Level Set based Bias Field Corrected Mammograms and Threshold Segmentation for the Detection of Breast Cancer

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ABSTRACT

Breast cancer is one of the usual cancers among the women in the worldwide population. The research paper is developing of a reliable tool to detect earlier signs of the breast cancer in mammograms. Accuracy rate of breast cancer in mammogram depends on image segmentation. Doctors and radiologists can miss the abnormality, due to inexperience's in the field of breast cancer detection. The image segmentation is very useful for doctors and radiologists to analysis the cancer stage. Image segmentation is very difficult process and challenging work in the field of medical image processing. The image segmentation algorithms are region-based and homogeneity of the image intensities in the regions of interest, which often fail to correct segmentation results due to intensity inhomogeneity. This paper proposed level set based bias corrected mammograms and threshold segmentation used to detect breast cancer with intensity inhomogeneities in the segmentation. This method is able to segment the image, estimate the bias field and used for bias correction. After bias corrected image, threshold segmentation and morphology techniques is applied to detect the breast cancer in mammograms with effective results.

Keywords

Image Segmentation, Mammogram, Intensity inhomogeneity, Breast cancer, Level set, Bias Correction image, Threshold, Morphology.

1. INTRODUCTION

Presently breast cancer is a leading cause of death among women and second main cause of death after lung cancer [1-7]. Breast cancer is the one of the important factors of mortality in women over the world. In 2010, 2, 10,203 women in the United States were diagnosed with breast cancer, 40,589 women in the United States died from breast cancer. In 2011, 2, 30,480 cases of non-invasive cancer and 56,650 cases of invasive cancer have been diagnosed during the year 2011. Incidence and death counts cover approximately 100% of the U.S. population. In 2012, about 2, 27,000 women in the United States will be diagnosed with breast cancer [6]. According to the international agency for research on cancer, which is part of the world health organization, there were approximately 79,000 women per year affected by breast cancer in India [4]. The National Cancer Institute estimates that one of the eight women in the United States breast cancer will develop at some point during her life-time [9]. The mortality rates of 30% in the U.S. and 45% in Europe have been demonstrated by the repeated, randomized, and controlled trials [10]. Currently, there are no effective ways to prevent the breast cancer [11], [12].

Mammography is one of the effective tools in early detection of breast cancer [8]. However, treatments of breast cancer in the early stages are more successful; therefore, early detection of breast cancer is an important and effective method to significantly reduce the mortality. There are several imaging techniques for breast examination, including MRI, ultrasound imaging, positron emission tomography (PET) imaging, computerized tomography (CT) imaging, optical tomography/spectroscopy, and X-ray imaging. Among them, mammography (X-ray image) is the most common technique for radiologists to detect and diagnose breast cancer [13], [14]. Two types of mammography are currently used: film mammography and digital mammography. Digital mammography is more welcomed by the physicians [15], [16] since it has better image quality, requires a lower X-ray dose, has a more confident interpretation for difficult cases, and offers faster diagnosis for routine cases [17]. There are some precincts for human observer such as some anomalies missed due to human error as a result of fatigue. These precincts are the main reason of false positive and false negative readings of mammograms. The false positive detection origin unnecessary biopsy and estimated that only 15-30% of breast biopsy cases proved to be cancerous [18]. On the other hand, false negative detection an actual tumor remains unobserved.

To improve the visual quality of mammographic images, more image data can be collected at the data acquisition stage, improving the image resolution [19]. On the other hand, the image visual quality can be enhanced during the post image processing stage in medical imaging systems. It utilizes different image enhancement techniques to enhance the contrast of mammograms. By this way, the visual quality of mammograms is improved without affecting the acquisition process or increasing the hardware costs [20]. The problem of mammogram interpretation using Computer Aided Detection system can be decomposed into two sub-problems. The first deals with the detection and localization of regions of interest (ROIs), which include suspicious areas. Such problem is called segmentation of mammogram. The second is the characterization of suspicious regions as cancer or non-cancer.

Intensity inhomogeneity frequently occurs in real-world images due to variation of different factors, such as spatial variations in illumination and imperfections of imaging strategy, which complicates a lot of problems in the image processing and computer vision. In particularly, image segmentation may be significantly not easy for images with intensity inhomogeneities due to the overlaps between the ranges of the intensities in the regions to segment. To identify these regions based on the pixel intensity is not possible. The broadly used image segmentation algorithms [21], [22], [23], [24] usually rely on intensity homogeneity and therefore are not applicable to images with intensity inhomogeneities. In normally, intensity inhomogeneity has been a challenging task and difficulty in image segmentation.

In this paper, the proposed breast cancer detection based on level set bias filed correction of mammograms with threshold segmentation and morphological operations. The generally conventional model of images with intensity inhomogeneities and derive a local intensity clustering property, local clustering criterion function for the intensities in a neighborhood of each point. The local clustering decisive factor integrated over the neighborhood center to define an energy function and converted to a level set formulation. Minimization of this energy obtained by an interleaved process of level set evolution and estimation of the bias field. This method used for segmentation and bias correction of mammogram images. The energy minimization framework used for image segmentation and estimation of bias field [25].

Threshold is one of the widely methods used for image segmentation. It is useful for discriminating foreground from the background. By selecting a proper threshold value T, the gray level image converted to binary image. The binary image should contain all the essential information about the place and shape of the objects of interest (foreground). The advantage of obtaining binary image that reduces the complexity of the data and simplifies the process of recognition and classification. The most common way to convert a gray-level image to a binary image is to select a single threshold value (T). It is very simple, easy implementation and the global threshold has been a popular technique in many years [26][27][28]. Our proposed method tested on digital mammograms obtained from standard database. This paper is explained as follows. Related works in Section II. Background study, Level set formulation, energy minimization In Section III, result and discussion and Experimental results in section IV. Conclusion and future work is given in Section V.

2. RELATED WORKS

In [29], the investigated multiphase piece wise image segmentation in a kernel-induced space. This may be led to a flexible and effective alternative to complex modeling of image data. This method used an active curve functional containing an original term, which reference image data altered through a kernel function. The algorithm iterated two successive steps: curve evolution and mean shift update of the regions parameters. The effectiveness of this method with a quantitative and comparative performance evaluation over a very large number of experiments on synthetic images, such as medical image, satellite and natural images as well as motion maps.

In [30], the level set image segmentation methods provided. The some regions assumed to know beforehand, As a result, it remains constant throughout functional. These methods investigate a region merging previous related to regions area to permit the some regions to vary automatically during curve evolution, thereby optimizing functional perfectly with respect to the some regions. The method tested with real images of intensity, color and motion.

In [31], the developed curve algorithm for segmenting the synthetic aperture radar (SAR) image into a fixed but arbitrary some Gamma-homogeneous regions. This algorithm consists in developing curves to decrease a statistical condition. This method led to partitions of the image domain following an unambiguous correspondence between segmentation regions and regions enclosed by evolving curves. The algorithm demonstrated on both synthetic and real SAR images. The projected technique improved by introducing a way to estimate the number of regions and extended to other representations of SAR images

In [32], this paper presented a level set multiregional competition algorithm; a natural level set extension to multiple regions of the well-known region competition algorithm. The developed algorithm reduces to the standard region competition algorithm when only two regions considered. Its main feature that the resulting segmentation, into a fixed but arbitrary some regions, guaranteed to be a divided of the image domain. This ensures that no ambiguities arise when assigning points to the various segmented regions. Our starting point was a Bayesian formulation of the segmentation problem, leading to curve evolution equations which are then formulated as level set partial differential equations. A growth of the multiregional competition algorithm which accounts for modeling inaccuracies and imperfections presented, leading to an outlier's rejection mechanism. The last segmentation remains a divided of the image domain; they also clearly highlight the difference in segmentation obtained with and without the extension for outliers' rejection.

3. PROPOSED METHOD

3.1 Background of study

Let Ω be the image domain, and I: $\Omega \dashrightarrow R$ gray level image. In [33], a segmentation of the image I achieved by finding a contour C, which divides the image domain into disjoint regions, and a piecewise smooth function u that approximates $\Omega_{1\ldots}\ldots\ldots\ \Omega_N$ the image I and is smooth inside each region Ω_I this can be formulated as a problem of minimizing the following Mumford-Shah functional

$$F^{MS}(u,C)= \int_{\Omega} (I-u)^2\ dX + \mu \int_{\Omega/C} |\nabla u|^2\, dX + v|C| \ ----1$$

Where I is the length of the contour, the right hand side of the equation (1), first term is the data term, which forces to be close up to the image I. The second term is the smoothing term, which forces to be smooth within each of the region separated by the contour. The third term introduced to regularize the contour.

Therefore, the above energy can be equivalently written as follows

$$\mathcal{F}^{MS}(u_1,\cdots,u_N,\Omega_1,\cdots,\Omega_N) = \sum_{i=1}^{N}\left(\int_{\Omega_i}(I-u_i)^2 d\mathbf{x} + \mu\int_{\Omega_i}|\nabla u_i|^2 d\mathbf{x} + \nu|C_i|\right) \text{---}2$$

Where u_i is a smooth function defined on the region Ω_i.

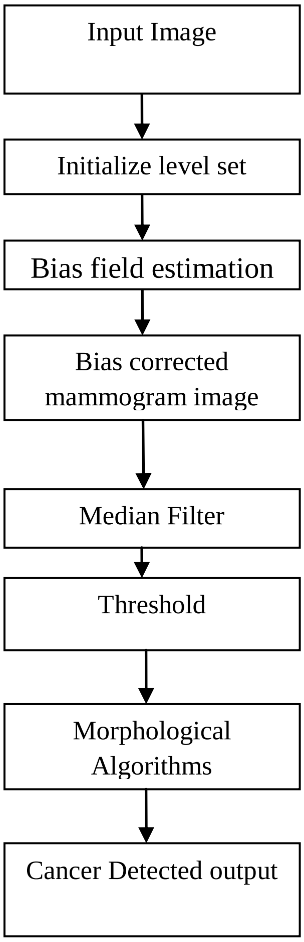


Figure1: proposed Method

This methods aiming to minimize energy are called piecewise smooth (PS) models. In [34], [35], level set methods were proposed as PS models for image segmentation. In a variation level set formulation [36], Chan and Vese simplify the Mumford-Shah functional as the following energy:

F^{CV}(¢,c1,c2)=

$$\int_\Omega |I(X) - C1|^2 H(\varphi(X))dX + \int_\Omega |I(X) - C2|^2 \left(1 - H(\varphi(X))\right) dX + v\int_\Omega |\nabla H(\varphi(X))| dX \text{----}3$$

Where H is the Heaviside function, and φ is a level set function, which's zero level contour $C = \{X : \emptyset(X) = 0\}$ partitions the

$\Omega_11 = \{X : \emptyset(X) > 0\}$ *and* $\Omega_12 = \{X : \emptyset(X) < 0$

Partition the image domain OHM into two disjoint regions and the first two terms in (2) are the data fitting terms, while the third term, with a weight v > 0, regularizes the zero level contours? Image segmentation is achieved by find the level set function and the constants and that minimize the energy F^{CV}. This model is a piecewise constant (PC) model, as it assumes that the image I can be approximated by constants C1 and C2 in the regions Ω_1 and, Ω_2 respectively.

3.2 Image Model and Problem Formulation

In order to deal with intensity inhomogeneities in medical image segmentation, formulate this method based on an image model that describes the composition of images, in which strength inhomogeneity is attributed to a component of a medical image. In this paper, we have considered the following multiplicative model of intensity inhomogeneity. From the physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image can be modeled as

$$I = bJ+n \text{ -------------- } 4$$

Where J is the true image, is the component that accounts for the intensity inhomogeneity, and n is additive noise. The component is referred to as a bias field. The true image J measures an intrinsic physical property of the objects being imaged, which is assumed to be approximately constant. The bias field is assumed to be slowly varying. The additive noise n can be assumed to be zero-mean Gaussian noise. In this paper, we consider the image as a function I: Ω: R defined on a continuous domain. The assumptions about the true image J and the bias field b can be stated more specifically as follows:

(A1) The image bias field is gradually varying, which implies that b can be well approximated by a constant in a neighborhood of each point in the image domain.

(A2) The true image J approximately takes N distinct constant Values C1… C_N in disjoint regions, respectively, $\Omega 1_{\dots}$……. Ω_N where forms a partition of the image domain, i.e. and for based on the model in (4) and the assumptions A1 and A

3.3 Energy Formulation

The local intensity clustering property indicates that intensities in the neighborhood O_y can be classified into N clusters, with centers m_i~b(y) $c_{i,}$ i=1,….,N. ; this allows to apply the standard K-means clustering to classify these local intensities. Specifically, for the intensities I(X) in the neighborhood $O_{y,1}$, the K-means algorithm is an iterative process to minimize the clustering criterion [37], which can be written in a continuous form as

$$F_y = \sum_{i=1}^{N}\int_{O_y}|I(X) - m_I|^2\ u_i(x)\,dx \text{ -------- } 5$$

We can rewrite F_y as

$$F_y = \sum_{i=1}^{N}\int_{\Omega i \cap O_y}|I(X) - m_I|^2\ dx \text{ ------ } 6$$

Therefore, we define energy

$$\varepsilon \triangleq \int \varepsilon_y \, dy, - - - - 7$$

i.e

$$\varepsilon \triangleq \int \left(\sum_{i=1}^{N} \int_{\Omega i} k(y-x)|I(x)-b(y)c_i|^2 \, dx \right) dy - -8$$

In this paper, omit the domain Ω in the subscript of the integral symbol (as in the first integral above) if the integration is over the entire domain Ω the medical Image segmentation and bias field estimation can be performed by minimizing energy with respect to the region $\Omega_{1\ldots}\ldots\ldots\ \Omega_N$, constants $C_1 \ldots C_N$, and bias field b. the kernel function K is chosen as a truncated Gaussian function defined by

$$K(u) = \begin{cases} \frac{1}{a} e^{-\frac{|u|^2}{2\sigma^2}}, & for\ |u| \le 0 \\ 0, & otherwise \end{cases} - - - - - 9$$

Where is normalization constant the energy in (8) can be expressed as the following level set formulation?

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int k(y-x)|I(x)-b(y)c_i|^2 \ M_i(\emptyset(x))dx \right) dy \quad - - - -10$$

The estimated bias field can be used for intensity inhomogeneity correction or bias correction for mammograms. The estimated bias field, the bias corrected medical image is computed as the quotient I/b. To prove the effectiveness of our method in simultaneous segmentation and bias field estimation, we applied it to three medical images with intensity inhomogeneities: an MR image of breast, an X-ray image of bones, and an ultrasound image of prostate. These images exhibit obvious intensity inhomogeneities. The ultrasound image is also degraded with serious speckle noise. A convolution with a Gaussian kernel applied to smooth the ultrasound image as a preprocessing step. The scale parameter of the Gaussian kernel is chosen as 2.0 for smoothing this ultrasound image.

3.4 Performance Evaluation and Method Comparison

The level set method provides a contour as the segmentation result. Therefore, we use the following contour- based metric for precise evaluation of the segmentation result. Let C be a contour as a segmentation result, and S be the true object border and also given as a contour. For each point P_i, i = 1,….,N , on the contour , we can compute the distance from the point to the ground truth contour , denoted by dist (Pi, S). Then, we define the deviation from the contour to the ground truth S by

$$e_{mean}(C) = \frac{1}{N} \sum_{n=1}^{N} dist(Pi, S) \text{-------------------} 11$$

This is referred to as the mean error of the contour C. This contour-based metric can be used to evaluate a sub pixel accuracy of a segmentation result given by a contour.

3.5. Robustness to Contour Initialization

There are able to quantitatively evaluate the performance of the different initializations and different settings of parameters. This method applied to a medical image with 20 different initializations of the contour and the constants. Even though the great difference of these initial contours, the corresponding results are almost the same, all accurately capturing the object boundaries. The image segmentation accuracy is quantitatively verified by evaluating these results in terms of mean errors. These experiments demonstrate the robustness of this model to contour initialization and a desirable accuracy at sub pixel level [38].

3.6. Relation with piecewise constant and piecewise smooth models

This model in the two-phase level set formulation in (12) is a generalization of the well-known Chan-Vese model [38]. When exchanging the order of integrations in equation (10), we can written as follows

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int k(y-x)|I(x)-b(y)c_i|^2 \, dy \right) M_i(\emptyset(x))dx \quad - - - -12$$

Which is a representative piecewise constant model. Our proposed energy in € (14) reduces to the data fitting term in Chan-Vese model when the bias field is a constant b=1. To show this, we need the fact that

$$\int K(y-x)dX = 1 \ - - - 13$$

And recall that

$$M_1(\emptyset) = H(\emptyset) \quad \& \quad M_2(\emptyset) = 1 - H(\emptyset)$$

Thus, for the case of b=1, by changing the order of summation and integration in (12), the energy can be rewritten as

$$\varepsilon = \sum_{i=1}^{2} \int (\int K(y-x)|I(X)-c_i|^2 M_i\big(\emptyset(x)\big)dy \,)dx$$

$$\varepsilon = \sum_{i=1}^{2} . \int |I(X) - c_i|^2 M_i(\emptyset(x)) \int K(y-x)\, dy\,)dx$$

$$\varepsilon = \sum_{i=1}^{2} . \int |I(X) - c_i|^2 M_i(\emptyset(x)) dx$$

$$\varepsilon = \int |I(X) - c_1|^2 H(\emptyset(X)) dx \ + \int |I(X) - c_2|^2 (1 - H\emptyset X) dx - -14$$

Our model is also closely related to the piecewise smooth Mumford-Shah model. The Mumford-Shah model performs image segmentation by seeking N smooth functions u_1…...,u_N defined on disjoint regions $\Omega_{1...}$……. Ω_N, respectively, through a computationally expensive procedure as briefly described in Section II. Different from the Mumford-Shah model, our model aims to find the multiplicative components of the image a smooth function b and a piecewise constant function. The obtained b and J yield a piecewise smooth function bJ as an approximation of the image. the energy minimization processes in our method and the Mumford-Shah model as described before, it is clear that the former obtains the piecewise smooth approximation, thereby yielding the image segmentation result, in a much more efficient way than the latter. A variation level set framework for segmentation and bias correction of images with intensity inhomogeneities. Based on a generally accepted model of images with intensity inhomogeneities and a derived local intensity clustering property [38], we define energy of the level set functions that represent a partition of the image domain and a bias field that accounts for intensity inhomogeneity. Image Segmentation and bias field estimation are therefore together performed by minimizing the proposed energy functional. The gradually varying property of the bias field estimation derived from proposed energy is naturally ensured by the data term in our variation framework, without the need to impose an explicit smoothing term on the bias field. This method is a lot more robust to initialization than the piecewise smooth model. Experimental results demonstrated better performance of this method such as accuracy, efficiency, and robustness.

3.7. Thresholds

Threshold is one of the methods used for medical image segmentation. It is useful for discriminating foreground from the background. By selecting an enough threshold value T, the gray level image converted to binary image. The binary image should have all of the necessary information about the position and shape of the objects of interest (foreground). The advantage of binary image is that it reduces the complexity of the data and simplifies the process of recognition and classification. The most common way to convert a gray-level image to a binary image is to select a single threshold value (T). Then all the gray level values below this T will be classified as black (0), and those above T will be white (1). The segmentation problem becomes one of selecting the proper value for the threshold T. A frequent method used to select T is by analyzing the histograms of the type of images that want to be segmented. The ideal case is when the histogram presents only two dominant modes and a clear valley (bimodal). In this case the value of T is selected as the valley point between the two modes. In real applications histograms are more difficult with many peaks and not clear valleys.

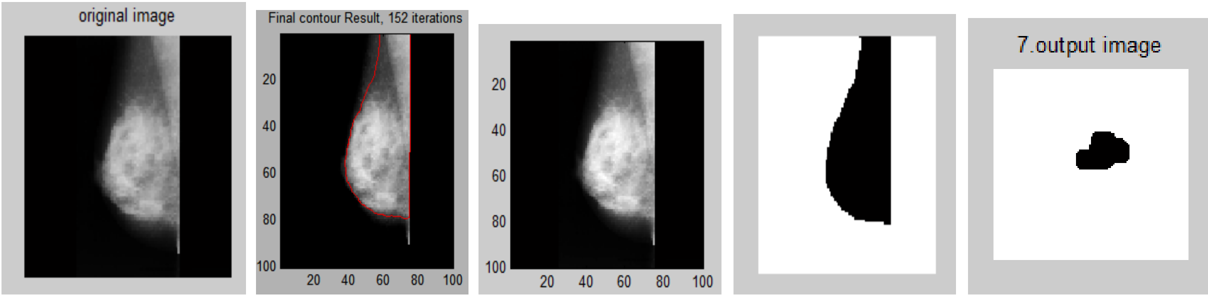
3.8. Morphological Operators

After converting the image in the binary format, some morphological operations applied to converted binary image. The purpose of the morphological operators is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown as white color. This portion has the highest intensity than other regions of the image. Some of the commands used in morphing are given below: 1) Strel: Used for creating morphological structuring element; 2) Imerode ( ): Used to erode (Shrink) an image.;3)Imdilate():Used for dilating (filling, expanding) an image.

4.RESULT AND DISCUSSION

The Mean Square error value is very less while compare with the level set threshold and watershed threshold. The MSE value for level set based bias corrected image and threshold (LSBCIT) is 126.78(for mdb001) and MSE value for level set threshold (LST), watershed threshold(WT) is 5.2464e+004 and 637.6124 (mdb001) respectively. So that the image quality of level set based bias corrected method is better than WT and LST. The small value of Peak Signal to Noise Ratio (PSNR) means that image is poor quality. The PSNR for LSBCIT is 27.1001 (mdb001) and 0.9322, 20.0852 for LST, WT respectively. The image quality is best for LSBCIT. Large value of Normalised absolute error indicates poor quality of the image and small value of Normalised absolute error gives good quality image. Normalised absolute error is 0.1538 (mdb001) for LSBCIT and Normalised absolute error is 6.0545, 0.6907 (mdb001) for LST and WT respectively. From the above observation the level set based bias corrected and threshold method is better than other methods. The proposed method tested for 322 mini database mammogram images. The corresponding parameters tabulated as shown in the table I, II and III, also bar chart is drawn.

Existing Method: Level set and threshold: Example: mdb225

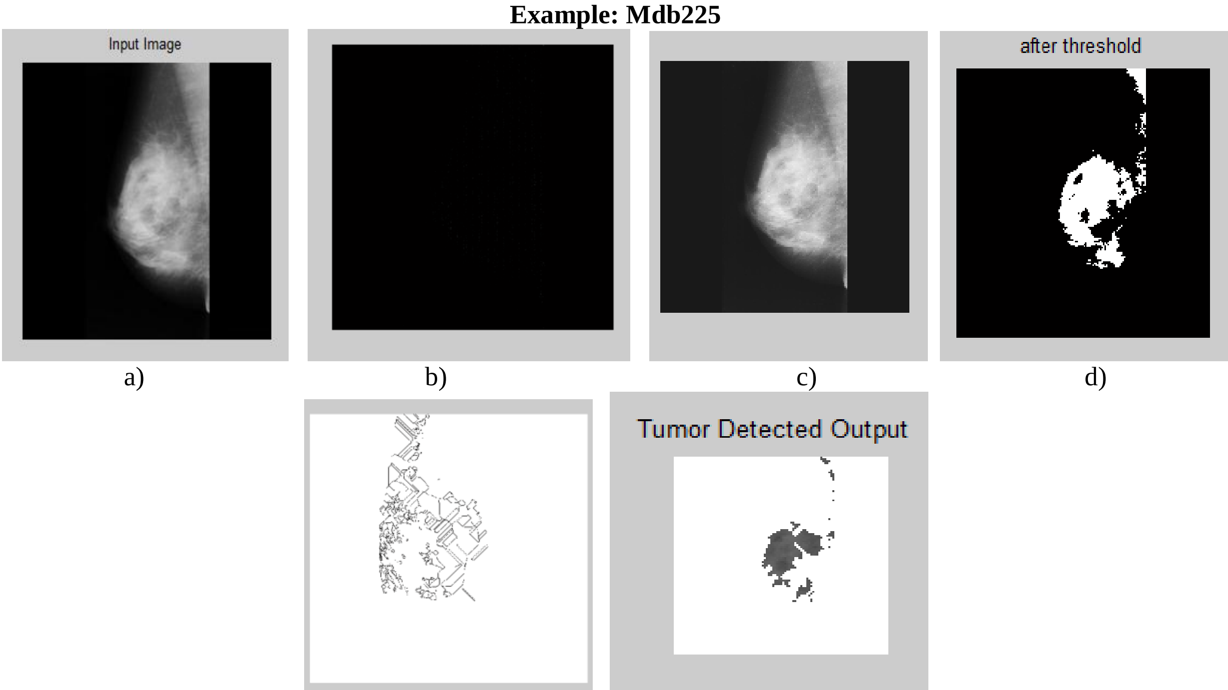


a) b) c) d) e)

Fig.2. level set and Threshold segmentation simulation results for image mdb225.jpg. [(a), (b), (c), (d), and (e)] Original input images, final contour image, enhanced image, threshold image, and tumor detected output respectively.

Existing Method: Watershed and Threshold

Example: Mdb225

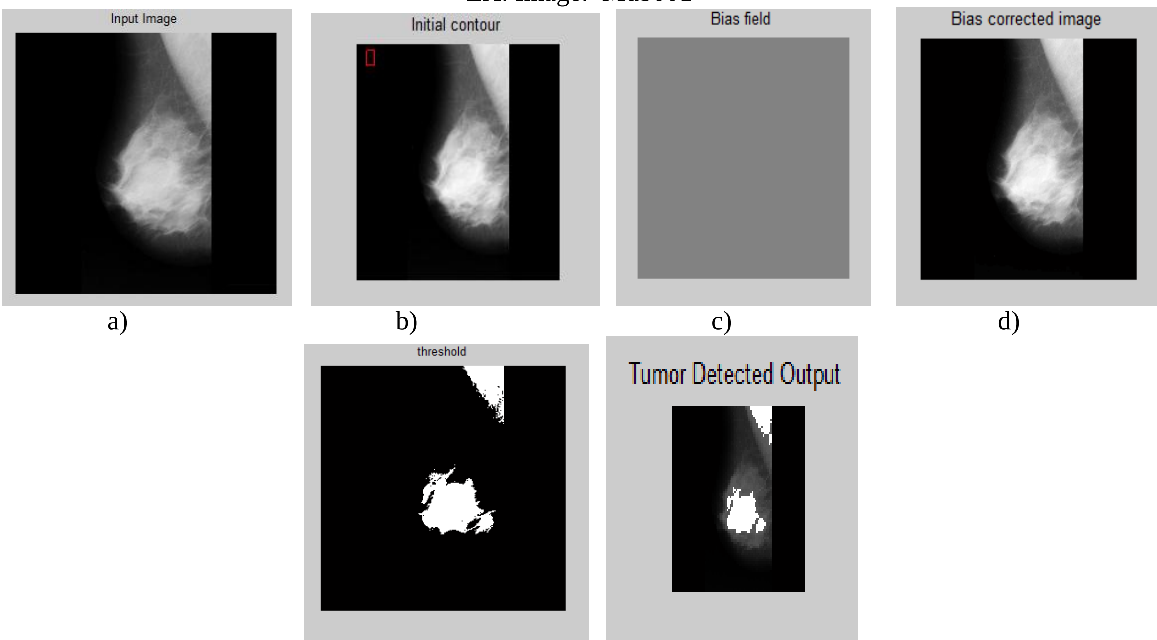


e) f)

Fig.3. Watershed and Threshold segmentation simulation results for image mdb225.jpg. [(a), (b), (c), (d), (e) and (f)] Original input images, after filter image, enhanced image, threshold image, watershed image and tumor detected output respectively

Proposed Method: bias corrected image based level set and threshold

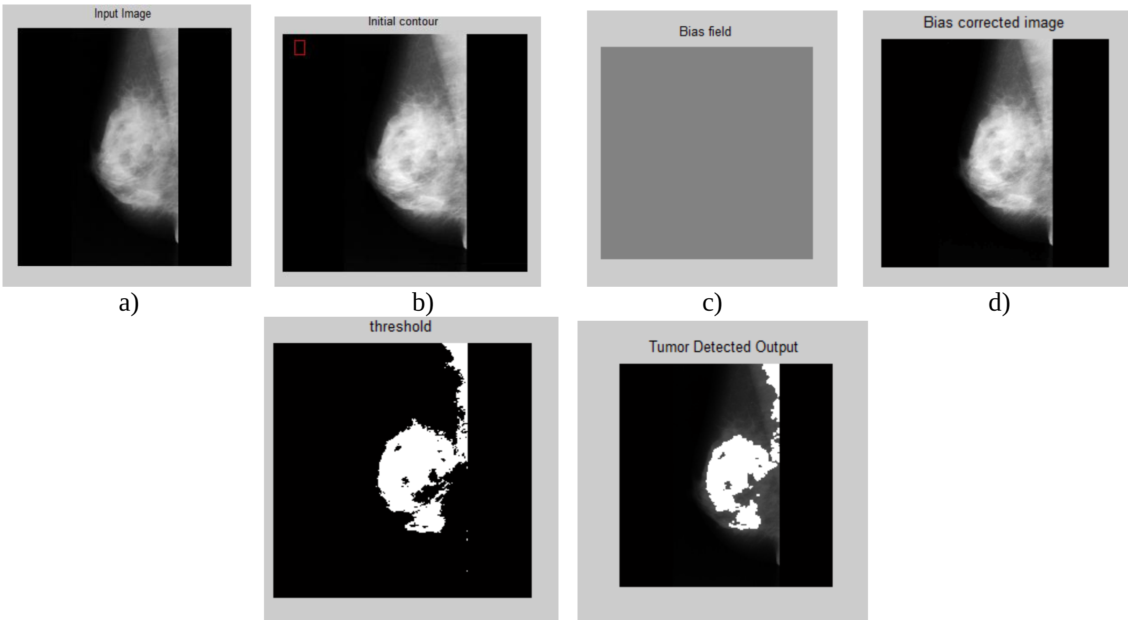
EX. Image: Mdb001



a) b) c) d) e) f)

Fig.4. level set bias field corrected image and Threshold segmentation simulation results for mdb001.jpg. [(a), (b), (c), (d), (e), and (f)] input images, initial contour, bias filed image, bias corrected image, threshold image, and tumor detected output respectively.

EX. Image: Mdb225



a) b) c) d) e) f)

Fig.5. level set bias field corrected image and Threshold segmentation simulation results for mdb225.jpg. [(a), (b), (c), (d), (e), and (f)] input images, initial contour, bias filed image, bias corrected image, threshold image, and tumor detected output respectively.

Table I: Comparison Evolution table

Existing Method: level set and threshold

S.No	Images	MSE	PS NR	NCC	AD	SC	MD	NAE
1	Image001 .jpg	5.2464e+004	0.9322	1.5524	-212.9534	0.0840	235	6.0545
2	Image 055.jpg	5.2428 e+004	0.9352	1.1977	-200.2850	0.1094	243	5.3339
3	Image 164.jpg	4.3802 e+004	1.7159	1.3935	-186.5596	0.1778	291	2.9561
4	Image225 .jpg	5.3655 e+004	0.8347	1.4311	-210.3454	0.0766	231	6.5939
5	Image 322.jpg	4.7354 e+004	1.3772	1.3489	-195.0436	0.1525	257	3.6735

Bar chart I for Image 1: mdb001.jpg

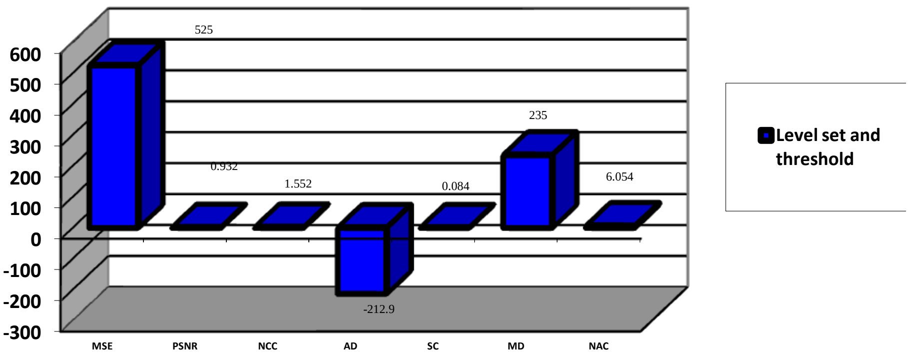


Table II Existing Method: watershed and threshold

S.No	Images	MSE	PS NR	NCC	AD	SC	MD	NAE
1	Image001 .jpg	637.6124	20.0852	1.1756	-25.2344	0.6802	-25	0.6907
2	Image 055.jpg	636.7215	20.0913	1.1566	-25.2178	0.7107	-25	0.6104
3	Image 164.jpg	643.6741	20.0441	1.1463	-25.3321	0.7409	-11	0.340
4	Image225 .jpg	637.7100	20.0846	1.1840	-25.2349	0.6665	-25	0.7353
5	Image 322.jpg	636.7689	20.0910	1.1446	-25.2174	0.7382	-15	0.4581

Bar chart II for Image 1: mdb001.jpg

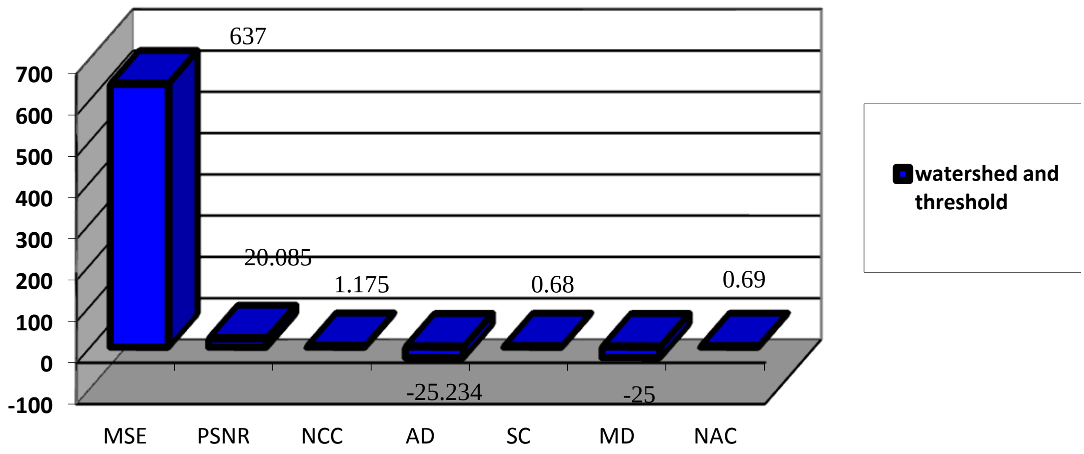
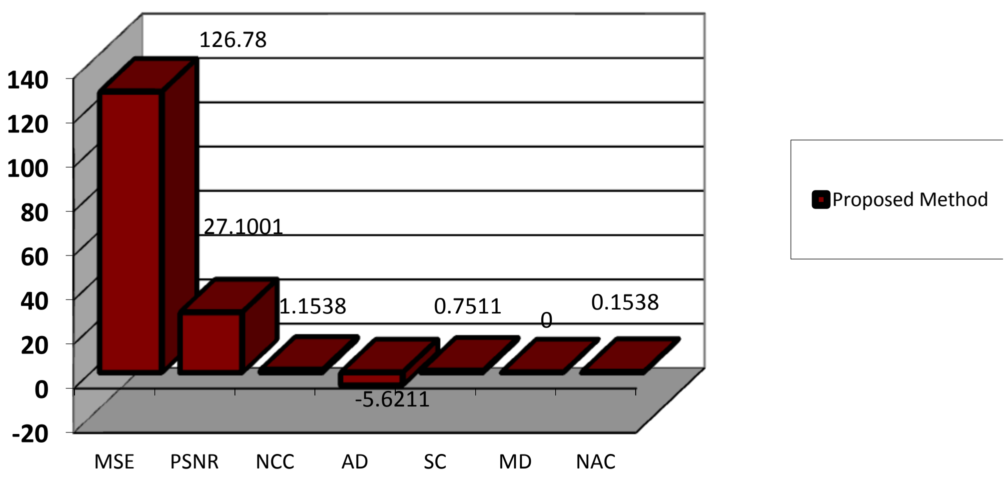


Table III. Proposed Method: level set based bias corrected image and threshold

S.No	Images	MSE	PS NR	NCC	AD	SC	MD	NAC
1	Image001 .jpg	126.78	27.1001	1.1538	-5.6211	0.7511	0	0.1538
2	Image 055.jpg	120.6676	27.3149	1.1333	-5.5082	0.7785	0	0.1333
3	Image 164.jpg	22.9523	34.5225	1.0451	-2.8988	0.9156	0	0.0451
4	Image225 .jpg	187.1510	25.4089	1.1972	-6.7669	0.6977	0	0.1972
5	Image 322.jpg	37.9958	32.3334	1.0625	-3.4403	0.8858	0	0.0625

Bar chart III: Image 1: mdb001.jpg



V.CONCLUSION

The proposed level set based bias corrected image, threshold segmentation and morphology techniques used to detect the breast cancer in mammogram images. In this paper evaluated some parameters of image quality, such as mean square error, peak signal to noise ratio, average difference, maximum difference, normalized absolute error, and normalized cross-correlation. These parameters compared with watershed and level set segmentation. It tested for 322 mammogram images [MIAS Database] and their output observations tabulated. The finally concluded from observations that level set bias field corrected image segmentation more right method. The quality of the image is better accuracy in level set based bias field corrected image segmentation. In our future research, need to improve the image segmentation techniques to detect the breast cancer with close to 100-percentage accuracy in the mammograms.

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