DETECTION OF MICROCALCIFICATION CLUSTERS USING STATISTICAL PARAMETERS AND DYADIC CONTOURLET TRANSFORM BASED PRECISION ENHANCEMENT

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Abstract—Recent scenario, breast cancer found to be a threat and dangerous carcinoma among women in the world. In contemplation of reducing the breast, cancer-related death needs an efficient computer-aided diagnosis (CAD) system. The discrimination of microcalcification clusters (MCCs) is an important manifestation for the early diagnosis of breast cancer. This paper focuses on the detection of breast cancers cells size below 2mm. To achieve précised enhanced cancer cell region an efficient technique dyadic Counterlet transform (DCTs) in two dimension is proposed. The enhancement of cancer cell region obtained through preserving the boundaries and borders with curvature for a small region.

Keywords —Breast cancer, Mammography, Microcalcification Clusters, Wavelet Transform, Dyadic Contourlet transform.

I. INTRODUCTION

Breast cancer yet exists to be noteworthy public health issues in the world. Breast cancer causes more mortality amid women, substantially in developed and underdeveloped countries. Report evaluation of the World Health Organization's International Agency for Research on Cancer (IARC) in Lyon France, says innumerable women die each year worldwide of breast cancer. In 2016 IARC organized Breast Cancer Awareness month, reports state deaths statistics in females, due to breast cancer around 521 907 worldwide in 2012 of which 231,013 in Asia.[1] In American women, breast cancers were found in one among three cancers found. During 2016, the American Cancer Society of United States assessed new cases of 2, 46, 660 invasive breast cancer, 61,000 new cases of carcinoma breast cancer (non-invasive and is the earliest form of breast cancer), diagnosed in women, and 40,450 mortality of women from breast cancer. [2] Breast cancer accounts for 23% of all the female cancers in the cities like Mumbai, Calcutta, and Bangalore in India.. Nevertheless, cervical cancer remains the number one in rural India.[3] Although the prevalence is lower in India than in the developed countries, the threat of breast cancer in India is alarming. Organ chlorines considered as a conceivable reason for hormone-dependent cancers Breast cancer normally develops from breast cells. It develops in the inner layer of milk ducts or the lobules, the milk-producing glands. A malignant tumor can escalate to different parts of the body. Lobular carcinoma breast cancer develops in lobules, another ductal carcinoma in the ducts.

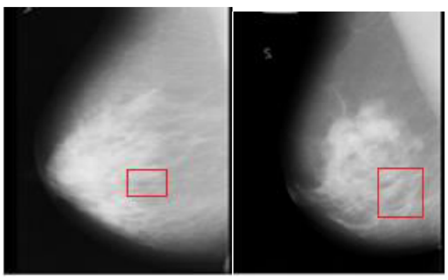

Fig.1.Normal Breast Mammogram (left) and Cancerous breast Mammogram (right). Areas in red marked boxes are suspicious mass regions.

Breast cancer spreads in two different ways, invasive (spreading) or noninvasive (non-spreading).Invasive cancer or Malignant can spread outside the breast or in other parts of the body by penetrating the wall of a duct. This is the most common type of cancer found in 80% of cases. Other invasive lobular carcinoma spread along with the hem of a lobule reports about 10% of all breast cancer. [4] This type probably appears in both the breasts, unlike other types of cancer. Noninvasive cancer is an abnormal cell that spread inside the breast lobules or ducts known as Benign. It will not spread outside the breast. In most cases, it can be easily removed, and will not come back..

Though diagnosis of breast cancer is a challenging task, there is wide use of mammography screening, and early-stage diagnosis of breast cancer could significantly reduce its morbidity and mortality. Mammography is done with an X-ray picture of the breast to examine abnormal tissue, e.g., benign or malignant masses. X-ray images that are different from normal tissue and mass tissue have shaped as circumscribed, speculated, and lobulated. Lack of expertise comment by radiologists and image quality affects the screening interpretation, which results in error-prone decision-making on the diagnosis of breast cancer. A recent study [a], reported, through routine screening, 30 percent misinterpretation of lesions takes place. Computer-aided diagnosis (CAD) can portray as clinical support in detecting abnormality in mammogram [5] [6]. In past decades studies show that CAD screening mammograms can boost the detection rate of initial-stage malignancies [7] [8]. Numerous CAD techniques have been lodged for mammography and captured the attention of computer scientists and radiologists [9] [10] [11] [12]. Most of them focused on detection, classification, and mass segmentation [13] [14] [15] [16] [17]. Others paid close heed to the detection of microcalcifications (MCs) and the classification of MC patterns [18] [19]. Despite the boosted detection rate, CAD systems generally usually lead to excessive false positives in malignant, which would adversely affect the clinical analysis. Recent years, researchers became increasingly interested in implementing Content-Based Image Retrieval (CBIR) [20] techniques to medical images [21] [22] [23] [24] [25].

II. RELATED RESEARCH

Luqman Mahmood Mina et al., [26] Following image pre-processing and image pruning, a Discrete Wavelet Transform (DWT) implied for feature extraction and image selection ahead of classification of the abnormal breast tissues into mass and microcalcification. Wavelet transform is a major mathematical tool used in CAD system for image processing. The Wavelet analysis is carried out with a mother wavelet to an image which decomposes the image into four quadrants with interpretations denoted as LL, LH, HL, HH blocks carrying coefficients. Because of the local similarities between neighboring pixels, several coefficients in the LH,HL,HH sub bands at different scales will be small and LL concentrate most of the image energy used for further decomposition. However, complete process finds difficult in searching the best block to fill to implement edge orientation. Because of this PSNR value goes low and the tumor below 2mm is difficult to locate.

Manas Saha et al, [27] introduces the Curvelet Transform of two dimensional waveform located in the spatial and frequency domains, it is also associated with proper orientation. In two dimensions the Curvelet provides the best sparse representation of singularities which are supported on C2 (twice continuously differentiable) curves. The digital Curvelet transform is popular as the Fast Discrete Curvelet Transform (FDCT) is simple, robust and based on frequency partitioning technique. Result shows the mammogram is denoised by the Curvelet transform in two different ways. Firstly, the Curvelet transform based on the conventional technique, HT is deployed for noise filtration. Secondly, the Curvelet transform based on the information of the neighboring coefficients - DRT, DCT and BCT have been used for noise removal and comparison with HT. The Curvelet Transform performs similar to the wavelet transform but with an additional feature of concentrating on curve edges and give better results. The main drawback on this system is that the directional specificity of the image is poor due to the fact the efficiency of the system is poor on comparing with the advanced systems.

Initially the Curvelet transform introduced by Candes and Donoho [28].DongfengGuo, et al., [29]. Proposed the characteristics of multi-resolution and multi-direction decomposition about Contourlet transform, by comparing with the wavelet transform, the advantages of Contourlet transform are introduced. This paper also talks the principle of threshold denoising, and put forward a new kind method of multi-threshold image denoising. The results shows image denoising method better than wavelet transform image and denoising effect is good, and this method is simple on calculation with fast speed Michael Unser, et al., [20] Described features of multi-band basic decomposition level of dyadic transformation is very simple to implement.

Hui Fan, et al., [31] proposed an image denoising algorithm based on dyadic Contourlet transform deploying the feature of NSCT translation invariance which can apply multi resolution, multi-direction transform, as per the energy of NSCT in all directions and in all scale adaptive denoising threshold. Experimental results show that compared to wavelet denoising and traditional Contourlet denoising, the method attains a higher PSNR value, while conserving image edge details, can effectively reduce the Gibbs distortion.

Yi Qin, et al., Utilized [32] a dyadic wavelet transforms with a dense time-frequency grid. The wavelet coefficients in an arbitrary scale in the proposed transform with respect to the reference signal produce the shift-invariance and next create the coefficients at a particular scale via demodulation and spectral analysis. Based on higher-density DWT explained the higher-density dyadic wavelet transform, discussed the possibility of its perfect reconstruction, and propose a fast decomposition and reconstruction algorithm based on the cascade filter scheme. The shift-invariance of the proposed transform was varified with unit step functions, and the higher-density DWT doesn't have this function. The proposed transform executed two denoising experiments and some other common wavelet transforms and resulted that the higher-density dyadic wavelet transforms have better denoising performance.

Besides, the higher-density dyadic wavelet transforms having intermediate scale, accomplish an excellent division of the frequency band of the signal, which improves the accuracy of mechanical fault diagnosis. But when the redundant wavelet transforms proposed samples to the time-frequency plane at a higher density, the redundancy increases, then the complexity of computation increases along in addition. This is the important drawback of the proposed transform.

E. Malar, et al., [34] presented the comparative analysis of Wavelet, Curvelet, and Contourlet based methods in digital mammogram denoising were performed. The experimental results show that the denoising based on curvelet gives a better performance as compared to wavelet and contourlet to most noises.

III.PROPOSED METHOD

This paper focuses on detection breast cancer cell region through dyadic wavelet transform to enhance the calcium deposits known as MCCs appears as a group of bright granular spots in very tiny size below 0.2mm in a mammogram. The enhancement of cancer cell region obtained through preserving the boundaries and borders with curvature for small regions less than0.2mm.

A. Problem Definition

Tiny circular objects appear, described as irregular, granular or linear and can vary in size from 0.1mm to 1mm having an average diameter about 0.3mm. Small MCCs ranging from 0 to 0.2mm can hardly see on the mammogram due to their overlapping on the breast parenchyma texture and noise. MCCs often appear in an inhomogeneous background describing the structure of a breast tissue. Some parts of the background have features such that the dense tissues may be brighter than the MCCs in the fatty tissue. Some MCCs have low contrast compared to their backgrounds such as breast tissues, blood vessels, mammary glands, and fat. In other words, the intensity and size of the MCCs can be very close to noise or an inhomogeneous background. Thus, the masses and MCCs are relatively difficult to detect and can be overlooked by radiologists in mammography screening.

B. Overview of Proposed System

On observing the specialties involved with the above transformations, Dyadic Contourlet Transform is an extended curvelet transform that can solve the problems of the existing systems. This system provides absence of redundancy for the analysis of subjects. The proposed method is suitable especially for the images with minute calcification below 0. 2mm also it can emphasize the calcification. We have select 70 images as random for classification from the MIAS data base. The number of microcalcification images in the MIAS database is 25. Two-third of total images were used for testing purpose.

Skew and Kurtosis are the measures of the shape and the width of the histogram obtained at the output. The skew symmetry explains which side of the distribution has longer tail and depends on that it can explain the nature of skew whether it is positive or negative otherwise equally distributed. The value observed above 2 is concluded as detection identification. The mean, median and mode describes the right or left aligned skew. Generally the shape of the histogram defines the value of the skew fig.2.

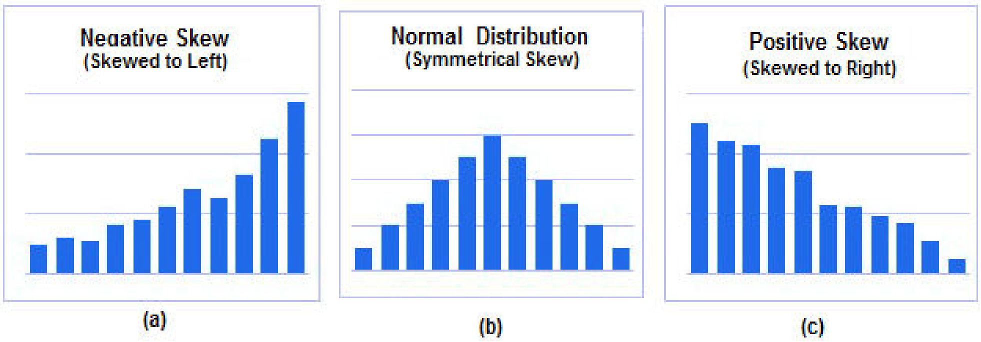

Fig.2

Mathematically, skew is usually measured by the third standardized moment

$$E\left(\left((X-\mu)/\sigma\right)^3\right)$$

where X is a random variable with mean $\mu$and standard deviation σ. Kurtosis is a measure for the width of the distribution found. It is also the measure of sharepeness. The normal value is upto15.If it is greater it is concluded as cancer. The distribution types defined are Leptokurtic, Mesokurtic and Platykurtic.

$$\text{Population kurtosis} = \frac{\sum f(X-\mu)^4 / (N)}{\sigma^4}$$

C. Dyadic Contourlet transformation

The dyadic transformation is also called as a dyadic map, double map, or bit shift map develops the relation of the recurrence by the rule. It is also called an iterated function map over the piecewise linear function. The Wavelet base function is a narrow band pass filter that conserves energy ahead and later during transformation. Dyadic transform is continuous in time and space domain but the scales are discrete.

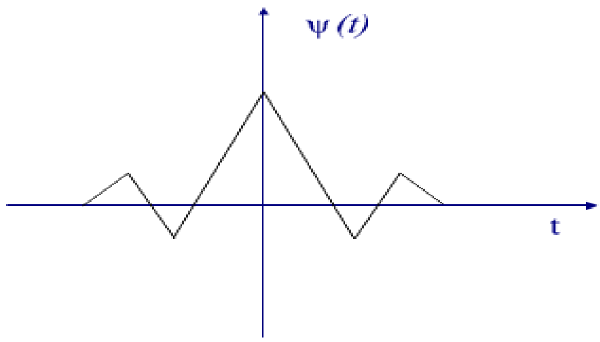

Fig .3. Basic Dyadic wavelet function

The above function can be represented as

$Wf(x,y) = \{W_{2j}^{1} \quad f(x,y)\, W_{2j}^{2}\; f(x,y)\}j \in Z$

Where $W_{2j}^{1} \quad f(x,y) = f(x,y) * \psi_{2j}^{-1}\,(x,y)$

$W_{2j}^{2}\; f(x,y) = f(x,y) * \psi_{2j}^{-2}\,(x,y)$ and

ψ_{2j}^{-K} (x,y) = (-x, -y) , K = 1,2

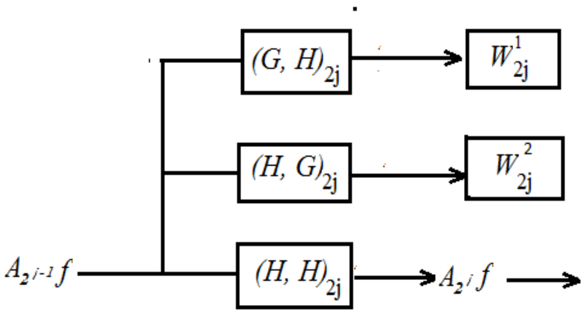

Fig .4. Dyadic Wavelet decomposition

Where W-wavelet function H-High pass filter G – low pass filter

Dyadic introduced by Duval- Destin a 2D technique can construct frames of isotropic wavelets and bring the angular selectivity by partitioning the mother Wavelet into several Discrete Wavelets. The construction is to segment the integral over scales and replace it with a sum. To start with the two-dimensional CWT is

$$f(\vec{x}) = \int_{0}^{\infty} a^{-1}\, da \int_{R^2} d^2\vec{b}\; Wf(a,b)\psi_{\vec{b}}, a(\vec{x})$$

Where $\int_0^{\infty} Wf(a,b) = C_{\psi}^{-1} a^{-2} \int_{R^2} d^2 \overline{\vec{x}\,\psi(a^{-1}}(\vec{x}-\vec{b})f(\vec{x})$

And $C_{\psi} = 2\pi \int_{R^2} d^2\, \vec{W} \frac{|\psi(\vec{W})^2|)}{\|\vec{W}\|2}$

The reconstruction function $f(\vec{x}) = \int_0^{\infty} \frac{da}{a} d_0(\vec{x})$

Where $d_0(\vec{x}) = \int_{R^2} d^2\vec{b}\, Wf(a,b)\psi\vec{b}$,a $(\vec{x})$

Thus we can build DWT starting from CWT. The Contourlet transform has multiple properties of multi resolution, directionality, critical sampling localization, and anisotropy. Its basic functions are multi-scale and multidirectional. To gets an appreciation of combining Laplacian Pyramid (LP) to capture edge dissimilarities through multi-scale decomposition and Directional Filter Banks (DFB) to realize multi-directional decomposition. In addition to this, the Directional Filter Banks (DFB) links the captured points and the excellent performance restores its dominant position in the transformation family. Contourlet transform is known for its multi resolution time-frequency analysis and has the appreciated characteristics of directional dissimilarity which uses fewer coefficients than wavelet transform. The counter in its solo performance has a lack of translation invariance but on combining with Dyadic, the arrival builds more directional sub-bands in all directions and achieves Peak Signal to Noise Ratio (PSNR) higher.

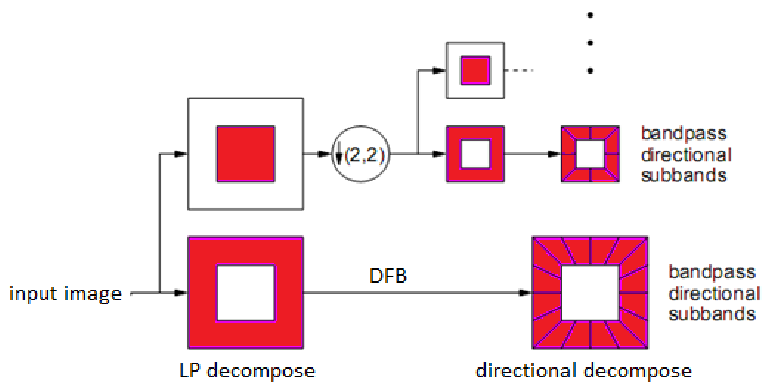

Fig .5.Contourlet transform structure

This paper integrates the qualities of Dyadic and non-sampled Contourlet transform to propose a DNSCT (Dyadic Non- Sampled Contourlet Transform) which decompose the image into basic units called Laplacian Pyramids (LP). Compared with traditional Contourlet transform Dyadic Contourlet transform has more directional sub-bands. Decomposition of each LP generates half the resolution of the original signal low frequency sub-band and high frequency sub-band with the same resolution. These sub-bands were down-sampled to get the approximation component. The high-frequency signal is the difference between the low and original signals after sampled and filtered. DNSCT constitute by Non-Sub-sampled Pyramids (NSP) and Non-sub-sampled Filter Banks (NSDFB).NSP realizes scale features and NSDFB gathers the multi-directional features. The NSDFB can be given to further iteration and the complete reconstruction conditions are

$H_0(z)G_0(z) + H_1(z)G_1(z) = 1$

In which $H_0(z)$-low pass decomposition filter

$H_1(z)$- high pass decomposition filter

$G_0(z)$ – low pass reconstruction filter

$G_1(z)$ –high pass reconstruction filter

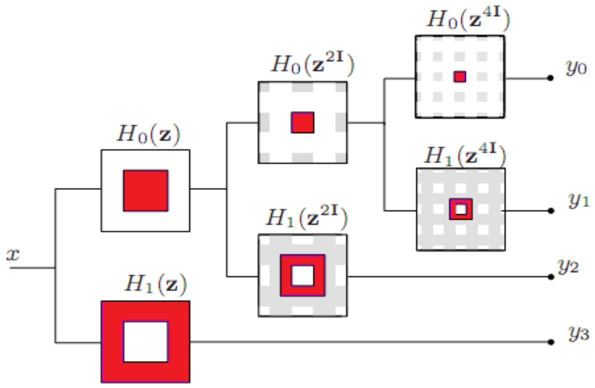

Fig.6. Three level NSP decomposition

The group of filters shown can divide the image into many low and high frequency sub bands.

The proposed breast cancer classification system is divided into four parts:

(1)ROI specification (2) Transformation (3) Feature Extraction

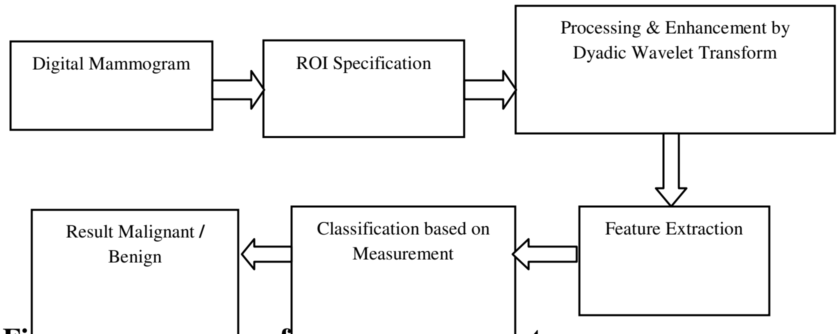

Fig .7. Block diagram for the proposed system

D. Source of data-MIAS (Mammographic Image Analysis Society)

The Mammography Image Analysis Society (MIAS), an organization of UK research institution, has developed a digital mammography database. The mammogram images of X-ray films selected in the database are from the National Breast Screening Programme. Images are, digitized with a microdensitometer with a resolution of 50 µm × 50 µm that can perform with the optical density range 0-3.2 and representing each pixel with an 8-bit word. The database contains left and right breast images for 161 patients on a DAT-DDS tape which consists of 322 images. This database involves three categories of images as Normal and abnormal, which include benign and malignant. The Database contains 208 normal, 63 benign, and 51 malignant images. Besides these expert radiologists provide more information like type, sort, and location with size to the information file. The experts analyzed, the database, includes four types of abnormities circumscribed mass, stellate lesions, architectural distortions, and calcifications). The database introduction file having the following information:

Type: a different type of images normal or abnormal

Sort: Abnormities are malignant or benign ones.
Size and Location: The original coordinates and diameters of the abnormities
E. Region of Interest selection (ROI)

Digital Mammogram (1024x1024pixels)is given as an input to the proposed system for classification whereas in local processing, only the Region of Interest (ROI) 256x256 pixels are given. The efficiency of the proposed classification system is measured by computing the classification accuracy.

F**.** Dyadic Transformation and feature extraction

Dyadic Contourlet transform is superior to the wavelet transform in the direction and anisotropy. Therefore dyadic Contourlet is introduced as an extension of Wavelet transform which combines Laplacian transform and can concentrate on point discontinuities on curved edges to fulfill the directional specificity. Its excellent properties can be used to extract the geometric feature of the original image, and provide more information on the image. The dyadic Contourlet transformation is not only provides the multi scale analysis, it also possesses abundant direction and shape, and thus it can effectively capture the smooth contour and geometric structure of images. Dyadic Contourlet decomposes the image in to number of radial sub bands and directional filter banks to project the subject from the background which is enhancing the tumors below 2mm. Dyadic Contourlet transform is superior to the wavelet transform in the direction and anisotropy.

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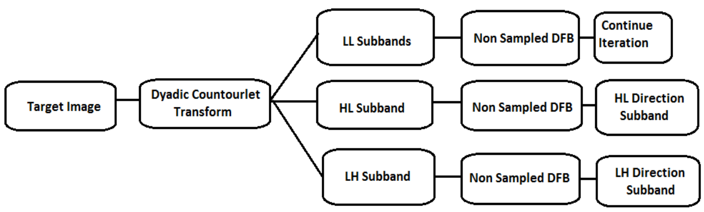

Fig .8. Dyadic sub band decomposition DFB- Directional Filter Bank

A dyadic wavelet transforms produced on convolving the original function, with dyadic mother wavelet. Let ψ be the mother wavelet function of the dilation j

$$\psi 2j(x) = \frac{1}{2j}\,\psi(\frac{x}{2j})$$

The wavelet transform is a sequence of functions

$$Wf = (W2f(x))j \in z$$

Where W is the dyadic transform operator. The reconstruction f(x) is with the infinite summation

$$f(x) = \sum_{j=-\infty}^{\infty} W2j\, f * X2j(W)$$

At each decomposition stage dyadic scale j, decomposes the input into detail coefficients $W_2^d f$ and approximation coefficients $S_2^d f$. The detail coefficients correspond to high frequency information which bears edge details whereas approximation coefficients correspond to low frequency information.

$$\begin{aligned}
& j = 0 \\
& \texttt{while}\ (j < J) \\
& \qquad W^d_{2j+1} f = \tfrac{1}{\lambda_j} \cdot S^d_{2j} f * G_j \\
& \qquad S^d_{2j+1} f = S^d_{2j} f * H_j \\
& \qquad j = j + 1 \\
& \texttt{end of while.}
\end{aligned}$$

Where H and G represents High and Low pass filter respectively. After the desired number of

$$\begin{aligned}
& j = J \\
& \texttt{while}\ (j > 0) \\
& \qquad S^d_{2j-1} f = \lambda_j \cdot W^d_{2j} f * K_{j-1} + S^d_{2j} f * \tilde{H}_{j-1} \\
& \qquad j = j - 1 \\
& \texttt{end of while.}
\end{aligned}$$

decomposition levels and analysis the signal is reconstructed by applying inverse transform where $\overline{H}$ the conjugate for high pass filter H. is

IV. RESULTS AND DISCUSSION

According to research, the suggested method is implemented in

MATLAB 15 with nearly 25 mammograms of MIAS database. The excellent Dyadic Counterlet transform used can resemble the properties of wavelet as well as Curvelet and is capable of extracting curved areas with all possible directions of the tumor and also enhancing the physical appearance of tumors to classify their types according to the level of risk. This evaluation of a CAD system is a task which carries out classification at the machine level for a suspicious region into benign or malignant. The preliminary results that assed on a restricted database demonstrated that the presented simple method was capable of detecting microcalcification by visual inspection itself by using the measurement of the tumor. The measured values agree well with the calculated values to enhance tumor size below 0.2mm without applying classifiers. The bins in the output histogram has higher amplitude levels and larger widths on comparing with the input histograms showing the fine details of the affected regions shown in fig. 11, 12,13.The pixel values in the output have been increased because of the sub sampling by a factor 2 shown in Table1 . In this research to increase the detection rate, features were extracted by applying Dyadic counter let transform in order to preserve the appropriate edge features in mammographic images. It is also used to increase the efficiency and to reduce the delay in the system since the classifiers were eliminated. Our results show that detection rate on extracted features from Dyadic counterlet is more than wavelet and curvelet features.

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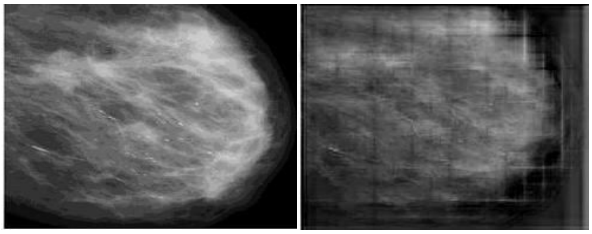
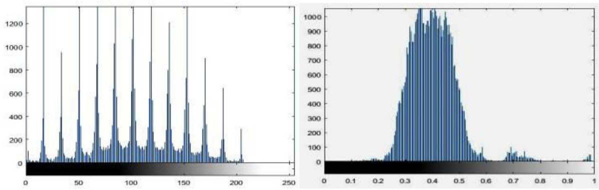
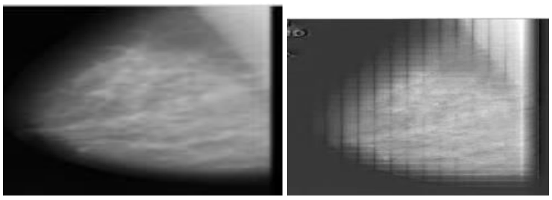


(a) (b)

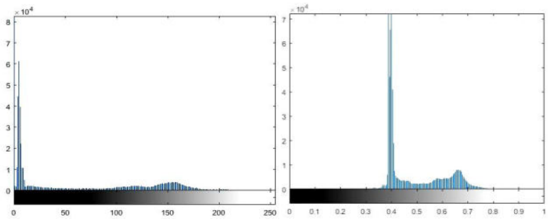


(c) (i) (c) (ii)

Fig .9. (a) Original Input Mammogram Images from the MIAS data Base R-Image Mdb148 – Malignant (b) Output mammogram Images using Dyadic contourlet transform R- Image Mdb148 – Malignant (c) Histograms of mammogram Malignant Image (i)Input original-Image Mdb148 (ii)Output dyadic Image R-Image Mdb148

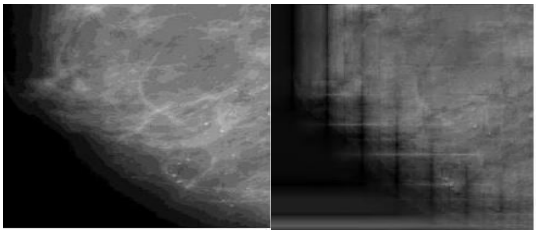


(a) (b)

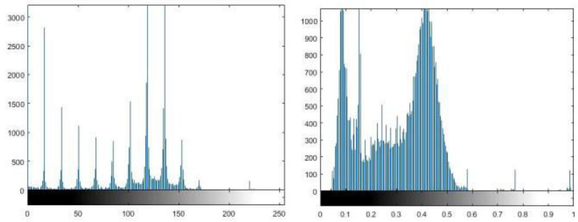


(C) (i) (C) (ii)

Fig 10. **(a)Original Input Mammogram Images from the MIAS data Base** L-Image Mdb091 Benign (b) **Output mammogram Images using Dyadic contourlet transform** L-Image Mdb091 Benign (c) Histograms mammogram Benign Image (i)Input original-Image Mdb091 (ii)Output dyadic Image L-Image Mdb091



(a) (b)



(c) (i) (c) (ii)

Fig .11.**(a) Original Input Mammogram Images from the MIAS data Base** L- Image Mdb245-Malignant **(b) Output mammogram Images using Dyadic contourlettransform** L- Image Mdb245-Malignant (c) Histograms of mammogram Malignant Image (i)Input original-Image Mdb245 –Malignant
(ii)Output dyadic Image L-Image Mdb245

Table.1 Input Pixel values comparing Output pixel values

Sl.No	Images	Input Image Pixel Value	Output Image Pixel Value
1	Mdb148 Malignant	18.97	27.78
2	Mdb245 Malignant	14.12	24.33
3	Mdb091 Benign	15.30	25.30

Table. 2. Input PSNR comparing Output PSNR Values

Sl.No	Images	MSE	PSNR Value in dB
1	Mdb148 Malignant	173.22	25.7788
2	Mdb245 Malignant	136.69	26.8075
3	Mdb091 Benign	17.61	35.7073

Table. 3. Output Histogram Skew and Kurtosis values

Sl.No	Images	Skew	Kurtosis
1	Mdb148 Malignant	5	18
2	Mdb245 Malignant	3	15
3	Mdb091 Benign	6	20

V.CONCLUSION

The Dyadic Contourlet Transform has translation invariance, can avoid image distortion, and can capture image information in the multi-scale; multidirectional level. Contourlets normally have directional multiresolution image representation. It also can show a detailed comparison of two non-linear images on comparing fine details using the histogram and PSNR values. This manuscript presented with tumor detection algorithm based on Dyadic Contourlet Transform employing the feature of NSCT translation invariance according to the energy of DNSCT in all directions and in all scales to achieve higher PSNR value with edge details. Experimental results show that, skew and kurtosis values of the output histograms confirm the cluster types, whether the cluster is Benign or Malignant. On comparing to Wavelet transform, Contourlet transform achieves higher classification accuracy and effectively avoid the classifiers in the detection of Breast tumors. It also can enhance the tumor affected region in the contrast level by varying the pixel value. The MSE and PSNR values clearly show that the system can give better reconstruction efficiency. The next step of research focuses on the improvement of image effect in the enhanced affected region.

The system uses dyadic contourlet transform which is superior than the wavelet transform and continues in time and space. The transform has angular selection, capable of defining the curved areas in the clusters sothat the boundries are well defined. The skew and kurtosis measures can give the shape, sharpness and the width of the output histograms which can well define the exact size of the microcalcification clusters. In this method we can very well avoid the classifiers which is a time consuming process and can improve the classification accuracy using the staststical parameters like skew and kurtossi. The value of skew and kurtosis concludes weather the calcification is cancerous or not. Skew above 3 and Kurtosis above 14 is concluded as detection.

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