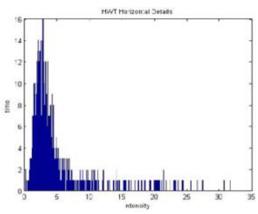


**Figure: 1.14 HWT horizontal details**

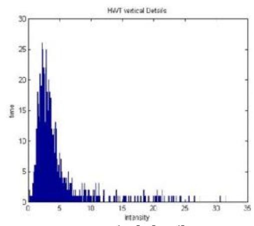


**Figure: 1.15 HWT vertical details**

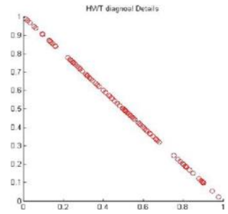


**Figure: 1.16 HWT diagonal details**

## Table 1.4 Preferred directions of HWT

| Coefficients Sub-bands | $Z_{R+}$ | $Z_{R-}$ | $Z_{I+}$ | $Z_{I-}$ |
|---|---|---|---|---|
| LH (horizontal) | $Tan^{-1}\left(\frac{1}{2}\right)$ | $-Tan^{-1}\left(\frac{1}{2}\right)$ | $Tan^{-1}\left(\frac{1}{2}\right)$ | $-Tan^{-1}\left(\frac{1}{2}\right)$ |
| HL (vertical) | $Tan^{-1}(2)$ | $-Tan^{-1}(2)$ | $Tan^{-1}(2)$ | $-Tan^{-1}(2)$ |
| HH (diagonal) | $\frac{\pi}{4}$ | $-\frac{\pi}{4}$ | $\frac{\pi}{4}$ | $-\frac{\pi}{4}$ |

The HWT implemented has preferential directions: $\pm Tan^{-1}\left(\frac{1}{2}\right)$, $\pm\frac{\pi}{4}$ and $\pm Tan^{-1}(2)$. The two – dimensional Discrete Wavelet Transform (2D – DWT) has only three preferential directions: $0$, $\frac{\pi}{4}$ and $\frac{\pi}{2}$, it does not make the difference between the two principal diagonals. The better directional selectivity of the proposed implementation of HWT versus the 2D DWT can be easily observed, comparing the corresponding detail sub–images. For the diagonal detail sub-images, for example, the imaginary part of the HWT rejects the directions: $-Tan^{-1}\left(\frac{1}{2}\right)$, $-\frac{\pi}{4}$ and $-Tan^{-1}(2)$, whereas the 2D DWT conserves these directions.

## Advantages of HWT

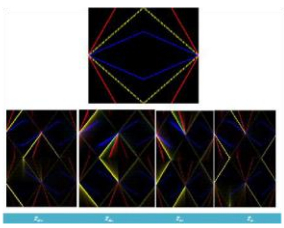


**Figure: 1.17 Illustrations of directional coeffiecients of HWT**

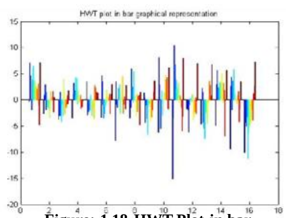


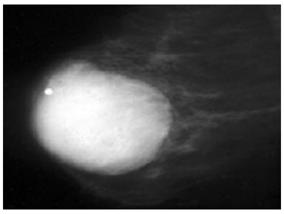
**Figure: 1.18 HWT Plot in bar graphical representation**

## MASS shape calculation

### Table 1.5: Performance evaluation of mass shape

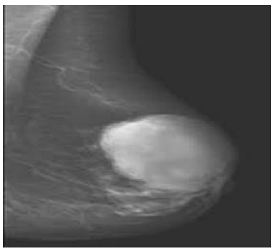
| Image Samples | Mam1 | Mam2 | Mam3 | Mam3 | Mam5 |
|---|---|---|---|---|---|
| Area | 5 | 8 | 6 | 9 | 5 |
| Perimeter | 189 | 177 | 169 | 188 | 192 |
| Max radius | 121.73 | 101.36 | 136.90 | 119.61 | 122.01 |
| Min.radius | 3.753 | 3.188 | 3.999 | 3.333 | 5.021 |
| Eccentricity | 9.933 | 9.633 | 8.933 | 7.933 | 9.996 |
| Equivdiameter | 2.256 | 2.566 | 1.255 | 2.666 | 2.996 |
| Eelongatedness | 1.812 | 1.916 | 2.762 | 2.832 | 2.976 |
| Entropy | 9.998 | 9.118 | 8.298 | 9.971 | 8.889 |
| Circularity1 | 3.296 | 3.299 | 3.796 | 3.299 | 3.797 |
| Circularity 2 | 1.976 | 1.763 | 2.977 | 2.976 | 1.666 |
| Compactness | 0.0329 | 0.035 | 0.066 | 0.053 | 0.033 |
| Dispersion | 23.33 | 22.86 | 21.55 | 23.09 | 23.66 |
| Thinness | 3290 | 3100 | 2920 | 3085 | 3211 |
| Standard Deviation | 0.123 | 0.133 | 0.167 | 0.183 | 0.133 |

The below represented mammographic image namely mass shape round, oval, lobular, and irregular are appropriately proposed in calculation of texture measures mass for the mammogram images.



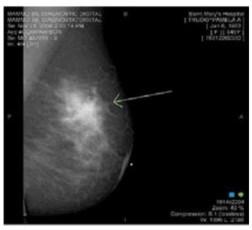
**Mass Shape Round Mammogram**

**Result For Round Mammo**

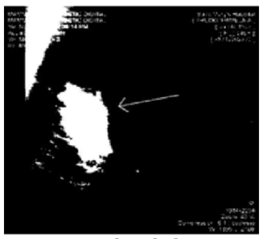


**Mass Shape Oval Mammogram**

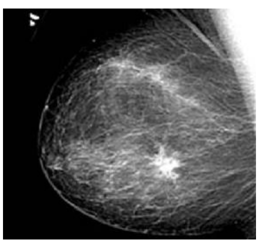
**Oval Mammogram Result**



**Lobular Mammogram**



**Result Lobular Mammogram**



**Irregular Mammogram**

**Result For Irregular Mammogram**

**Mass Density Clasification Using Texture Measures**

**Table 1.6 : Texture measures mass density for the mammogram images**

| Image Samples | Average Intensity | Standard Deviation | Entropy | Smoothness | Third Moment | Uniformity |
|---|---|---|---|---|---|---|
| Mam1 | 23.6300 | 3.3189 | 5.8317 | 0.9168 | 2.8595 | 0.5309 |
| Mam2 | 33.1200 | 13.9318 | 6.6575 | 0.9955 | 0.8633 | 0.2177 |
| Mam3 | 27.3300 | 10.3903 | 7.0973 | 0.9908 | 1.9011 | 0.2527 |
| Mam3 | 32.0800 | 5.8133 | 7.3255 | 0.9713 | 5.7375 | 0.1537 |
| Mam5 | 33.3800 | 2.8373 | 5.5573 | 0.8895 | 2.3276 | 0.5803 |
| Mam6 | 15.3600 | 5.3993 | 6.7259 | 0.9668 | 1.0066 | 0.2673 |
| Mam7 | 22.2300 | 8.5673 | 6.0523 | 0.9866 | 2.0387 | 0.3637 |
| Mam8 | 18.1600 | 2.5137 | 5.3763 | 0.8633 | 2.8109 | 0.3639 |
| Mam9 | 22.3000 | 12.3672 | 6.5677 | 0.9935 | 2.2260 | 0.2738 |
| Mam10 | 33.2300 | 3.5868 | 5.8397 | 0.9536 | 2.7132 | 0.5527 |

**Table 1.7 Classification of mammogram images basedon texture features**

| Texture features → / Tissue categories | Average Intensity | Average Contrast | Smoothness | Third Moment | Uniformity | Entropy |
|---|---|---|---|---|---|---|
| Uncompressed Fatty tissue | 40.2 | 44.03 | 0.021 | 0.37 | 0.82 | 4.4888 |
| Fatty tissue | 63.85 | 67.21 | 0.0672 | 1.28 | 0.33 | 2.8 |
| Non uniform tissue | 57 | 81.83 | 0.05 | 7.6 | 0.21 | 3.2 |
| High density Tissue | 49 | 68 | 0.047 | 4.2 | 0.41 | 3.1 |

**CLASSIFICATIONUSINGNEURO FUZZY**

In the field of artificial intelligence, **neuro-fuzzy**refers to combinations of artificial neural networks andfuzzy logic.

The authors [38], [116], proposed various methodsbased on 2D Wavelet Discrete wavelet transform which considers horizontal and vertical edges neglecting diagonal edges leading to inappropriate diagnosis as it does not take microcalcification which are present in diagonals into consideration.

The proposed mass detection algorithm focus on enhancing shift variance and directional selectivity.

The enhancement of the directional selectivity of the HWT is made through linear combinations of detail coefficients belonging to each sub – band of each of thefour 2D – DWTs.

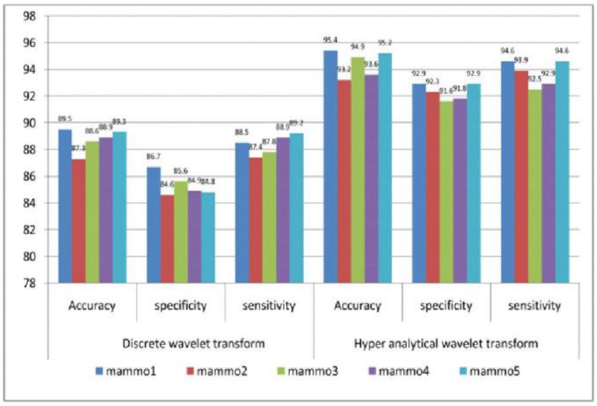
**1.5. EVALUATION OFPROPOSEDFUZZYRULE**

**Table 1.8 Evaluation of proposed fuzzy rule**

| Mass type | No. of rules | Rule depth | Features used by rules | Classification using Fuzzy Rules (%) |
|---|---|---|---|---|
| I,O | 8 | 1 | En, Esd, Rmax, SI, SD, Dp | 96.99 |
| I,L | 8 | 1 | Entpy, En, Rmin, Peri, CN, C2, SI | 93.06 |
| I,R | 2 | 3 | Peri, En | 93.09 |
| O,R | 2 | 3 | CN, ECT, Rmin,C2,Area,Peri | 98.63 |
| L,O | 3 | 1 | Dp, Area, Rmin | 95.06 |
| L,R | 3Ta | 1 | Peri, C2 | 95.45 |
| I,L,R | 6 | 1 | Eqd, SD, Rmin, CN, ECT | 94.36 |
| I,L,O | 12 | 1 | Esd,CN,Entpy,SD,DP,ECT, SI,C2,Area | 93.99 |
| L,O,R | 6 | 1 | Peri,Rmin,DP,EULN | 86.03 |
| I,O,R | 8 | 1 | SD,Peri,En,Rmax,EULN,CN,DP, Area | 89.33 |
| I,L,O,R | 12 | 6 | Esd,Rmin,CN,En,SI | 88.36 |
| I,L,O,R | 2 | 8 | Esd,Rmin,CN,SI,En | 93.06 |

**Table 1.9 Evaluation of 2D-DWTAND HWT**

| | Discrete wavelet transform | | | Hyper analytical wavelet transform | | |
|---|---|---|---|---|---|---|
| | Accuracy | Specificity | Sensitivity | Accuracy | specificity | sensitivity |
| Mammo1 | 89.5 | 86.7 | 88.5 | 95.4 | 92.9 | 94.6 |
| Mammo2 | 87.3 | 84.6 | 87.4 | 93.2 | 92.3 | 93.9 |
| Mammo3 | 88.6 | 85.6 | 87.8 | 94.9 | 91.6 | 92.5 |
| Mammo4 | 88.9 | 84.9 | 88.9 | 93.6 | 91.8 | 92.9 |
| Mammo5 | 89.3 | 84.8 | 89.2 | 95.2 | 92.9 | 94.6 |




## 1. 6. CONCLUSION

The proposed Mass Detection Technique for breast cancer using digital image processing and using threshold CLAHE algorithm which can lead to an enhanced image calculated with 2D DWT for different components and to compare 2D DWT and HWT using geometric extraction with gabor filter for texture feature extraction in SFTA (Segmentation Feature Texture Analysis ) and automatic ROI using OTSU thresholding for calculating texture measure of mammograms and mass density calculation using the above features. Applying fuzzy c-means clustering in mass density based on distribution of pixels and to apply circular transform to detect mass shape, and to train neuro fuzzy classifier with mass features pave way for fruitful results in the detection of tumors comparison to edge detection algorithm.

Finally the experiment results show that the proposed methodology of mass detection algorithm to maintain optimum diagnosis to enhance accuracy improve the poor directionality and selectivity for massdetection. This helps in the early detection of breast cancer that leads to premature control and disclose manypossible solutions.

## 1.7. REFERENCES

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