International Journal of Engineering & Technology, 7 (2.25) (2018) 113-120

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

A comparative study on segmentation methods of micro calcification in mammogram

Bincy Babu [1] *,R. J. Hemalatha [1], A. Josephin Arockia Dhivya [1], T. R. Thamizhvani [1], R. Chandrasekaran [1]

[1] *Department of Biomedical Engineering, Vels Institute of Science, Technology and Advanced Studies , Pallavaram, Chennai-600117, India*

**Corresponding author E-mail: a.dhivya.se@velsuniv.ac.in*

Abstract

The primary indication of breast cancer is the presence of calcification clusters. It is challenging and lengthy process for radiologists to identify and classify micro calcifications as non-cancerous or cancerous. In this proposed work, a novel method for the detection of micro calcification clusters in mammograms is explained that consists of two main sections. First, mammogram preprocessing is done. Second, micro calcification are segmented out. In preprocessing noise and label are removed as well as contrast is enhanced. Then various segmentation methods are used for comparison of calcification region. Watershed segmentation, Marker controlled watershed segmentation (MCWS), Texture segmentation and Level set segmentation methods are applied to Digital Database for Screening Mammography (DDSM) database. Results show that the MCWS provides quite acceptable detection performance. The major advantage of this method is its capability to detect micro calcifications perfectly even in case of very dense mammograms. The performance of different methods is evaluated by comparing the obtained segmented image with expert radiologist data. The comparison study aptly shows that the micro calcifications can be exactly segment and can avoid over segmentation problem of existing method.

Keywords: *Micro Calcification; Mammogram; Marker Controlled Watershed Segmentations*

1. Introduction

Recent studies show that breast cancer is considered as one of the prominent causes of cancer linked deaths in women [1]. Early detection and diagnosis of breast cancer can reduce this mortality rate. X-ray mammography is presently recommended for the initial detection of breast cancer and it is most reliable and simple imaging method. Breast images contain two different types of calcifications such as Micro and Macro calcifications. Computer-aided diagnosis (CAD) system supports doctors and radiologist in undependable and accurate diagnosis of breast cancer. Sickles in [2] states that in describing, identifying and evaluating calcifications that non-cancerous and cancerous calcification clusters have dissimilar characteristic mammographic appearance.

In this paper Digital Database of Screening Mammography (DDSM) [3] is taken for evaluation of mammogram. The case images in DDSM contain lossless compressed digitized mammograms and then pathologies verified by biopsy. Mammogram segmentation plays an important part in detection of calcification. Y W u et al [4] proposed global threshold segmentation method which is simple and easy to implement. The major problem with global threshold is that intensity is only considered and not any relationships between the pixels so that there is no assurance that these identified pixels is neighboring.

D H Davies et al [5] proposed local threshold method for mammoram segmentation. Here threshold value is determined locally. In case of dense mammogram detection, local threshold is better than global thresholding. But the problem is that it can't correctly isolate the pixels into appropriate groups and it is commonly applied as an initialization step in other methods.. H R Jin et al [6] proposed region growing approach. Selection of seed points is the important step in this method. This method failed to adjust the similarity criteria therefore will produce undesirable results. In Fuzzy C-Means clustering (FCM) segmentation method [7,8], which is an addition of K-means clustering is also broadly used for intensity based segmentation. An extension to this is sub segmentation by probabilistic fuzzy c-means (PFCM). It encompasses segmentation within the cluster, hat is considering for less representative data inside the cluster.

Balafar et al [9] also proposed Fuzzy C-Means to segment medical images. In their method, FCM is applied to mammogram images and the centers of clusters are used in a lower scale to decide the initialization membership for the present scale. Here neighborhood desirability was used to further reduction of noise in clustering. Deka et.al. [10] proposed watershed method from a mammogram image having suspicious mass region. There may probably lot of false positives in mammogram database images. These false positives were decreased by using learned dictionaries. H Li et al [11] proposed a segmentation of mammogram abnormality called fractal models in which fractal objects are used to represent image. In general fractal models are attractors of group of two dimensional affine transformations. The elementary property of fractal object is that the mammogram structures are having great resemblance. Drawback of this technique is that, it takes too much calculation time. D Song et al. [12] suggested a wavelet transform method which spatially pinpoints high frequency components. The proposed method is a smart alternative for the finding of high spatial frequency components. Overall idea of these methods is decomposition of region of interest into sub-bands and mammogram micro calcifications are enhanced by weighting the coefficients of those sub-bands. H.Yoshida et.al [13] proposed a system which is constructed on discrete wavelet transform, which has the advantage of multi resolution properties. Here enhancement of the calcification clusters is done

by morphological top-hat algorithm. Level set methods for micro calcification are proposed by Hua L I et al [14]. These methods can also be seen as deformable models and can be implemented in two different ways such as narrow banding and reshaping.
Main complications faced by the existing methods are over segmentation of significant region, interference of pectoral muscle and enhancement of background noise [15-18]. In this proposed system four different approaches for efficient micro calcification segmentation are explained and the mammogram images are taken from DDSM database. The work is arranged as: Section II describes the methodology which is used in this comparison work. Section III discusses the output comparison and study that obtained from different techniques. Conclusions and overall result of this study is detailed in Section IV.

2. Methodology

The proposed system comprises of two phases: mammogram pre-processing and calcification cluster segmentation. The mammogram image pre-processing stage involves: Noise removal of mammogram image, Contrast enhancement of filtered image and finally label and pectoral muscle removal. The pre-processing is then followed by segmentation stage which extracts the micro calcification region. [Table/Fig-1] summarizes the outline of proposed approach. The suggested system worked in MATLAB 7.8.0.

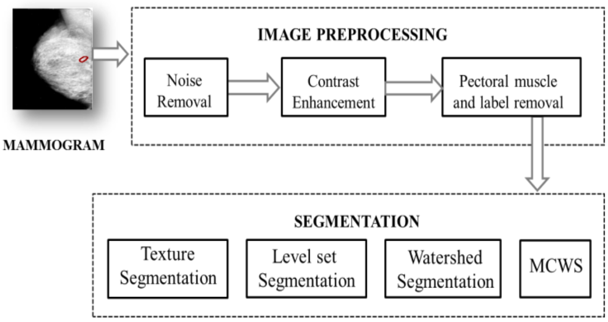

Fig. 1: Proposed Block Diagram.

Generally noises detected in mammogram are of high intensity nature, tape artifacts and low intensity rectangular label. Mammogram preprocessing involves three steps. First, removal of impulse noise then contrasts enrichment and finally deletion of label and pectoral muscle. Adaptive median filter is used for removing salt and pepper noise, CLAHE for contrast enhancement.
The commonly used nonlinear filter is Median filter which is effective in eliminating salt and pepper noise. The main advantage of this filter is its capability to preserve the sharpness of mammogram. Adaptive median filter works on a rectangular region, M_{xy}. Compared to median filter adaptive median filter removes noise effectively by increasing window size. The window size of M_{xy} changes throughout the noise removal procedure. These changes depend on following conditions. In result image each pixel comprises the medium value of surrounding pixel and zeros are applied to the edges of images. The following symbolizations are used where M_{max} is maximum pixel value, P_{med} is median pixel value and Z_{min} is minimum pixel value in M_{xy} at coordinates (x, y). The advantage of adaptive median filter is that it removes non-repulsive noise from mammogram and preserve image without blurring edges.
Section A: X1 = Pmed - Pmin
X2 = Pmed - Pmax
If X1 > 0 and X2 < 0, go to Section A
Else, increase the window size
If window size < Mmax,
Repeat Section B else output Zxy
Section B: Y1 = Pxy - Pmin
Y2 = Pxy - Pmax
If Y1 > 0 and Y2 < 0, output M_{xy}
Else output M_{med}

Contrast Limited Adaptive Histogram Equalization (CLAHE) is related to Adaptive Histogram Equalization (AHE). Here histogram is calculated for each pixel in breast image and the intensity of pixels is converted. Over amplification of noise in the homogeneous regions of mammogram is the limitation of adaptive histogram equalization. To prevent this problem CLAHE method is used which computes by clipping the histogram before computing CDF, Cumulative Distribution Function.
If an image having gray values $g_0, g_1, g_2 \ldots g_{L-1}$, then histogram can be expressed as the discrete function given by equation (1)

$$P\,(g_k) = \frac{nk}{n} \tag{1}$$

Where number of pixels with gray value g_k is represented as nk and n denotes total number of pixels in breast image. This methodology is to plan a transformation function f (.) such that output contains grey values uniformly distributed in [zero, 1]. Consider for an instant that the input digital image to be enhanced, with g= one representing white and g=0 representing black. Here gray value transformation can be represented by equation (2).

$$T = f(r) \tag{2}$$

Which is created based on input mammogram's histogram and boost contrast of image.
Mammograms have two main views. They are Cranio caudal and medio-lateral oblique views. The medio-lateral oblique views contain pectoral muscle which is major density region in mammogram. For accurate performance of cancer detection this pectoral muscle region must be removed. When the medio-lateral oblique view is properly evaluated, pectoral muscle look like a triangular region diagonally in upper margin of the mammogram.
The earlier research works are useful in analysis and study of mammograms. These studies indicated that pectoral muscle region and malign tissues have almost similar texture appearances. When detecting cancerous region these pectoral muscle can lead to false detection. But the portion coming under the pectoral muscle has the possibility of cancer so radiologist tested these regions to avoid wrong results. Therefore elimination of pectoral muscle is a significant part in cancer detection. Normally for removing things that touch the border of an input image reconstruction method is used. The vital part of this method is to choose the suitable marker to accomplish the desired effect. Let assume the marker image, M_i as

$$Mi\,(x,y) = \begin{cases} N\,(x,y) & \text{if } (x,y) \text{is on the border of N} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$L = RB\,(M_i) \tag{4}$$

Where N is the image after filtering and contrast enhancement, M as the mask image, R reconstruction and L that contains only the objects touching the border. The objects from the B that do not touch the border is denoted as 1 – L.
Segmentation is considered as primary phase in breast image classification and cancer detection. This phase include techniques to identify the positions of calcification regions. In this proposed system four segmentation methods are used. They are Texture segmentation, Watershed, Marker controlled watershed and level set segmentation.
Texture segmentation to detect regions based on mammogram image's texture [19]. Here we are using two kinds of fabric in breast image using texture filters. First local entropy of grey scale image is calculated. Then rescale the texture image for make its values in the default range. Second step is segmenting the bottom texture by creating rough mask. Here threshold the image for segmenting the textures. Finally top structure is extracted by using rough mask.Mostly, the watershed transform is calculated on the gradient of the digital input image and the catchments basin boundaries are found at high gradient peak points. Owing to many advantages the watershed transform has been broadly used in the fields of medical image segmentation. This method is fast and produces a segmented

result even if the contrast of input image is poor and thus avoiding the need for contour joining.
The mathematical expression for watershed segmentation is shownin equation(5). Let take $B_n(M_i)$ as set of point coordinates which is related with minimum M_i which is taken as flooded at stage n.

$$B_n (M_i) = B (M_i) \cap T [n] \quad (5)$$

$$\mathrm{Bn(Mi)} = \begin{cases} 1 & \text{if } (x,y) € \mathrm{Bn(Mi)} \text{ and } (x,y) € \mathrm{T[n]} \\ 0 & \text{otherwise } \mathrm{Bn(Mi)} = 0 \end{cases}$$

Marker-controlled watershed segmentation (MCWS) approach can be explained as, firstly calculate the magnitude gradient of preprocessed mammogram. Then compute the external and internal marker in order to detect all regional minima's that have greater values than a definite threshold. Next step is to suppress all other minima's excluding the minima's state from the gradient image and obtain the revised gradient image. Finally compute the watershed of that gradient image to create the watershed ridge lines.
The main tasks in marker controlled segmentation are computing gradient of image, closing, opening, erosion and dilation. Linear filtering method is used to compute the gradient magnitude. It is a type of preprocessing technique which is used before introducing watershed transform. Let assume $S(x, y)$ is a gray scale image. The gradient vector magnitude of $S(x, y)$ can be calculated as follows in equation (6) where (x,y) is the co-ordinates.

$$S(x,y) = \sqrt{(s_1{}^2(x,y) + s_2{}^2(x,y))} \quad (6)$$

Closing and opening are main operators from mathematical morphology which are taking from basic fundamental procedures of erosion and dilation. The morphological opening of P by Q, represented by P○Q is basically erosion of P by Q and then followed by dilation of output by Q as shown in following equation (7). P○Q is union of all translations of Q that is suitable fully within P. The morphological operation opening eliminates completely areas of an object that does not cover structuring element. It smooth the object contours and breaks thin connection or protrusions.

$$P \circ Q = (P \Theta Q) \oplus Q \quad (7)$$

In general, binary morphology observes an input by way of a subclass of a Euclidean space, Es. The main idea is to analysis the image with a distinct contour and then plotting decisions on how contour fits the shapes or misses in the input image. Let assume Es as a Euclidean space. The erosion operation of the P by Q is represented as equation (8) where P is a binary image and Q is structuring element. The expression for Q_z is shown in equation (9). The translation of Q by the vector z is denoted as Q_z.

$$P\Theta Q = \{z \epsilon E | Q_z \underline{C} P \quad (8)$$

$$Q_z = \{q+z | q \epsilon Q\}, \square z \epsilon E \quad (9)$$

The morphological reconstruction, it solely extracts the connected components of input image. Dilation is a morphological reconstruction method which is constructed based on marker and mask image. For both mask and marker have same size and low intensity. The result of reconstruction process may be a binary or intensity image. The morphological closing operation can be described as dilation operation then followed by erosion as given in equation (10). P●Q represents closing operation of P by Q. The closing operation has same features as that of opening. It smooth the object contours of binary image. Closing operation have one advantage is that it have the ability to fill up holes that are smaller than structuring element and also join the narrow breaks present in binary image.

$$P \bullet B = (P \oplus Q) \Theta Q \quad (10)$$

The dilation is an operation in mathematical morphology that converts structuring element all over the area of binary image. If the structuring element overlays any 1-value pixel in the binary image then output image is 1 at every one location of the structuring element. Mathematically, the dilation operation can be is defined in terms of set procedures where dilation of P by Q, denoted by P⊕Q as given in equation (11).

$$P \oplus Q = \{z | Q^z \cap P \neq \phi\} \quad (11)$$

Compared to other segmentation methods it has the ability to handle cavities, convolution, splitting and merging. This method is widely used to capture and track boundaries. It has been implemented in a many applications such as areas where minimum surface generation is needed ie, moving interfaces and curves.
Let assume the initial point, M0(x) as zero level set of φ where φ is higher dimensional function and associate progress of this φ function to the progress of the boundary over a problem that is time dependent. The contour M (t) symbolized as zero level set of φ at each interval. It can be written as equation(12).

$$(M (t), t) = 0; t + \nabla (M (t), t).\partial M / \partial t = 0 \quad (12)$$

From $\partial M/\partial t = Zn$ and $\nabla\varphi / |\nabla\varphi|$, the expression can be written as shown in equation(13).

For

$$\Phi: t + Z \nabla = 0 \quad (13)$$

$$(X, 0) = M0 (x)$$

In this technique it is easy to confine the computation domain into group of cells to decrease of the computational cost and these groups are around zero level set of φ (x, t). If identification of initial curves is accurate then only this method can provide satisfactory results.

3. Results and discussion

3.1. Experimental data

Digital Database for Screening Mammography (DDSM) database[a] is used for mammogram analysis and study. This database enclosing 300 mammogram images with ordinary size of 482 × 450 pixels. The images were digitized by various scanners such as Howtek 960 (12 bits ,43.5 µm per pixel), Howtek Multi Rad 850(12 bits, 43.5 µm per pixel), DBA M2100 Image Clear (16 bits , 42 µm per pixel) and Lumisys 200 Laser (12 bits , 50 µm per pixel. Hologic Selenia mammography unit having resolution of 70 µm per pixel is used to capture the mammogram images. In this work, all micro calcifications in each breast image are considered to be portion of a particular micro calcification cluster.

3.2. Experimental results

A sample mammogram DDSM image is shown in [Table/Fig-2]. This sample mammogram consist of various components such as high intensity rectangular label, low intensity marker or label, pectoral muscle, near skin tissue, fatty tissue, glandular tissue, artifacts and background region. For better analysis of mammogram, it is important to avoid interference of pectoral muscle and labels.

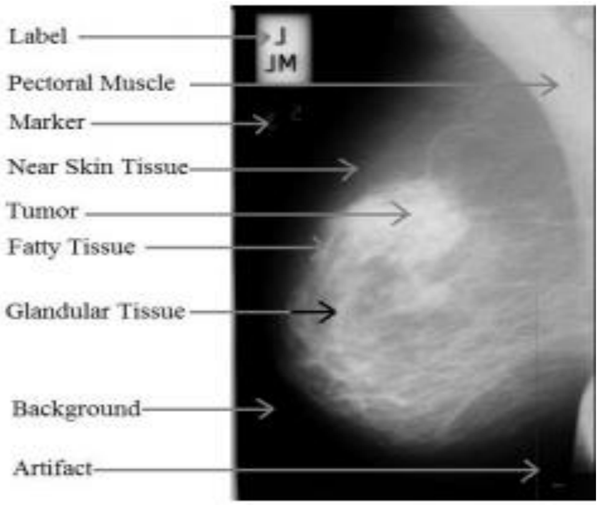

Fig. 2: Sample DDSM Image.

Mammogram preprocessing is a major step in mammogram analysis. This procedure includes processing of mammogram to detect anomalies without leaving the momentous data. Generally mammograms are of low contrast and contain noises during acquisition. The DDSM images are taken for preprocessing. Salt and pepper noise is effectively removed using adaptive median filter [Table/Fig-3], contrast is enhanced using CLAHE method [Table/Fig-4], unwanted parts such as pectoral muscle and label is eliminated as shown in [Table/Fig-5].

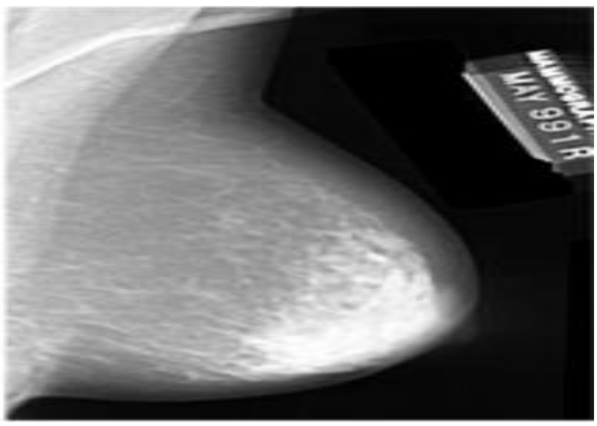

Fig. 3: Filtered image.

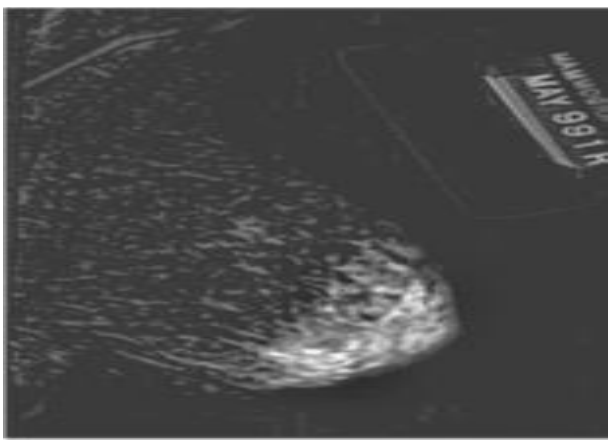

Fig. 4: CLAHE Image.

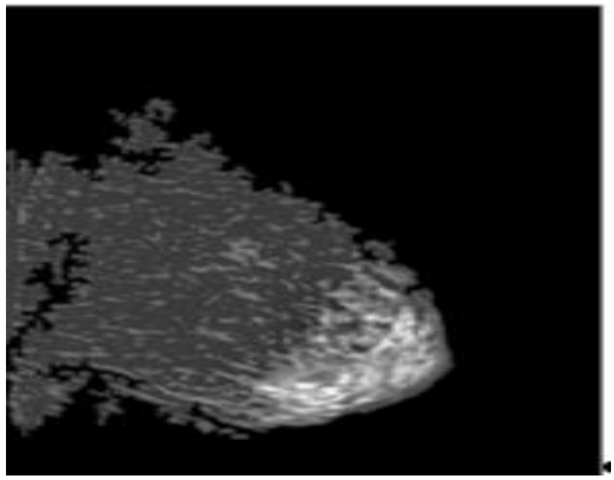

Fig. 5: Pectoral Muscle and Label Removed Image.

Four different type segmentation methods are used here such as watershed segmentation, marker controlled watershed segmentation, texture segmentation and level set segmentation methods. Watershed segmentation can be compared with MCWS in which over segmentation in mammogram can be avoided.

If directly applying watershed transform to breast image, it may lead to over segmentation of image. Over segmentation means large number of segmented regions and it happened because of noise present in particular image. Here in watershed segmentation [Table/Fig-6], it over segment the mammogram anomalies instead of segmenting micro calcification area. MCWS is applied to avoid over segmentation problem of watershed method and MCWS [Table/Fig-7] is based on the idea of markers. Level set method [Table/Fig-8] is a framework that is used for image processing. It has the ability to handle cavities and holes. Level set method is important in tracking shapes that vary topology. Texture segmentation [Table/Fig-9] works based on the nature of mammogram texture variation.

Fig. 6: Watershed Segmented Image.

Fig. 7: MCWS Segmented Image.

Fig. 8: Level Set Segmentation Result.

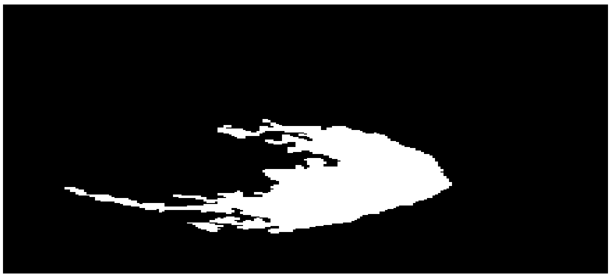

Fig. 9: Texture Segmentation.

3.3. Comparison

Segmented image is superimposed on original image for better comparison of four segmentation methods. [Table/Fig-10] shows watershed and [Table/Fig-11] shows MCWS. Super imposed results of Level set method [Table/Fig-12] and texture method [Table/Fig-13] are analysed. In watershed transform, the DDSM image after preprocessing is changed into another image whose catchment basins are objects that we want to identify (micro calcification regions). From segmented output of watershed method, it can be observed that regions apart from micro calcification are also segmented and over segmentation problem occurred. Marker controlled segmentation method have an advantage that it computes internal and external markers for segmentation.

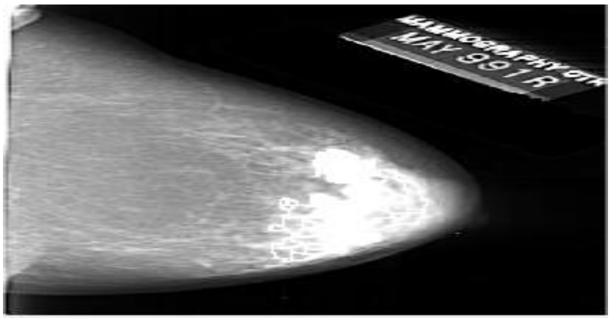

Fig. 10: Segmented Output Superimposed on Original Mammogram- Watershed.

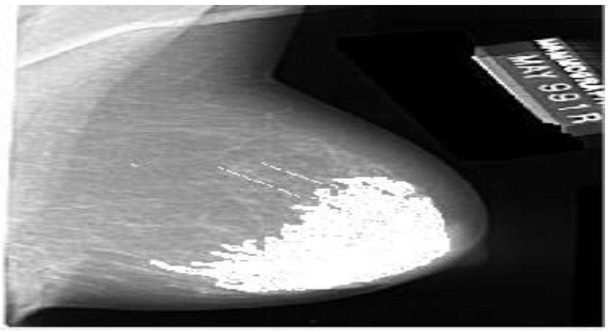

Fig.11: MCWS.

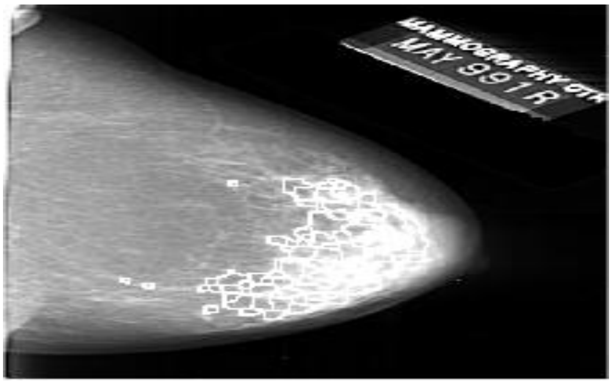

Fig. 12: Segmented Output Superimposed on Original Mammogram Level Set.

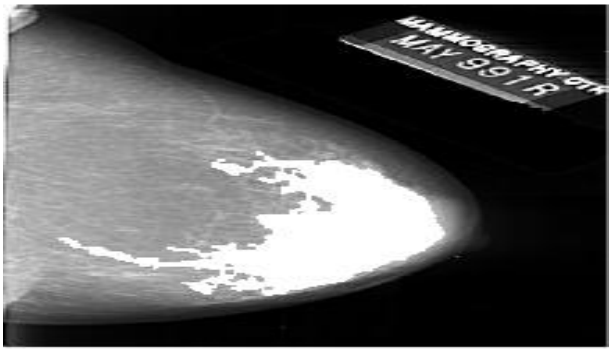

Fig. 13: Texture Segmentation.

In level set segmentation it can be visible that area nearer to the pectoral muscle also segmented. When texture segmentation is superimposed on original mammogram, it can be observed that micro calcification region is oversegmented. Fig.7 shows ground truth and MCWS segmented outputs. From this we can easily compare the result.

Accuracy, Specificity and sensitivity can be calculated by compairing ground truth [Table/Fig-14], MCWS [Table/Fig-15] and various segmented output. Accuracy [Table/Fig-16], specificity [Table/Fig-17] and sensitivity [Table/Fig-18] are calculated as shown in following graphs. These comparisons are done by comparing with ground truth data. In accuracy bar chart analysis MCWS method gives better result compared to all other methods. Watershed segmentation result is showing very poor response in detection of calcification. Over segmentation of watershed can be solved in MCWS method where foreground and background markers are calculated. Level set segmentation provides segmented result better than watershed and segmentation methods. Texture based segmentation method gives over segmentation result. All these methods failed in accurate detection of cancer. By analyzing accuracy, specificity and sensitivity, can conclude that MCWS method is better in cancer detection.

Fig.14: Ground Truth.

Fig. 15: MCWS Result.

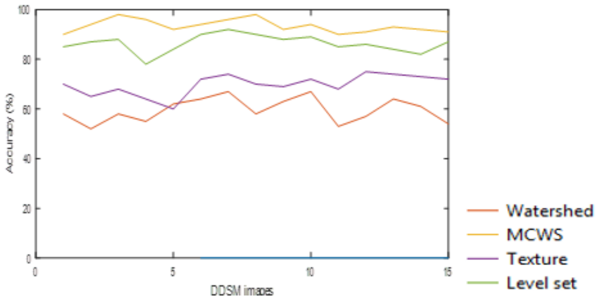

Fig. 16: Accuracy Analysis of Different Segmentation Methods.

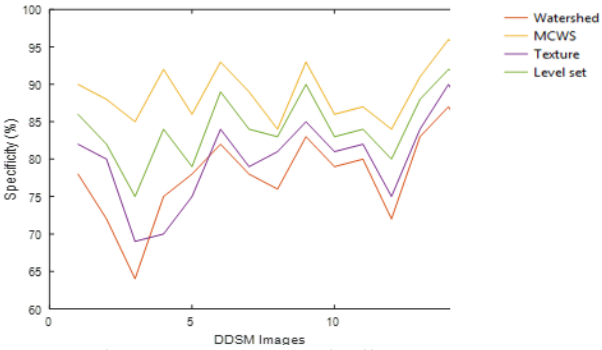

Fig. 17: Specificity bar Chart Analysis of Different Segmentation Methods.

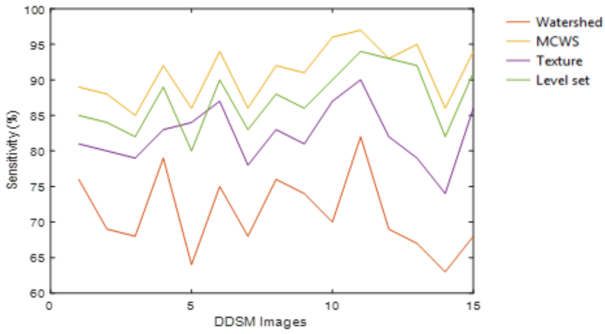

Fig. 18: Sensitivity bar Chart Analysis of Different Segmentation Methods.

[Table/Fig-19] shows perimeter of micro calcification segmented output that has been obtained from four different methods.. The main advantage of level set method is that it can easily handle images having concavities, cavities, convolution and splitting. These are important to consider when dealing with mammogram images.
Eccentricity micro calcification characteristics are calculated for all segmented methods as shown in [Table/Fig-20]. Even though level set have so many advantages, they need the prior choice of initial location of the seed point, degree of smoothness and appropriate propagation speed function. The drawback of existing methods is that most of them depend on boundaries of calcification region. The main important characteristics, i.e. area of calcification region are obtained for all methods as shown in

Table 1: Micro Calcification Perimeter Comparison for Different Segmentation

Image Type	Watershed	MCWS	Texture	Level set	Ground Truth
Malignant- 1	0.50	0.46	0.51	0.52	0.48
Malignant- 2	0.63	0.51	0.62	0.60	0.57
Malignant- 3	0.47	0.38	0.45	0.44	0.41
Malignant- 4	0.62	0.55	0.61	0.61	0.58
Malignant- 5	0.65	0.61	0.67	0.65	0.62
Begninant-1	0.82	0.72	0.81	0.78	0.74
Begninant-2	0.88	0.81	0.89	0.87	0.83
Begninant-3	0.83	0.74	0.82	0.81	0.76
Begninant-4	0.73	0.69	0.74	0.72	0.70
Begninant-5	0.85	0.78	0.85	0.84	0.81
Normal-1	0.98	0.97	0.98	0.99	0.99
Normal-2	0.93	0.89	0.94	0.92	0.87
Normal-3	0.83	0.82	0.85	0.84	0.83
Normal-4	0.98	0.94	0.97	0.96	0.97
Normal-5	0.97	0.98	0.98	0.99	1.00

Table 2: Micro Calcification Eccentricity Comparison for Different Segmentation

Image Type	Watershed	MCWS	Texture	Level set	Ground Truth
Malignant- 1	3.91	5.81	4.21	4.92	5.93
Malignant- 2	69.54	85.49	72.53	79.25	84.9
Malignant- 3	52.31	67.92	58.67	62.31	65.2
Malignant- 4	0.972	1.79	1.01	1.20	1.96
Malignant- 5	90.21	98.76	90.23	94.56	100.02
Begninant-1	135.24	149.39	140.82	142.31	152.36
Begninant-2	118.74	132.56	125.27	128.79	133.23
Begninant-3	195.94	217.98	199.53	208.34	217.58
Begninant-4	212.37	251.87	220.18	231.64	253.21
Begninant-5	335.42	351.21	340.74	347.25	355.47
Normal-1	708.96	732.40	716.28	728.63	735.91
Normal-2	447.25	471.92	457.11	468.23	476.23

Normal-3	521.14	568.13	529.24	535.87	572.10
Normal-4	524.75	558.18	538.21	542.78	560.72
Normal-5	626.14	646.73	635.73	640.12	650.21

Table 3: Micro Calcification Eccentricity Comparison for Different Segmentation

Image type	Watershed	MCWS	Texture	Level set	Ground Truth
Malignant- 1	498.4	964.87	654	759	966.52
Malignant- 2	162.4	327.18	202.4	292.5	329.23
Malignant- 3	923.4	2161.87	1044.96	1772.25	2168.75
Malignant- 4	152.7	459.56	292.35	389.34	462.35
Malignant- 5	925.21	1432.58	1032.38	1325.41	1438.64
Begninant-1	2754.87	4879.95	3687.5	3872.33	4882.10
Begninant-2	1921.89	3389.87	2624.23	2723.58	3394.21
Begninant-3	1821.87	3897.65	2412.69	2989.36	3864.24
Begninant-4	2778.20	4425.63	3875.63	4023.58	4389.23
Begninant-5	3675.57	5874.36	3982.20	4987.36	5897.32
Normal-1	19899.25	25341.37	26993.21	27002.45	25352.2
Normal-2	3233.21	6291.42	4923.56	5433.52	6358.74
Normal-3	95879.34	114731.5	105895.98	116666.25	114736
Normal-4	31789.35	515127.2	394786.28	424425.62	515189.3
Normal-5	4213.24	6291.42	4958.34	5433.52	6300.21

From the comparison of the micro calcification characteristics of watershed, texture, level set and MCWS with ground truth, it can visible that MCWS provide almost closer result to ground truth where watershed segmentation is limited by markers in order to avoid over segmentation. Fifteen DDSM images characteristics are shown here. MCWS is suitable for almost all type of mammograms where overlapped or more clustered calcifications are present.

4. Conclusion

In this work four micro calcification segmentation methods are compared. The accurate detection of the cancerous region is done by the elimination of the pectoral muscle and the preprocessing takes place using adaptive median filtering and CLAHE. Mammogram images are taken from DDSM database. Mammogram images cover salt and pepper noise. Adaptive median filtering is used to remove this type of noise from DDSM images. Mammograms are generally low contrast images and so that Contrast Limited Adaptive Histogram Equalization is applied for contrast enhancement. Both pectoral muscle region and calcification region have almost similar texture characteristics. It can leads to detection of false positives when identifying micro calcification region. Reconstruction methods are used to remove pectoral muscle. After that four different types of segmentation methods are used such as Watershed, MCWS, level set and texture segmentation. From the observed result, it is visible that MCWS method provides almost similar segmented output to ground truth. Over segmentation of tumor region is the disadvantage of Watershed segmentation. MCWS avoids over segmentation problem of watershed segmentation algorithm and decreases false detection. Results for performance measures show that MCWS produce better result than existing methods. The MCWS output is compared with level set segmentation method and found that output of MCWS matches with ground truth data about the area of calcification.

5. Future work

Future work of this paper is to extract the texture features and classify micro calcification into benign or malignant from segmented calcification cluster.

References

[1] H-C. Kung, D. L. Hoyert, J. Xu, and S. L. Murphy, 'Deaths: final data for 2005,' National Vital Statistics Report, vol. 56, no.10, pp. 1–121, April 24, 2008.

[2] E.A.Sickles,'Breast calcifications: Mammographic evaluation,'Radiology, vol. 160, pp. 289–293, 1986.

[3] 'USF digital mammography home page,' http: //marathon.csee.usf.ecu/Mammography/Database.html,(accessed May 18, 2009).

[4] Y. Wu and K. Doi,'Computerized detection of clustered microcalcifications in digital mammograms: Applications of artificial neural networks,' Med. Phys., Vol. 19, No. 3, pp.213-217,1992.

[5] D. H. Davies and D. R. Dance,'Automatic computer detection of clustered calcifications in digital mammograms', Phys. Med., Biol., Vol. 35, No. 8, pp. 1111–1118,1990.

[6] H.R. Jin,'Extraction of microcalcifcations from mammograms using morphological filter with multiple structuring elements', System Comput. Jpn. Vol.24,No.11, pp.66–74,1993.

[7] H. Cheng, Y. M. Lui, and R. I. Freimanis,'A novel approach to microcalcifications detection using fuzzy logic techniques', IEEE Trans. Med. Imag.. Vol. 17,No. 3, pp. 425-430,1998.

[8] Bhattacharya, M. and Das, A,'Fuzzy logic based segmentation of microcalcification in breast using digital mammograms considering multiresolution',International Machine Vision and Image Processing Conference,Vol.36.No.121, pp. 98–105 ,2007.

[9] Balafar, M.A., Ramli, A.R., Saripan, M.I., Mahmud, R., Mashohor, S.andBalafar, M, 'New multi-scale medical image segmentation based on fuzzy C-mean (FCM)',The 2008 IEEE Conference on Innovative Technologies in Intelligent Systems and Industrial Applications, pp. 66–70,2008.

[10] Deka B, Ghosh D,'Watershed segmentation for medical ultrasound images', IEEE Int Conf Syst Man Cybernet,Vol.35,No.54, pp.3186,2006.

[11] H. Li, K. J. Liu, and S. B. Lo,'Fractal modeling and segmentation for the enhancement of microcalcifications in digital mammograms', ZEEE Trans. Med. hag., Vol. 16, No. 6.pp.356-360,1997.

[12] D. Song, W. Qian, L.P. Clarke,' Digital mammography: hybrid M-channel wavelet transform for microcalcifcation segmentation', 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam,Vol.20,No.13, pp. 1069–1070,1996.

[13] H. Yoshida, W. Zhang, W. Cai, K. Doi, R.M. Nishikawa, M.L. Giger,,'Optimizing wavelet transform based on supervised learning for detection of microcalcifications in digital mammograms', Proceedings of the IEEE International Conference on Image Processing, Vol. 3, No.3, pp. 152–155,1995.

[14] Hua LI, Elmoataz AL, Fadilia J, Ruana Su, 'An improved image segmentation approach based on level set and mathematical morphology.' France: Dept. of Electronics & Inf. Eng., Huazhong Univ. of Science & Tech.; Vol.25,No.19,pp.189-195,2003.

[15] R.B. Dubeya, M. Hanmandlub, S.K. Gupta, 'A comparison of two methods for the segmentation of masses in the digital mammograms',Computerized medical imaging graphics ,pp 185-191, 2010.

[16] B. Sahiner, H. Chan, N. Petrick, M. Helvie, and L. Hadjiiski, 'Improvement of mammographic mass characterization using spiculation measures and morphological features,'Med. Phys., Vol. 28, No. 7, pp. 1455–1465,2001.

[17] Kim, J.K., Park, J.M., Song, K.S. and Park. W,'Adaptive Mammographic Image Enhancement Using First Derivative and Local Statistics', IEEE Transactions on Medical Imaging, Vol. 16, No. 5, pp. 495-502,.1997.

[18] P. F. Stetson, F. G. Sommer, and A. Macovski, 'Lesion constrast enhancement in medical ultrasound imaging', IEEE Trans. Med. Imag.,Vol. 16, pp. 416–425,1997.

[19] Anna N. Karahaliou, Ioannis S. Boniatis, Spyros G. Skiadopoulos, Filippos N. Sakellaropoulos, Nikolaos S. Arikidis, Eleni A. Likaki, George S. Panayiotakis, and Lena I. Costaridou,'Breast Cancer Diagnosis: Analyzing Texture of Tissue Surrounding Microcalcifications', IEEE Trans., Vol. 12, No. 6, pp. 725- 731,2008.