International Conference on Control, Engineering & Information Technology (CEIT'13)
Proceedings Engineering & Technology - Vol.3, pp. 179-184, 2013

Mass Abnormality Segmentation in Mammographic Images for Different Densities of Tissue

Khamsa Djaroudib[#1], Abdelmadjid Zidani[#2], Abdelmalik Taleb Ahmed[*3]

[#]*University of Batna, UHL, Computer Science Department, Algeria*
[1]*khamsa.djaroudib@yahoo.fr*
[2]zidani@free.fr

[*]*University of Valenciennes, LAMIH Laboratory, France*
[2]Abdelmalik.Taleb-Ahmed@univ-valenciennes.fr

***Abstract*— Today, detect abnormalities of breast cancer (mass or micro-calcification) at an early stage helps to decrease considerably woman's mortality rate by this cancer. Unfortunately, due to the large variability of size, shape and margin, and its confusion with the mammary tissue, mass abnormality detection is still a very difficult task for the researchers more than micro-calcification abnormalities detection. In this paper we present an approach using texture parameters of Gray Level Co-occurrence Matrix (GLCM) to segment mass by detecting their contour. Indeed, mass region and tissue surrounding this region can have the same texture. Statistics parameters computed by GLCM in any pixel of ROI image give information to resolve this problem, on condition to apply an appropriate enhancement processing. We applied the proposed approach to some challenging breast images in BIRADS database including poor contrast tissue density (fatty, dense or granular) and preliminary results of segmented mass done by our algorithm is compared to segmentation carried by an expert radiologist by measuring Dice coefficient, F-measure, Precision, Recall. Preliminary results show that texture information given by contrast descriptor give good results for edges mass detection. Enhancement processing is a determining step for this approach.**

***Keywords*— segmentation, edges, mass, tissues, densities, enhancement, GLCM**

I. Introduction

Breast cancer is the first cause of death by cancer at the women. To detect anomalies (mass or micro-calcification) at an early stage helps to decrease mortality rate, and Computer Aided Diagnosis (CAD) being an effective tool for radiologist [1]. The detection and segmentation is the first and key stage in the complete process of CAD [6][9].

Masses are characterized by their location, size, shape and margin [2][3] and the large variation in size and shape in which masse can appear, make mass segmentation a challenging task for researchers. In additional, at the most of cases, mammograms exhibit poor image contrast tissue density (fatty, dense or granular), then tissue can overlap with breast tumor region [5] as the mass abnormality [4]. According to these problems, many mass segmentation and/or detection methods are developed. We can see review and recent advance of them in [17] [6], [7], [8]. For example, pixel based methods [18] [19] [20], such as region growing and its extensions; region based methods [21][22], e.g., filter based methods; and simple edges based methods [23], e.g., the gradient filters, are employed widely in the early stage for mass segmentation. Though these types of methods are easily to implement, it is still difficult to acquire satisfied segmentation results for masses of ambiguous boundaries. This is because simple feature cannot handle the complex density distributions and topologies of the masses and normal breast tissue. To find more accurate boundaries of masses, some researchers use active contour methods [24][25][26], the efficiency of depends for adjusting parameters.

Many methods cited above use texture information, because textures features are more rich information in segmentation process [30][31], these have been proven to be useful in differentiating mass and normal breasts tissues [27]. Earlier [28] show that the area of a tumor exhibit typically low texture compared to normal parenchyma, and the authors in [5] concluded that the texture features demonstrate more prominent differences between tumor and normal tissues than the intensity feature. In this idea, most methods include textures features use GLCM in segmentation or classification stage of CAD [29] and most of them segment mass in region approaches [10][11].

In this paper, we contribute and propose a mass segmentation method by edges detection approach, based on GLCM and textures images representing textures parameters. Our idea is based on the fact that variance or contrast parameter can detect the spatial change between mass and non mass tissue in region border. Then texture descriptor as the contrast extract from GLCM is compute in each pixel in ROI (Region Of Interest) image give an important information to detect edges mass contours.

Our approach split in two stages. At first, we applied smoothing (denoising) and enhancing method to enhance breast image [12]. Respectively, an anisotropic filter diffusion SRAD (Speckle Reducing Anisotropic Diffusion) [13] and Contrast-limited Adaptive Histogram Equalization (CLAHE) are used. Second, for each pixel in a ROI, a contrast descriptor is computed from the co-occurrence matrix of the pixels, and the contrast image is obtained. Mass contour is identified. We applied the proposed algorithm to some challenging breast images in BIRADS database including poor contrast tissue density (fatty, dense or granular) and the segmented mass done by our algorithm is compared to segmentation carried by an expert radiologist by measuring Dice coefficient and area under the ROC (Receiver Operating Characteristic) curve.

II. Data Description

Our method was applied on the MIAS dataset [15]. It is available online freely for scientific purposes and consists of 161 pairs of medio lateral oblique view mammograms. The images of the database originate from a film-screen mammographic imaging process in the United Kingdom National Breast Screening Program. The films were digitized and the corresponding images were annotated according to their breast density by expert radiologists, using three distinct classes: Fatty (F) (106 images), Fatty-Glandular (G) (104 images) and Dense-Glandular (D) (112 images), similar to Mavroforakis et al. [16]. Any abnormalities were also detected and described, including calcifications, well-defined, spiculated or ill-defined masses, architectural distortion or asymmetry. Each pair of images in the database is annotated as Symmetric (146 pairs) or Asymmetric (15 pairs). The severity of each abnormality is also provided, i.e., benignancy or malignancy.

III. Methodology: GLCM for Edges Mass Detection

A. *Enhancement Images*

The performance of methods based on texture information is highly dependent on the pre-processing (enhancement) of the input image [28], so many researchers focus in this stage of CAD.

For our approach, this stage is our key to have the best results for the mass segmentation stage. Most mammogram images have low intensity contrast, then we applied smoothing (denoising) and enhancing method to enhance breast image [12]. We suggested applying respectively, an anisotropic filter diffusion SRAD (Speckle Reducing Anisotropic Diffusion) [13] and Contrast-limited Adaptive Histogram Equalization (CLAHE) for enhancing image, are used.

Instead of most studies, in our approach and in the aim to perform texture information, denoising and enhancing steps are applied in whole breast image and then, we extract suspicious ROI image. So, our SRAD algorithm can take speckle for every image independently of another one which makes this approach is more efficiency for image speckle reducing.

Images in Fig.1, show an example for input image and enhancing image with delimited ROI, and then zoom of ROI extraction image.

We used the YU scripts for SRAD [13] and results of this step are shown at Fig.1. In this figure, the image of enhancement show clearly more regions in the breast image. The clear regions are even clearer, which can correspond to a region of the masses tissue, and the dark regions are darker, what can correspond to the regions of the normal tissue (without mass).

Besides in Fig.1, we showed an image mdb004 which represents the most difficult case for the detection of the mass in the clear normal tissue, that is the case where the mass is surrounded with a dense tissue. For other cases, the images are even more contrasted to improve the next stage of our methodology which is the computing of the images of texture.

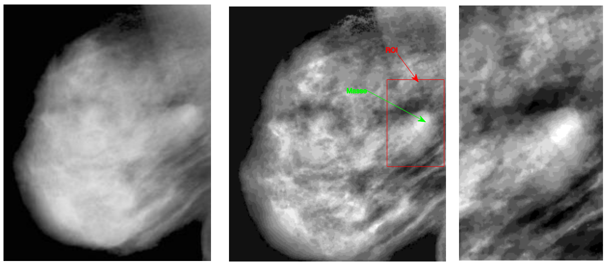

Fig. 1 Breast image mdb004 input (left), mdb004 enhancement (center) show ROI (red) and mass (green), image zoom of ROI (right)

B. *Edges mass detection by computing GLCM*

In ROI image, we compute GLCM according to three important parameters: direction (angle) and a neighbourhood size, and texture descriptor of Harralick [14].

1) *Compute direction:* Compute one angle 0°, 45°, 90°, 135° do not give closed outlines, then we compute all directions and calculate their sum, see Fig. 2A.

Fig. 2A, is an example of Brodatz image. We show images of texture which is contrast descriptor of Harralick [14], in direction 0°, 45°, 90°, 135° and image representing the sum of these four images. In the image sum, we see clearly more closed outlines.

Fig. 2, is our mammographic ROI image of breast mdb004. We confirm the remark on the Brodatz image of Fig 2A.

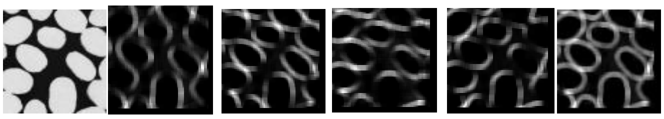

Fig 2A. From left to right, Brodatz D75 image, Image Contrast in 0°, Image Contrast in 45°, Image Contrast in 90°, Image Contrast in 135°, Image Contrast Sum (0°+ 45°+ 90°+135°).

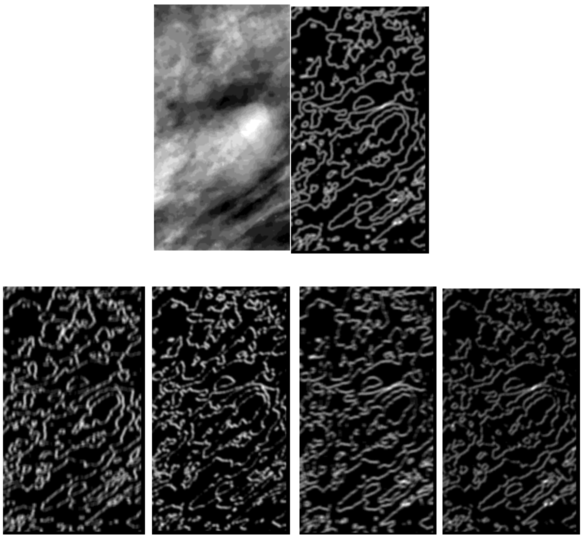

Fig. 2 Top: in left, mdb004 image input, in right the image sum of four directions contrast image which shows closely contours. Bottom: Four images of contrast , from left to right, respectively in 0°, 45°, 90°, 135°.

2) *Compute a neighbourhood:* For synthetic Brodatz images, we can see on Fig.2B that in mask 3x3, edges are more smooth than mask 7x7 and 9x9. The detected edges are more fuzzy if the neighbourhood size is big. But in reality, the choice of the size of the neighbourhood depend on textures of objects in image. For the images of mammography, neighbourhood in mask size of 7x7 give better smooth edges than mask size of 3x3 and finer outlines than mask size of 9x9.

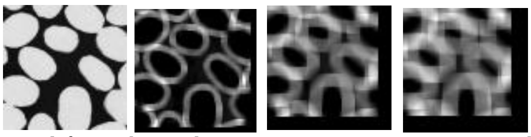

Fig. 2B From left to right, Brodatz D75 image, Image Contrast in mask 3x3, Image Contrast in mask 7x7 and Image Contrast in mask 9x9.

3) *Compute texture descriptor:* Instead of taking the most known four descriptors extracted from GLCM, we take only the contrast descriptor, which measures the heterogeneity of an image and detect spatial variations of grey level intensity in image. Besides, it can summarize all the information of texture we needs.

To extract texture images, and according to these previous parameters (direction, neighborhood size), we compute contrast descriptor of Harralick [14]. Each pixel of ROI image is replaced by this descriptor.

In this work, we use "Matlab" formulation of contrast descriptor:

$$contrast = \sum_{i,j} |i - j|^2 \, p(i, j)$$

This equation returns a measure of the intensity contrast between a pixel p and its neighbourhood in the size of 7x7. Then our algorithm computes this descriptor over the whole image.

IV. Experimental Results

A. *Edges mass detection in different densities of tissue*

We applied the proposed approach to BIRADS database of breast images. Tests are done in images with different densities of tissue, fatty, dense or granular. For each image, contrast descriptor of Harralick [14] is compute, we obtain the contrast texture images where the mass is identified by its borders.

In Fig 3., the examples of three images mdb004, mdb005, mdb019 which represent respectively in first an breast image with a dense tissue, regions are of clear white colour on the images of mammography; in second an image with a fatty tissue, regions are of dark grey colour on the images; and finally an image with a glandular tissue, regions are of mixed colour, clear white time and grey dark on the mammographic images. These information are given according to the annotations of the MIAS database which we study. In mdb004 image we can see two mass, but we chose an image ROI with a single mass for our tests.

In Fig. 4, Fig. 5 and Fig.6, ROI images of mdb004, mdb005, mdb019 are show respectively in first column. The images in second column show the borders of mass region (lines in white colour) delimited by an expert radiologist. In third column, the texture images representing the texture descriptor contrast of GLCM are shown. This descriptor detects the variations of levels of grey. So, because the images of mammography show a big diversity of regions of tissue, every region and so bounded. But we focus our comments in the borders of mass region according to the borders delimited by an expert, and we notice that for mdb004 (Fig 4) and md005 (Fig 5), the borders of the mass are detected well by closed outlines, compared with mdb019 (Fig6), where the borders of the mass are detected well but by outlines not closed and intermittent in certain places. We analyse results quantitatively in the paragraph which follows.

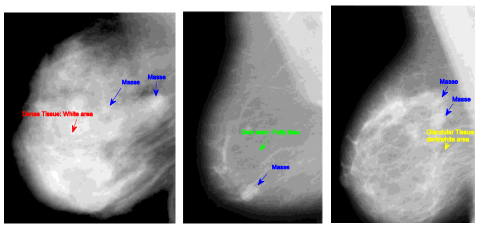

Fig. 3 mdb004 breast, mdb005 breast, mdb019 breast, Blue: masses, red: dense tissue, green: fatty tissue, yellow: Glandular tissue.

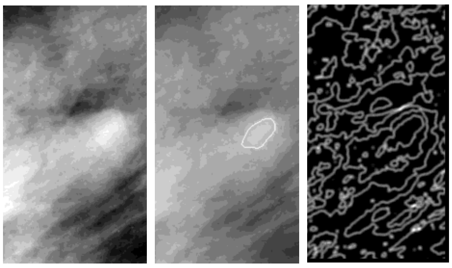

Fig. 4. In dense tissue: From left to right: Input image, Edges mass by expert, Texture image

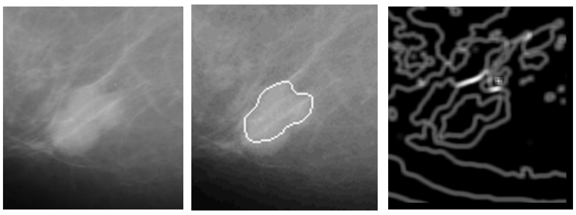

Fig. 5. In fatty tissue: From left to right: Input image, Edges mass by expert, Texture image

Fig. 6.In glanular tissue: From left to right: Input image, Edges mass by expert, Texture image.

B. *Quantitative evaluation of mass edges detection*

For evaluating edge detection, we select identified mass contours, according to expert image and we compute Dice Coefficient at first. Second we compute Precision, Recall and F-measure in order to calculate the area under the curve and compare our results with the recent results of masse detection and/or segmentation methods in the literature.

1) *Quantitive evaluation with Dice Coefficient:* The segmented mass is compared to segmentation carried by an expert radiologist by measuring Dice coefficient.

Our approach was applied and tested in the challenging images of the MIAS dataset, we show here the most representative and speaking cases. We quote, the cases where the tissue is dense (e.g. Fig.7), the cases where the tissue is fatty (e.g. Fig.8) and the cases where the tissue is glandular (e.g. Fig.9).

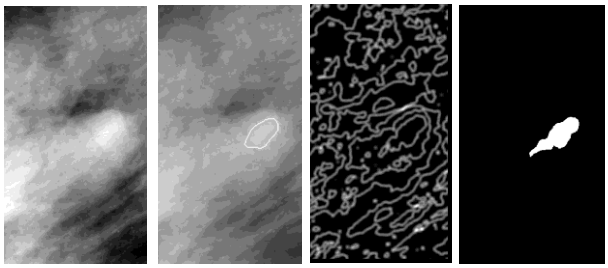

Fig. 7. From left to right: ROI image, ROI image with borders (whites) of the mass region by the expert radiologist, image ROI of the texture with mass detection, image mass segmentation by applied mask, Dice Coeff = 93.39%

Fig. 7 shows the case where tissue surrounding region of mass is dense. The borders delimited by our method are more complete than the borders (white lines) delimited by expert radiologist. But with a good Percentage of resemblance compute by Dice Coefficient 93.39%. This will certainly help the expert to interpret better the shape of the mass such as detected.

The borders delimited by our method are more complete than the borders (white lines) delimited by expert radiologist. But with a good Percentage of resemblance compute by Dice Coefficient 93.39%. This will certainly help the expert to interpret better the shape of the mass such as detected.

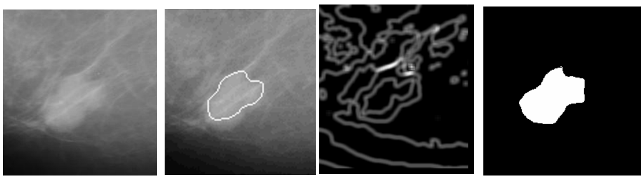

Fig. 8. From left to right: ROI image, ROI image with borders (whites) of the mass region by the expert radiologist, image ROI of the texture with mass detection, image mass segmentation by applied mask, Dice Coeff. = 97.74%

Fig. 8 shows the case where tissue surrounding region of mass is Fatty. Here, other borders inside the region of mass delimited by the expert are detected by our method. If we follow the expert, the coefficient of resemblance will be very good 97.74%, otherwise it will not be satisfactory. Fig 8A shows the case where we take the mask detected inside mass region, with Dice coeff=69.35%.

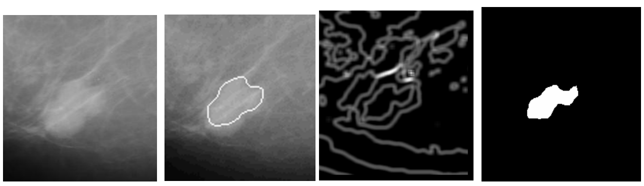

Fig. 8A. From left to right: ROI image, ROI image with borders (whites) of the mass region by the expert radiologist, image ROI of the texture with mass detection, image mass segmentation by applied mask, Dice Coeff. = 69.35%

Fig 9 and Fig 9A show the case where tissue surrounding region of mass is Glandular. The same comment as Fig 8, other borders inside the region of mass delimited by the expert are detected by our method, and the rate of resemblance with the demarcations of the expert is 86.18%, see Fig 9A. But if we take the borders following the borders delimited by expert, the rate of resemblance remains good 96.67%.

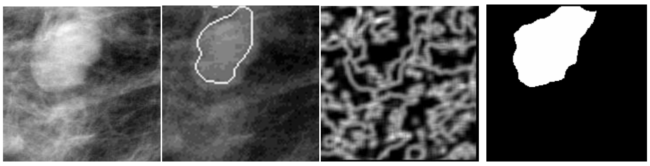

Fig. 9. From left to right: ROI image, ROI image with borders (whites) of the mass region by the expert radiologist, image ROI of the texture with mass detection, image mass segmentation by applied mask, Dice Coeff. = 96.67%.

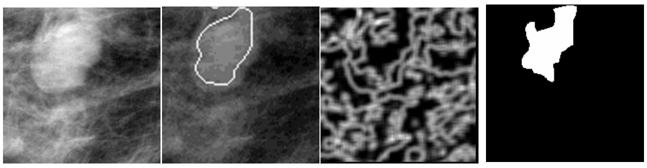

Fig. 9A. From left to right: ROI image, ROI image with borders (whites) of the mass region by the expert radiologist, image ROI of the texture with mass detection, image mass segmentation by applied mask, Dice Coeff. = 86.18%.

2) *Quantitative evaluation with F-measure:* We compute another evaluation in order to compare with other methods of detection and/or segmentation of mass abnormality, by area under the curve.

Tab. 1 shows the Precision, Recall and F-measure for the three cases of images cited above.

Then, we compared with the works of Arnau Oliver in [6], who summarized recently all the methods of mass detection and/or segmentation and who gives the obtained better results, applied also on MIAS Database. These results calculated by area under de curve Az and is between Az=0.751 and Az=0780. For our method, area under the curve Az=0.81.

Image	Precision	Recall	F-measure
mdb004, mass in dense tissue	0.9978	0.9933	0.9956
mdb005, mass in fatty tissue	0.9983	0.9781	0.9881
mdb0019, mass in Glandular tissue	0.9997	0.9375	0.9676

Tab 1.Quantitative evaluation of the segmentation of breast mass, in training images mdb004, mdb005 and mdb019.

V. Discussion And Conclusions.

The stage of the detection and/or the segmentation of the cancerous anomalies in mammographic images is the key step of the performance or not the system CAD.

Unfortunately and mostly, the low contrast of the mammographic images and the complexity of the breast tissues visually and quantitatively, make that until now the most difficult task is really the discrimination between the mammary tissue and the abnormality in the process of detection and/or segmentation of these abnormalities. The more the tissue is white in mammographic image (dense), the more the confusion increases.

In this study, we contributed to clear up the cases for three types tissues (dense, fatty and glandular) most often present in the breast and we discriminated between normal tissue and tissue abnormality using texture descriptor (descriptor of the contrast) given by the GLCM.

We used the texture descriptors extracted from these matrices in a contour approach while mostly they are used in a region approach. Detecting mass edges can help expert radiologist to find size, shape and margin of mass, which are very important in order to classify mass as benign or malign cancer. Our approach is especially easier and fast in times of answer for the specialist.

We applied our algorithm in ROI region for two essential reasons. The first reason is the diversity of tissues (three types of tissues can appear in the same breast), thus it would be necessary to work locally, and we choose tissue surrounding directly the abnormality, it is the most important. The second reason is the computing time of the GLCM, thus to take small zones including suspicious abnormality.

This work is not thus finished. Several anomalies of masses can appear in the same breast, thus see how detecting and/or segmenting these anomalies globally. Studies have already shown that the descriptors of GLCM can segment the various regions of tissues in whole the breast. Concerning computing time, these GLCM are known for the importance of this time and many authors work in the sense of the optimization.

We also concluded that the enhancement stage is also a key stage in our approach. To use SRAD and CLAHE in a different way, or to use other enhancement methods, would give less successful and different results.

The Dice coefficient, F-Measure, Precision and Recall results are very promising, the descriptor of the contrast already manages to detect the margins and thus the shape of the mass. It is necessary to mention that these results are given with a rate of error due to the fact that we took back the localization of the shape of the anomaly on the shape given by the expert.

The database used for our tests is not a trump card to detect automatically abnormality of masses, (the images are scanned). Tests on a better quality of images would have been desirable.

Finally, we can say that texture information is a key to remove the ambiguity between the regions of the anomalies and the healthy regions. However, this information does not obey a well defined mathematical formalism and this area of research remains open to any contribution which can clear up this notion to end why not in a clearer and more formal mathematical definition of the texture.

REFERENCES

[1] Zheng, B., Leader, J.K., Abrams, G.S., Lu, A.H., Wallace, L.P., Maitz, G.S. and Gur, D., "Multiview-based computer-aided detection scheme for breast masses," 2006, Med. Phys. 33 (9), 3135–3143.

[2] Sampat, M.P., Markey, M.K., Bovik, A.C., "Computer-Aided Detection and Diagnosis in Mammography," 2005, handbook.

[3] Naga Mudigonda, R., Rangayyan, R.M. and Leo Desautels, J.E, "Detection of Breast Masses in Mammograms by Density Slicing and Texture Flow-Field Analysis," 2001, IEEE transactions on medical imaging, Vol. 20, No. 12, 1215-1227.

[4] Vyborny, CJ., Giger, ML., "Artificial intelligence in mammography," 1994, AJR 162, 699-708.

[5] Yao, J., Chen, J. and Chow, C., "Breast Tumor Analysis in Dynamic Contrast Enhanced MRI Using Texture Features and Wavelet Transform, 2009," IEEE Journal of selected topics in signal processing, Vol. 3, No. 1.

[6] Arnau, O., Freixenet, J., Marti, J., Perez, E., Pont, J., R.E. Denton, E., Zwiggelaar, R., "A review of automatic mass detection and segmentation in mammographic images," J.Medical Image Analysis, 2010, Vol. 14, 87–110.

[7] Tang, J., Rangayyan, RM., Xu, J., El Naqa, I. and Yang, Y., "Computer-Aided Detection and Diagnosis of Breast Cancer With Mammography: Recent Advances," IEEE Biomedi-cine, 2009, Vol. 13, No. 2.

[8] Bandyopadhyay, SK., "Survey on Segmentation Methods for Locating Masses in a Mammogram Image," International Journal of Computer Applications, 2010, VOL.9, No.11.

[9] Elter and Horsch, "Review on approaches for masses and micro-calcifications diagnosis, segmentation of ROIs for extracting shape and contour features, and their posterior classification," 2009.

[10] Kanta Maitra, I. and *al*., "Identification of Abnormal Masses in Digital Mammography Images," International Journal of Computer Graphics, Vol. 2, No. 1, May, 2011.

[11] Meenalosini, S., 2J. Janet and 1E. Kannan "A Novel Approach in Malignancy Detection of Computer Aided Diagnosis," American Journal of Applied Sciences 9 (7): 1020-1029, 2012.

[12] Mencattini, A., Salmeri, M., Lojacono, R., Frigerio, M., and Caselli, F., "Mammographic Images Enhancement and Denoising for Breast Cancer Detection Using Dyadic Wavelet Processing," 2008, IEEE transactions on instrumentation and measurement, Vol. 57, No. 7.

[13] Yongjian Yu and Scott T. Acton, "Speckle Reducing Anisotropic Diffusion, IEEE Transaction on image processing," 2002, vol.11, no.11.

[14] Haralick, R. M., "Statistical and Structural Approaches to Texture," Proceedings of the IEEE, vol. 67, pp.786-804(1979).

[15] Arodz, T., Kurdziel, M., Popiela, Sevre, T.J., E.O.D., Yuen, D.A. 2006. "Detection of clustered microcalcifications in small field digital mammography, "Comput. Methods Programs Biomed. 8 (1): 56–65.

[16] Basim,A. & al. 2007. "Mammography breast cancer image detection using image processing functions." Information Technology Journal 6(2): 217-221.

[17] H.D. Cheng, X.J. Shi, R. Min, L.M. Hu, X.P. Cai, H.N. Du, Approaches for automated detection and classification of masses in mammograms, Pattern Recognition 39 (2006) 646–668.

[18] M.A. Kupinski, M.L. Giger, Automated seeded lesion segmentation on digital mammograms, IEEE Transactions on Medical Imaging 17 (4) (1998) 510–517.

[19] H.D. Li, M. Kallergi, L.P. Clarke, V.K. Jain, R.A. Clark, Markov random field for tumor detection in digital mammography, IEEE Transactions on Medical Imaging 14 (3) (1995) 565–576.

[20] R.M. Rangayyan, L. Shen, Y. Shen, J.E.L. Desautels, H. Bryant, T.J. Terry, N. Horeczko, M.S. Rose, Improvement of sensitivity of breast cancer diagnosis with adaptive neighborhood contrast enhancement of mammograms, IEEE Transactions on Information Technology in Biomedicine 1 (3) (1997) 161–170.

[21] N. Petrick, H.P. Chan, B. Sahiner, D. Wei, An adaptive density-weighted contrast enhancement ?lter for mammographic breast mass detection, IEEE Transactions on Medical Imaging 15 (1) (1996) 59–67.

[22] H. Kobatake, M. Murakami, H. Takeo, S. Nawano, Computerized detection of malignant tumors on digital mammograms, IEEE Transactions on Medical Imaging 18 (5) (1999) 369–378.

[23] A. Rocha, F. Tong, Z.Z. Yan, Logic filter for tumor detection on mammograms, Journal of Compute Science and Technology 15 (6) (2000) 629–632.

[24] M. Xiao, S.R. Xia, S.W. Wang, Geometric active contour model with color and intensity priors for medical image segmentation, in: Proceedings of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology, 2005, pp. 6496–6499.

[25] J. Shi, B. Sahiner, H. Chan, J. Ge, L. Hadjiiski, M.A. Helvie, A. Nees, Y. Wu, J. Wei, C. Zhou, Y. Zhang, J. Cui, Characterization of mammographic masses based on level set segmentation with new image features and patient information, Medical Physics 35 (1) (2008) 280–290.

[26] F. Zou, Y. Zheng, Z. Zhou, K. Agyepong, Gradient vector flow field and mass region extraction in digital mammograms, in: Proceedings of the 21st IEEE International Symposium on Computer-Based Medical Systems, 2008, pp. 41–43.

[27] A Mohd. Khuzi, BEng, R Besar, WMD Wan Zaki, MEngSc, NN Ahmad, Identification of masses in digital mammogram using gray level co-occurrence matrices.

[28] Richard Pfisterer and Farzin Aghdasi, Comparison of Texture Based Algorithms for the Detection of Masses in Digitized Mammograms0-7803-5546-6/99/$10.00 *0* 1999 IEEE.

[29] Xiaoming Liu, Jun Liu, Dongfeng Zhou and J Tang, "A Benign And Malignant Mass Classification Algorithm Based on An Improved Level Set Segmentation and Texture Feature Analysis", IEEE, 2010.

[30] Laws K. I., "Textured image segmentation", Report 940, Image Processing Institute, University Southern California, Los Angeles, 1980.

[31] Mirmehdi M, Xie X, Suri J. Handbook of texture analysis. CRC Press, 2009.