ELSEVIER

Proc. of Int. Conf. on Advances in Computer Science, AETACS

Automatic Detection of Breast Lesion Contour and Analysis using Fractals through Spectral Methods

Spandana Paramkusham[1], Dr.K.M.M.Rao[2], and B.V.V.S.N.Prabhakar Rao[3]
[1]Bits Pilani Hyderabad Campus / EEE, Hyderabad, India
Email: spandanamadhav@gmail.com
[2,3] Bits Pilani, Hyderabad Campus / EEE, Hyderabad, India
Email: kundammrao@gmail.com[2], budhiraju@bits-hyderabad.ac.in[3]

***Abstract*— Lesions and its contours are prominent signatures to determine malignancy in mammograms. Detection of the masses and their spread in mammogram is important for radiologists. It is also important to detect the shape of the contour or boundary to delineate malignant and benign lesions as malignant lesions have speculated or ill-defined boundary and benign mass have smooth boundary. Automatic detection of boundary helps the doctors in analyzing the lesion in less time and prevents unnecessary biopsies. In this paper we proposed algorithms for 1) Image enhancement using homomorphic filtering and adaptive histogram equalization technique 2) Segmentation using Enhanced K means clustering 3) Contour Extraction using morphological operations 4) Fractal analysis of the signatures of contours using Power spectra 5) Extraction geometric features from the lesions. These algorithms have been tested on 34 mammograms.**

***Index Terms*— Lesion, Boundary, Fractal dimension, Circularity, Image Processing.**

I. INTRODUCTION

Breast cancer cases have been raised globally from last few decades. Mostly in developing countries like India, breast cancer patients are prone to death due to lack of low cost medical facilities and non-availability of good physicians. Nearly**,** 100,000 new breast cancer patients are estimated to be diagnosed annually in India. Early stage detection of breast cancer is very important to decrease the mortality rate. Mammograms play vital role in the detection of breast cancer. Mammograms with computer algorithms help radiologists to detect breast cancer easily in less time and forbid unnecessary biopsies. A mass or a lesion is an important change seen in mammograms. Masses can be cancerous and non-cancerous. Boundaries of these masses are the prominent signatures of malignancy in the breast mammograms. According to the Breast Imaging Reporting and Data Systems (BIRADS), masses are space occupying lesions seen in at least two different projections. They are characterized by their shape (round, oval, lobular, irregular) and margins (circumscribed, microlobulated, obscured, indistinct, spiculated). Many image processing algorithms have been developed to pre-process, segment mass regions and detect their boundaries, as the mammograms have low contrast and noisy and the lesions overlap with the breast tissue in the mammogram. Extraction of these features from lesions and boundaries help doctors to delineate malignant and benign mass in less time.
Many algorithms are developed for segmentation of medical images. Segmentation of mass is a crucial

task in mammograms. Work has been done on segmentation of mass in past to know the spread of spiculation in the breast tissue. Mean shift algorithm and Fuzzy C-means and active contour models are used in [1] for the detection of masses. Breast density is calculated by segmenting fibrogladular tissue in [2]. Suspicious focal areas are found for testing morphologic concentric layer (MCL) criteria, to detect mass region in mammogram [3]. Gradient vector flow (GVF)snake and multi-scale analysis using Gaussian pyramid has been proposed in[4] to segment masses in mammogram .At first they applied gaussian pyramid to make the image coarse , so that GVF snake is able to converge to the mass contour easily and quickly with less computation. Shape features like elongatedness, eccentricity, Euler number, Max Radius, Min Radius were used to distinguish four different shapes round, oval, lobular, irregular of mass by using C5.0 decision tree algorithm in [5]. Gabor filter banks are used for extracting local spatial textural properties of masses at different orientations and scales [6]. Multilevel wavelet decomposition method is proposed to extract mean, variance, standard deviation, entropy and mean of absolute deviation from wavelet components [7]. Boundary extraction of this mass is also very important, so that radiologists can judge whether the mass is benign or cancer. Rangayan et al in [8] proposed a region-based measure of image edge profile acutance by polygonal approximation and measured shape features like compactness, Fourier descriptors, central invariant moments and chord-length statistics to distinguish between circumscribed and spiculated tumors.

II. Implementation

A. Image enhancement

In this paper, we proposed an algorithm based on hybrid approach combination of both frequency domain homomorphic filtering and spatial domain morphology as in [9] and adaptive histogram equalization technique to the output of hybrid approach. Homomorphic filtering is applied to the input image to improve the contrast of image and morphological operations are applied to remove the noise and to smooth the edges of the image.

Procedure:

Step1: Apply homomorphic filter to compress brightness range and enhance contrast of image as shown in Fig.1. It removes non-uniform illumination without any loss. Let the output be G. Following are the steps in homomorphic filtering process

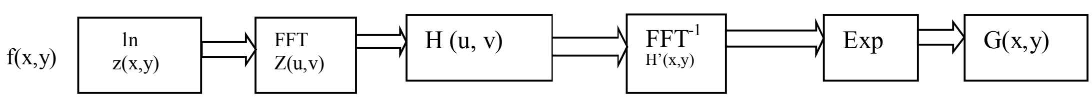


Fig.1.Homomorphic Filter

f(x, y) is an input image. Z(x, y) is the output after log transformation. Z (u, v) is the output of Fourier transform.

H (u, v) is a transfer function of frequency domain filter. $H^{'}$ (u ,v) is output of the Z(u, v) filtered with H(u, v). Exponential is applied to the $H^{'}$ (x,y) to get the output G (x, y).

$H(u, v) = (r_H - r_L)\,[1\text{-}\exp(c\,(D/D_0^2)]$

Where r_H is the regulation parameter to change high frequency, r_L is regulation of parameter to change low frequency, where $r_H>1$ and $r_L<1$, c is sharpening parameter and D is balance parameter. r_H =1.414 and r_L= 0.18.

$D(u, v) = u^2+v^2$, D0 is harmonic coefficient, $D0 = ((\max-\mu)^2 + (\min-\mu)^2)/ a$

Step2: Tophat transform is applied to G using disk of radius 15 as a structuring element. Shape and size of structuring element is selected based on the shape and size of the masses. It can be used to separate the objects .Let the output be thf.

Step 3: Dilation operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels **.** It is applied to smooth the borders of tophat transformed image. Let the output be thf1.

Step4: Bothat transform is applied to the original image to smooth the objects in original image. Let the output be bhf.

Step 5: These images are combined using Image arthimetic addition and subtraction.

Enhanced image = (G+thf1) – (bhf)

Step6: Adaptive histogram equalization technique is applied to improve local contrast. Adaptive method computes several histograms on small tiles of image and improves local contrast giving more details. Fig 2. shows original image and output of the proposed algorithm. Table I gives quality measures EBCM (Edge based contrast measure), Standard deviation, Entropy for the original mammogram and for the enhanced image by the proposed method.

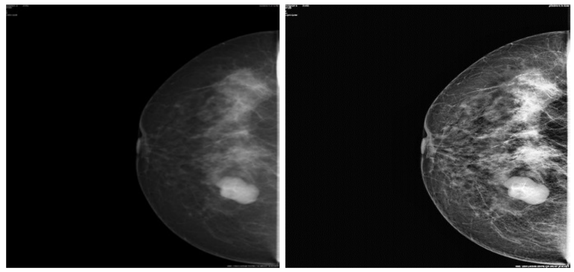


Fig.2. a) Original Mammogram b) Enhanced Mammo

This algorithm is implemented on four benign images and five cancer images taken from KIMS, Hyderabad. The enhancement measures for these images are also given in Table I.

B. Image Segmentation

In this paper, we use the K-Means clustering algorithm and morphological operators to segment mass and extract the border. Fig.3 shows the flow chart of algorithm.

Procedure

Step1: K-means Clustering
Step2: Morphological operations
Step 3: Morphological gradient
Step 4: 1D Signatures from 2D contours
Step 5: Fractal analysis with PSA
Step6: Extraction of Geometric features from mass

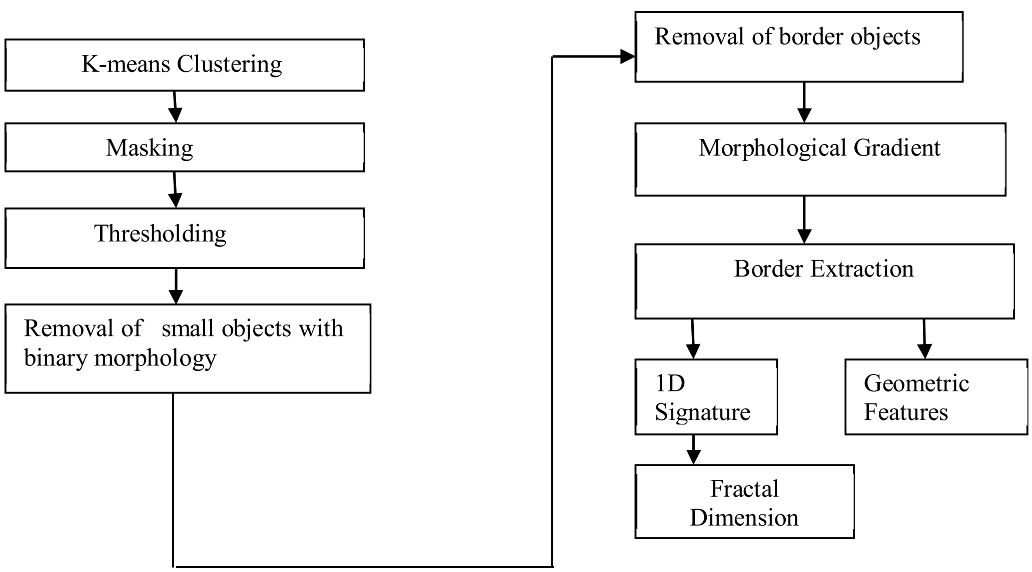


Fig.3. Flow chart for extraction of border and features

K-Means Clustering:

This is an algorithm to group objects into a K number of clusters based on features, where K is a positive integer number. We segment mass region using k-means algorithm. We consider the input as image pixels and their features are their grey-level values. The algorithm aims at minimizing sum of any pixel point to cluster centroid distances, we have chosen Euclidean distance as distance measure. Fig.4a, Fig.4b, Fig.4c shows the original mammogram, output after k-means clustering and segmented mass.

Fig.4.a)Original b)K means output c)Malignant Lesion d) Boundary

Binary Morphology:
Opening operation is used to remove small objects in the image and border object. Opening is used to remove small, bright details, border pixels while leaving the overall pixel intensity values and large bright objects undisturbed. Opening of image f with structuring element b is given by

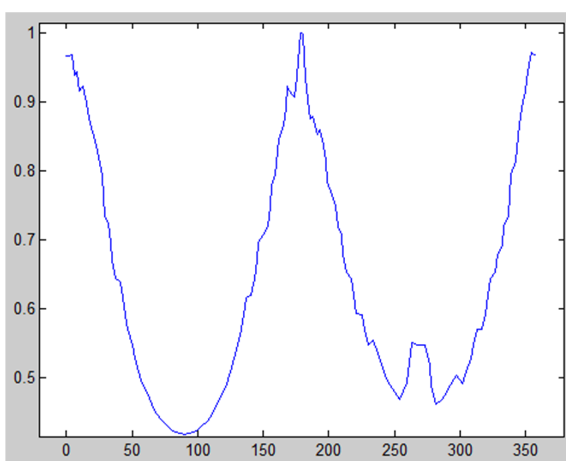
$$f \circ b = (f \theta b) \oplus b$$

It is the erosion of f by b followed by a dilation of the result with b.
Morphological gradient:
Dilation acts like a local maximum operator. Erosion acts like a local minimum operator. Combination of Dilation, Erosion, Image subtraction gives morphological gradient. The dilation thickens regions in an image and the erosion shrinks them. Subtraction operation tends to remove the constant intensity areas and edges are enhanced. Fig.4d shows the boundary of the lesion. f is an input image.

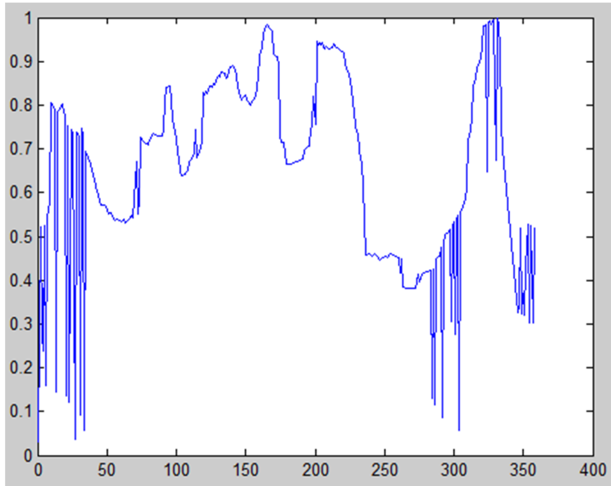
Morphological Gradient = Dilation (f) – Erosion (f).

Signature:
A signature is a 1D functional representation of a boundary. It is a plot of the distance from the centroid to the boundary as a function of angle. Fig.5a, 5b. show the borders of benign mass and Malignant mass. Fig.5c, 5d shows the signatures of this borders.

Fig.5. a) Benign b)Malignant



c) Signature of 5a



d) Signature of 5b

Fractal Dimension via power spectra analysis:

Fractal dimension signifies the complexity of the boundary. Complexity means degree of space occupied by a 1D signal [10]. The rampification of a signal can be analyzed in time domain, frequency domain, or in the phase spectrum of the system. Power spectrum of a signal follows power law that is if S(f) is a power spectrum , it is directly proportional to $1/f^{\beta}$ where β is a spectral component . As β value increases, highest frequency content decreases as in [11]. Let discrete Fourier transform of a 1D signal is represented by

$$F_k = \sum_{n=0}^{M-1} fn \exp(-j2\pi nk/M)$$

fn represents discrete samples of a signal ranging from 0 to M-1 . F_k represents k^{th} fourier coefficient. $|Fk|^2$ represents Power spectral amplitude at k^{th} frequency, then $|Fk|^2 \; \alpha 1/k^{\beta}$. k denotes frequency index corresponding to the frequency f. Fractal dimension of 1D signal with slope β is given by FD = 5-β/2.Power spectrum of 1d signatures are calculated using welch method in matlab. In calculating fractal dimension with power spectrum we selected certain frequency range specified in [11]. Low frequency details like zero frequency component and high frequency which includes noise and other articrafts are removed from power spectrum. For malignant tumors we could observe that most of the power is concentrated in the initial frequencies. We selected frequency range from [0.2 to 1.6 rad/sec] to linear fit and calculated slope. Fractal dimensions for 34 images, consists of 15 benign mass signatures and 19 malignant mass signatures are calculated.

Geometrical Feature Extraction:

Geometric features of Lesion boundary can be used to characterize malignant or benign lesion. Seven morphologic features were extracted from each lesion to describe features such as shape, contour, and size as in [12], [13], [14].

Circularity Index: Perimeter divided by the circumference of a circle with the same area. The closer the shape of a lesion is to a disk, the closer the circularity index to 1

Area: No of pixels contained in the lesion.

Perimeter: Circumference of Lesion.

P: A: It is the ratio of perimeter to area of the lesion.

*L: S Ratio***:** It is the length ratio of the major (long) axis to the minor (short) axis of the equivalent ellipse of the lesion. If L: S ratio is more, it is likely the lesion is malignant.

E: N (Elliptical normalized circumference): Anfractuosity is a common morphological feature for malignant contour. ENC is circumference ratio of the lesion and its equivalent ellipse. Anfractuosity of a lesion contour is characterized by ENC.

III. Results

Algorithms have been implemented on 34 mammograms of which nine mammograms are from KIMS, Hyderabad and 25 mammograms are from DDSM database [15]. From this 15 mammograms have benign lesions and 19 mammograms have malignant lesions. We implemented image enhancement algorithm on 9 mammograms that are taken from KIMS, Hyderabad, as they are high quality digital mammograms compared to DDSM mammograms. Parameters to test image algorithms are given in Table I. EBCM3 is more than EBCM1, EBCM2 in Table I.

Quality measures of image enhancement :

Entropy: Image entropy is a quantity which measures the information of an image. It is represented by H (I)

$$H(I) = -\sum_{i=0}^{n-1} Pi \ln Pi$$

Where Pi is probability of ith gray level intensity value n is a gray level number in the image. If the entropy is greater, the image is more clear .We observed E3 is more than E1, E2

Standard Deviation (SD): It is a value on the gray level axis, showing the average distance of all pixels to the mean. SD of the histogram tells us about the average contrast of the image. Greater the Standard deviation, greater is the contrast of the image, std3 is greater than std1, std2 in Table I.

Edge based contrast measure (EBCM): EBCM measures the intensity of edge pixels in small windows of the image

Fractal Dimension Measurements

With increasing slope β, high frequency components decrease i.e , benign masses has higher slope and malignant masses have lower slope. Fractal dimension is high for malignant masses and fractal dimension is low for benign masses. From Table II, it is observed that all benign patients have FD<1.2 and malignant patients have FD>1.2, except for the patient B3and patient C6 .We achieved 82% accuracy with fractal dimension as a parameter.

TABLE I: QUALITY MEASURES OF ENHANCED IMAGES

Patient No	E 1	E 2	E 3	EBCM 1	EBCM 2	EBCM 3	SD 1	SD2	SD3
B1(Benign)	3.539	3.6343	4.3212	7.031	33.87	37.1511	45.8664	66.5682	69.7457
B2	3.5152	3.6510	4.2569	6.7810	14.7596	22.9931	36.0448	53.6151	65.0046
B3	5.5791	5.796	6.5181	9.3704	37.27	53.7703	46.17	70.616	76.845
B4	5.256	5.4046	6.1457	8.3318	29.5916	48.7951	50.811	59.9	69.9
C1(Cancer)	3.8772	4.0004	4.6669	7.3638	15.6643	27.6947	42.6	52.7	60.83
C2	2.4818	2.5614	3.2791	6.6	10.54	19.91	34.73	44.106	51.97
C3	2.38	2.404	3.173	5.6248	12.21	16.128	36.47	45.3492	49.4295
C4	2.3574	2.4315	3.0488	4.2700	9.0822	14.94	34.4025	43.6677	47.9602
C5	3.8456	4.0420	4.7982	7.60	10.8361	22.9557	31.7649	41.8829	53.2317

E1:Entropy of original Mammogram, E2:Entrophy with homomorphic filtering and Morphology,E3:Entropy with proposed algorithm, EBCM1:Edge based contrast Measure of original mammogram, EBCM2:Edge based contrast measure with homomorphic filter and morphology,EBCM3: Edge based contrast measure with new algorithm,SD1 Standard deviation of original mammogram,SD2:Standard deviation with homomorphic filter and morphology,SD3 :Standard deviation with New algorithm.

Geometric Feature analysis:

Table III gives the geometric feature measurements with FD of all 34 patients. We achieved 82%, 67.64%, 82%, 80%, 82% accuracy with circularity index, P/A, L:S, FD ENC as a parameters individually with thresholds equal to 1.29, 0.1354, 2.7, 1.2,2.7 for delineating benign and malignant masses. But by combining all the geometric parameters with FD, we achieved 97% accuracy.

IV. CONCLUSION

The algorithms have been tested on thirty four images of which nine images are taken from KIMS, Hyderabad and twenty five images are taken from DDSM database. We implemented image enhancement and segmentation methods to extract the border and calculated fractal dimensions using power spectrum analysis, geometric features of the border. We achieved 97% accuracy by combining FD and geometric Feature for classifying benign and malignant lesions. In future we would like to develop algorithms for classification of cancer and non-cancer patients by considering different types of abnormalities like Microcalcifications, Architectural distortion, Lesions, Bilateral Asymmetry in mammogram.

TABLE II : FRACTAL DIMENSIONS OF BOUNDARIES

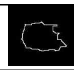
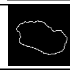
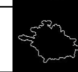
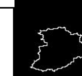
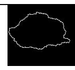
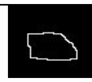
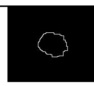
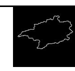
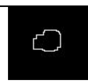
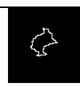
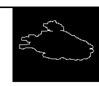
Patient No (Benign)	Boundary	(Slope β)	FD	Patient No (Malignant)	Boundary	Slope β	Fractal Dimension
B1		2.6314	1.16	C1		2.3676	1.3162
B2		2.6679	1.16	C2		2.1045	1.4299
B3		3.0943	0.9528	C3		2.2616	1.3692
B4		2.3409	1.3296	C4		2.0544	1.4728
B5		3.4784	0.7608	C5		1.7403	1.6299
B6		3.2066	0.8967	C6		3.8	0.600
B7		2.9	1.05	C7		2.4872	1.2564
B8		4.5	0.25	C8		2.78	1.11
B9		3.1	0.95	C9		2.361	1.3195

TABLE III: EXTRACTED FEATURES

Patient No	Circularity	P/A	L:S	FD	Major Axis	Minor Axis	Perimeter	ENC
B1	1.2219	0.079	2.60208	1.16	92	36	234	3.0123
B2	1.11805	0.0731	2.00011	1.16	80	39	213	3.4
B3	1.19	0.078	2.38267	0.9528	74	39	218	3.8497
B4	1.18	0.058	2.28	1.3296	127	55	300	2.9
B5	1.194	0.136	2.4429	0.8967	61	29	131	2.72
B6	1.10498	0.133	1.92157	0.8967	45	23	113	3.25
B7	1.08820	0.087	1.81846	1.05	170	67	171	1.1944
B8	1.11207	0.169	1.96433	0.25	36	18	91	3.2527
B9	1.40827	0.223	3.69	0.95	48	13	111	2.4083
B10	1.19	0.136	2.44293	0.15	54	22	131	2.9147
B11	1.225	0.15078	2.62283	0.65	52	20	125.09045	2.8294
B12	1.07595	0.2795	1.74094	0.8	20	11	52.018	3.4368
B13	1.27	0.257	2.97455	0.65	104	20	80	0.7241
B14	1.348	0.079	3.33	1.28	80	34	287	4.375
B15	1.63416	0.14157	5.1466	0.85	124	123	236	2.433
C1	1.3	0.0801	2.755	1.3162	103	37	244	2.72
C2	1.539	0.087	4.5198	1.4299	150	33	341	2.22
C3	1.26	0.0833	2.826	1.3692	101	35	239	2.68
C4	1.99	0.087	7.82172	1.4728	254	32	568	1.91
C5	1.500	0.105	4.266	1.6299	116	27	266	2.2772
C6	1.112	O.169	1.96433	0.600	80	15	91	1.0638
C7	1.418	0.076	3.75665	1.2564	330	143	38	0.1414
C8	1.34353	0.098	3.3078	1.15	228	98	29	0.1557
C9	1.44	0.076	3.88	1.32	337	147	38	0.1388
C10	1.33	0.1644	3.22	0.90	57.77	18	134	2.5
C11	1.29109	0.1253	3.00058	1.505	71	23	167	2.6038
C12	1.60519	0.089	4.95130	1.6097	160	32	362	2.1520
C13	1.13	0.2232	2.12	0.25	29	14	73	3.2039

TABLE III: EXTRACTED FEATURES

C14	1.64726	0.07154	5.24	1.486	210	40	476	2.1284
C15	1.86792	0.1354	6.83186	1.95	144	21	323	1.98
C16	1.85531	0.084	6.7359	2.31	226	33	508	1.98
C17	1.5763	0.185	4.76	1.49	73	16	167	2.2321
C18	1.974	0.106	7.66309	1.357	204	27	457	1.9393
C19	1.54435	0.209	4.5508	0.55	62	13	143	2.2224
Accuracy	82%(1.2900)	0.1354(67.64%)	82.53%(2.7)	80%(1.200)				2.7(82%)

ACKNOWLEDGEMENT

We thank Director, BITS, Hyderabad for supporting our research work and providing facilities. Authors gratefully acknowledge KIMS, Hyderabad for supporting the research work by providing mammographic images, analyzing the outputs and providing useful comments.

REFERENCES

[1] Arianna Mencattini et al. “Automatic breast masses boundary extraction in digital mammography using spatial fuzzy c-means clustering and active contour models”, IEEE International Workshop on Medical Measurements and Applications Proceedings (MeMeA), 2011, pp.632-637.

[2] Spandana Paramkusham, K. M. M. Rao, B. V. V. S. N. Prabhakar Rao, “Automated Approach for Qualitative Assessment of Breast Density and Lesion Feature Extraction for Early Detection of Breast Cancer”, TECHNIA, International Journal of Computing Science and Communication Technologies, vol.6, No.1, July. 2013 (ISSN 0974-3375)

[3] Nevine H. Eltonsy, Georgia D. Tourassi, Adel S. Elmaghraby, “A Concentric Morphology Model for the Detection of Masses in Mammography”, IEEE Transactions on Medical Imaging, 2007, Vol. 26 , pp: 880 – 889.

[4] Hongwei yu, Lihua Li, Weidong Xu, We Liu, Juan Zhang, Guoliang Shao, Gaussian Pyramid Based Multi-Scale GVF Snake for Mass Segmentation in Digitized Mammograms, IEEE International Conference on Bioinformatics and Biomedical Engineering, ICBBE,2009, pp:1-4.

[5] A. Vadivel, B.Surendiran “A fuzzy rule-based approach for characterization of mammogram masses into BI-RADS shape categories”, Computers in Biology and Medicine , May 2013, Vol 43, Issue 4, pp:259-267.

[6] Muhammad Hussain, Salabat Khan, Ghulam Muhammad, Mohamed Berbar and George Bebis, “Mass Detection in Digital Mammograms Using Mammograms”, IET Conference on Image Processing **,** 2012**,** pp:1-5.

[7] M.Vidhya, N. Sangeetha, M.N.Vimalkumar, Dr.K.Helenprabha, “ Early Stage Detection of Cancer in Mammogram Using Statistical Feature Extraction” International Conference on Recent Advancements in Electrical, Electronics and Control Engineering (ICONRAEeCE) , 2011, pp: 401-404.

[8] Rangayyan,R.M. , El-Faramawy,N.M., Desautels, J.E.L, Alim O.A, “Measures of Acutance and Shape for Classification of Breast Tumors”, IEEE Transaction on Medical Imaging, Vol.16, Issue 6, pp:799-810.

[9] Zhang Chaofu, MA Li-ni, Jing Lu-na, “Mixed Frequency domain and spatial of enhancement algorithm for infrared image”, IEEE international Conference on Fuzzy Systems and Knowledge Discovery, FSKD, 2012, pp:2706-2710.

[10] B. S. Raghavendra, and D. Narayana Dutt, “Computing Fractal Dimension of Signals using Multiresolution Box-counting Method”, International Journal of Information and Mathematical Sciences , 2010.

[11] Rangarai.M, Rangayam, Faraz Oloumi, Thanh M. Nguyen, “Fractal Analysis of Contours of Breast Masses in Mammograms via the Power Spectra of the Signatures”, IEEE Annual InternationalOn Engineering in Medicine and Biology,EMBS, 2010, pp:6737-6740.

[12] P.Spandana, Dr.Kunda.M.M.Rao, Dr.B.V.V.S.N Prabhakar Rao, Early Stage Detection of Breast Cancer Using Novel Image Processing Techniques, Matlab and Labview Implementation, IEEE International Conference in Advanced Communication Technology, ICACT, 2013(in press).

[13] Chung-Ming Chen, PhD, Yi-Hong Chou, MD,Ko-Chung Han, MS,Guo-Shian Hung, MS,Chui-Mei Tiu, MD,Hong-Jen Chiou, MD,See-Ying Chiou, MD, Breast Lesions on Sonograms Computer-aided Diagnosis with Nearly Setting-Independent Features and Artificial Neural Networks, in pubmed database.

[14] Rahil Garnavi , Mohammad Aldeen, James Bailey, Computer-Aided Diagnosis of Melanoma Using Border- and Wavelet-Based Texture Analysis, IEEE Transactions on Information Technology in BioMedicine, Vol.16, N0.6, 2012, pp: 1239-1252.

[15] “USF digital mammography home page,” http://marathon.csee.usf.edu/Mammography/Database.html.