

A New Breast Border Extraction and Contrast Enhancement Technique with Digital Mammogram Images for Improved Detection of Breast Cancer

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Abstract

Purpose: Breast cancer can be cured if diagnosed early, with digital mammography which is one of the most effective imaging modalities for early detection. However mammogram images often come with low contrast, high background noises and artifacts, making diagnosis difficult. The purpose of this research is to preprocess mammogram images to improve results with a computer aided diagnosis system. The focus is on three preprocessing methods: a breast border segmentation method; a contrast enhancement method; and a pectoral muscle removal method. **Methods:** The proposed breast border extraction method employs a threshold based segmentation technique along with a combination of morphological operations. The contrast enhancement method presented here is divided into two phases. In phase I, a bi-level histogram modification technique is applied to enhance the image globally and in phase II a non-linear filter based on local mean and local standard deviation for each pixel is applied to the histogram modified image. The pectoral muscle removal method discussed here is implemented by applying a region growing algorithm. **Results:** The proposed techniques are tested with the Mini MIAS dataset. The breast border extraction method is applied to 322 images and achieved 98.7% segmentation accuracy. The contrast enhancement method is evaluated based on quantitative measures like measure of enhancement, absolute mean brightness error, combined enhancement measure and discrete entropy. The proposed contrast enhancement method when applied to 14 images with different types of masses, the quantitative measures showed an optimum level of contrast enhancement compared to other enhancement methods with preservation of local detail. Removal of the pectoral muscle from MLO mammogram images reduced the search region while identifying abnormalities like masses and calcification. **Conclusions:** The preprocessing steps proposed here show promising results in terms of both qualitative and quantitative analysis.

Keywords: Mammogram images- histogram equalization- contrast enhancement- breast border- pectoral muscle

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Introduction

Breast cancer amongst women has emerged as the second most commonly occurring cancer worldwide with nearly 1.7 million new cases in (Breast Cancer Statistics, 2012). The incidence of breast cancer is rapidly increasing in the Asia Pacific regions (Youlden et al., 2014). It can be cured if diagnosed early but in these regions cultural and economic obstacles persist. Abnormal growth in breast can be detected by screening mammograms as a first line testing tool. Digital mammography is the most effective and inexpensive imaging modality for early detection of breast cancer. In most of the developed country screening mammogram has become a mandate for women after a certain age as a routine checkup. In developing countries too, like India, this technique is being seriously adopted by Government and Non-government organizations in

screening camps, trying to reach out far and wide, to reduce the burden of incidence of breast cancer. With this, the population of mammograms has increased highly over time in comparison to constant number of available radiologists. This has resulted in a highly skewed patient: radiologist ratio. The burden of screening hundreds more mammogram images has now fallen on the shoulders of radiologists. Added to this problem, digital mammograms often contain noise, artifacts and poor contrast making it difficult for the radiologists to give proper and timely judgment. In such a scenario a computer aided tool for analyzing mammograms could be highly helpful. It could be used successfully to strain out the normal cases and leave only the suspicious cases for the experts (radiologists) to review.

Diagnosis is more accurate if a better quality image is provided no matter whether inspected by a radiologist

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or a CAD tool. This work is basically focusing on breast border extraction, contrast improvement, and pectoral muscle suppression. In the first phase of this work a breast border extraction is proposed to segment the breast area from the background. Breast border extraction plays an important role for any CAD system. Segmenting the breast region accurately from the background limits the search area for the localization of masses or microcalcifications, hence increasing the chances of improved detection. A contrast enhancement method is proposed to increase the brightness of the subtle signs like masses and calcifications in the second phase. Lastly an automated segmentation technique to remove the pectoral muscle is applied as the intensity range of pectoral muscle is very similar to as that of masses. The objective of this research work is to produce better preprocessed mammogram images for input to a Computer Aided Diagnosis (CAD) system, which would eventually assist in better diagnosis.

M'endez et al., (1996) used a smoothed version of the original mammogram to obtain the breast border. A spatial averaging filter was applied to smooth the images. Prior to this a histogram based thresholding was applied in order to get optimal result. After smoothing the region was partitioned into three parts to track the boundary using the gradient. Mario et al., (2009) presented a bit depth reduction and wavelet decomposition approach for breast border extraction and pectoral muscle detection with 85% good result. Raba et al., (2005) presented an adaptive histogram based method to separate breast area from the background as first phase of their work. In the next phase of their work a region growing based method was applied to mammograms to remove the pectoral muscle. A multiresolution scheme was exploited in (Karssemeijer and Brake, 1998). They used Hough transform to estimate the position of pectoral muscle. In this method the pectoral muscle were assumed to be a straight line. Ferrari et al., (2000) modified the technique proposed by Karssemeijer and Brake (1998) to detect the pectoral. A method based on different threshold values is presented in Abdel et al., (1996). A nonlinear diffusion algorithm was presented in Mirzaalian et al., (2007) to remove pectoral muscle. A method using Radon's transform was used in Kinsosita et al., (2008) to estimate the pectoral muscle boundary. A graph cut based segmentation method was proposed by Camilus et al., (1998) to identify pectoral muscle. The result of this segmentation produced ragged lines which were further corrected using Bezier curve. An automated pectoral muscle detection method using discrete time Markov chain and an active contour model was discussed in Wang et al, (2011). Chakraborty et al., (2011) utilized shape based features, average gradient and position to detect pectoral muscle boundary as a straight line. The straight line was later on tuned to a smooth curve to represent the pectoral muscle more accurately using a local gradient search technique. Another histogram based thresholding technique was presented by Chen and Zwiggelaar (2012) to segment the breast area from the background. Using connected component labeling algorithm the breast area was identified from the thresholded binary image. In this work a region based technique was used to remove the pectoral muscle starting

at a seed point closer to the pectoral muscle boundary.

Kwok et al., (2001) presented a pectoral muscle removal technique based on iterative threshold and area estimation. In Maitra et al., (2011) a triangular region is defined to isolate the pectoral muscle from the rest of the tissue. A region growing technique to remove pectoral muscle is applied within the defined region to remove the pectoral muscle.

Since decades contrast enhancement techniques have been used for videos and images to make them visually more appealing. It can be done both locally and globally. So far many state of the art techniques for contrast enhancement are available in the literature. However conventional techniques are not found to be effective for enhancing the contrast of mammogram images as these images were textured in nature.

In past two decades various techniques have been proposed for contrast enhancement of low contrast mammogram images. Cheng et al. presented a detailed survey on contrast enhancement techniques for mammogram images (Cheng et al., 2003). In their study, they categorized contrast enhancements techniques into conventional, region based and feature based techniques. Conventional techniques discussed in Cheng et al., (2003) include contrast stretching, histogram equalization, neighborhood processing and convolution mask. Using morphological top-hat and bottom hat operators, Stojic et al., (2005) proposed a method for local contrast enhancement and background noise suppression. Rangayyan et al., (1997) developed a method using adaptive neighborhood contrast enhancement (ANCE) for contrast enhancement for mammogram images. They analyzed the effectiveness of their method for increasing the sensitivity of breast cancer diagnosis. An improved histogram based contrast enhancement technique for X-ray images was presented in Ming et al., (2012) by using gray level information histogram. Jiang et al. presented a technique to enhance the contrast of mammograms by using structure tensor and fuzzy enhancement operators Jianmin et al., (2005).

Materials and Methods

The proposed preprocessing techniques were tested on the images collected from popular publicly available Mini-MIAS dataset (Suckling et al., 1994). This dataset contains MLO mammogram images obtained from 161 patients; per patient two images were collected consisting both left and right mammograms. This dataset includes benign, malignant and normal cases. The images are arranged in pairs of left and right mammograms of a single patient, odd filename numbers are used for all right mammograms and even filename numbers are used for all left mammograms. All the images have a spatial resolution of 200 micron per pixel and have 1,024 x 1,024 total pixels with 8 bit gray level resolution.

Breast Border Extraction

A breast border extraction method based on global thresholding and morphological operations is proposed in algorithm 1.

Algorithm 1 Breast Border Extraction

Step 1: Convert an input grayscale image, I into a binary image, BW using a global threshold.

Step 2: Apply morphological closing operator to BW to obtain the closed image C using a line structuring element, H.

$$C = BW \bullet H$$

Step 3: Apply morphological erosion to the closed image, C using a disk structuring element D.

$$E1 = C \ominus D$$

Step 4: Apply morphological erosion to the eroded image obtained in the previous step using disk structuring element D used in step 3

$$E2 = E1 \ominus D$$

Step 5: Subtract E2 from E1 to get the breast border

$$B = E1 - E2$$

Step 6: Superimpose the breast border over the original image to get image R

Step 7: Mask all pixels outside the breast region of R by assigning a zero value

Contrast Enhancement

Histogram Equalization

The histogram of a digital image is defined by the number of occurrence of each intensity level present in that image. For a digital image with gray levels in the range $[0, L-1]$, the histogram can be expressed as a discrete function $g(r_k) = n_k$, where r_k is the k^{th} gray level and n_k is the number of pixels in the image having gray level r_k . The basic idea behind histogram equalization is to make uniform distribution of intensities by reassigning the intensity value of pixels. In histogram equalization each intensity level r_k is transformed into a new intensity s_k by the following transformation:

$$s_k = T(r_k) = (L - 1) \sum_{j=0}^k p(r_j) \quad (1)$$

Where $(r_k) = n_k/n$ is the number of pixels with intensity r_k and n is the total number of pixels in the image. For $k=0, 1, 2 \dots L-1$.

Brightness preserving Bi-Histogram Equalization (BBHE)

BBHE is a modified form of traditional HE. In this method, the histogram of the original image is divided into two parts based on the mean intensity value to preserve the brightness of the original image. These two sub-histograms are then equalized independently.

Contrast Limited Adaptive Histogram Equalization (CLAHE)

The histogram equalization technique enhances an image without considering the local details; hence the adaptive histogram equalization (AHE) came to the

existence. But the general AHE enhances images by using integration operations yielding large values for the regions having almost uniform intensity distributions with several peaks. This results in over enhancement of regions having noise and sharp changes in the original image. CLAHE is special type of AHE that solves this problem of AHE by introducing a user defined clip level to limit the local histogram in such a way that optimum level of enhancement can be obtained.

Unsharp Masking (US)

In conventional US, image enhancement is performed by subtracting a low pass filtered image from its original image. The main objective of this is to enhance the sharp areas of the original image. But enhancing sharp areas may perform over amplification of noise and over enhancement of sharp areas.

Histogram Modified-Local Contrast Enhancement (HM-LCM)

It is a two phase method, discussed in (Sundaram et al., 2011), for the contrast enhancement of mammogram images. In the first phase a histogram modification method by using a mapping function of uniform histogram and original was applied to the entire image. The objective of this phase was to make the modified histogram as close as possible to uniformly distributed histogram. In the second phase local contrast enhancement method was applied to enhance the local details. The method used local variance and local mean as a basis to design local enhancement filter. Prior to this a histogram based thresholding was applied in order to get optimal result

Proposed Bi-level Histogram Modification-Adaptive Nonlinear Filter (BHM-ANF)

In this section a two phase contrast enhancement method is proposed. In the first phase, a Bi-level histogram modification technique is applied to enhance the contrast globally and in the second phase, an Adaptive Nonlinear Filter is applied to enhance local contrast based on the value of local mean and standard deviation of each pixel. The proposed method, BHM-ANF is illustrated in Fig 1.

Phase I: Bi-level Histogram Modification Technique

Histogram equalization aims to distribute intensities uniformly. However it does not consider local contrast of image regions which leads to producing over enhanced images. And also HE does not provide any flexibility for controlling the level of enhancement. A histogram modification framework that gives user to control the level of enhancement was presented in (Tarik et al., 2009). A similar technique was presented in (Agarwal et al., 2014). These two techniques uniformly modify the histogram of the original image in such a way that the modified histogram is close to uniform histogram.

In this work we propose a slightly different form of histogram modification technique. The main objective of this technique is to preserve the brightness in the resultant image by applying different amount of stretching to two different groups of intensity levels in spite of stretching all intensity level uniformly. Two sub histograms of the

input image are generated using mean intensity level of the breast area extracted in phase I. Let us consider $hist_{orgl}$ and $hist_{orgu}$ be representing the histogram of the intensity level lower than the mean intensity, I_{mean} and the histogram of the intensity level higher than the mean intensity, I_{mean} respectively and $hist_u$ is the uniformly distributed histogram. The histograms $hist_{orgl}$ and $hist_{orgu}$ are modified using equation (2) and equation (3) respectively.

$$hist_{modl} = (1-\alpha)hist_{orgl} + \alpha hist_u \quad (2)$$

$$hist_{modu} = \alpha hist_{orgu} + (1-\alpha)hist_u \quad (3)$$

Where $0 \leq \alpha \leq 1$ and $hist_{orgl}, hist_{orgu}, hist_{modl}, hist_{modu}, hist_u \in \mathbb{R}^{256 \times 1}$.

When the value of $\alpha=0$ then the modified histogram, will be same as the uniform histogram, $hist_u$ and when $\alpha=1$ then the modified histogram will be same as the histogram of the original image. By varying the value of α a various levels of contrast enhancement can be achieved. This gives a flexibility to tune the output by changing the value of α .

After modifying the sub histograms separately, the overall modified histogram, $hist_{mod}$ is obtained using equation (4).

$$hist_{mod} = hist_{modl} + hist_{modu} \quad (4)$$

Phase II: Nonlinear Filter for Local Contrast Enhancement

A global contrast enhancement method performs enhancement for the overall image, but it does not consider the local properties of an image. Different image areas have different contrast levels and to enhance an image effectively, a transformation must consider the local contrast of an image subarea. Solution to this is always a local contrast enhancement method. In this section an adaptive nonlinear filter for enhancing contrast considering local properties of the image regions is proposed. This proposed method is applied to the resultant image of the first step. The basis of this adaptive nonlinear filter is the local mean and local standard deviation of the original image.

For each pixel local mean and standard deviation is calculated by placing a fixed size window over it. Higher mean values indicate brighter areas with uniform intensity distribution while higher standard deviation indicates random intensity distribution.

Let us consider a window of size $n \times n$ is placed over an image, I , centered at a pixel position (x,y) , then the local mean at this position, μ_{xy} is calculated as follows:

$$\mu_{xy} = \frac{1}{n \times n} \sum_{(i,j) \in SI_{xy}} r_{ij} \quad (5)$$

Where SI_{xy} is the sub image of I of size $n \times n$ centered at position (x,y) , (i,j) is a coordinate position in SI_{xy} and r_{ij} is the intensity of the pixel at (i,j) .

The standard deviation for the sub image SI_{xy} is calculated as:

$$\sigma_{xy} = \sqrt{\frac{1}{n \times n} \sum_{(i,j) \in SI_{xy}} (r_{ij} - \mu_{xy})^2} \quad (6)$$

The proposed non-linear filter is applied by utilizing the non-linear function as given by equation (7):

$$t = t_{min} + (t_{max} - t_{min}) \left(\frac{s - s_{min}}{s_{max} - s_{min}} \right)^\gamma \quad (7)$$

where s_{max} and s_{min} are the minimum and maximum value in the input domain s respectively while t_{max} and t_{min} are respectively the minimum and maximum value in the transformed domain t . If the intensity range in both the input and the transformed domain is $[0-L]$ then the transformation function can be expressed as mentioned in equation (8).

$$t = L \left(\frac{s}{L} \right)^\gamma \quad (8)$$

In the proposed method, each pixel value is modified using equation (6). The value of γ is chosen adaptively for each pixel by considering mean and standard deviation value of around the neighborhood about the pixel. A γ value equals to 1 maps input to output linearly, a γ value within the range 0 to <1 maps the input to a higher value of output while a γ value greater than 1 maps the input to a lower value of output. Figure 2 shows the mapping from input to output with different values of γ .

Pectoral Muscle Suppression

The method for pectoral muscle removal is adopted from our earlier work presented in (Hazarika and Mahanta, 2017). The method is divided into three phases. In the first phase a triangular area over the image is defined in such a way that it separates the pectoral area from the main breast area. The second phase employs a region growing method in order to segment out the pectoral muscle from the image. The region growing is restricted within the defined triangle so that the region growing cannot propagate to the other part of the image. The region growing technique misclassifies some of the image pixels which need further modification of the images. So in the final phase a refinement technique is applied to the resultant image obtained from the second phase.

Results

Breast Border Extraction

The breast border extraction method is applied to 322 images of mini MIAS dataset. For the closing morphological operation, a line of length 10 and angle 15 degrees was taken as a structuring element. And for the morphological erosion operation we have chosen a disk structuring element of radius 2. After localizing the breast boundary, all the pixels outside appearing outside the breast boundary are masked by a zero value. Except a very few exceptional cases, labels along with some artifacts are appearing outside the breast boundary and so masking the area outside the breast boundary removes such labels and artifacts. Our method achieved a very good result for breast boundary extraction. Out of the 322 images, proposed method detected boundaries correctly in case of 318 images. However partially correct boundaries detected in case of 4 images due to presence of some artifacts. The results are obtained based on the

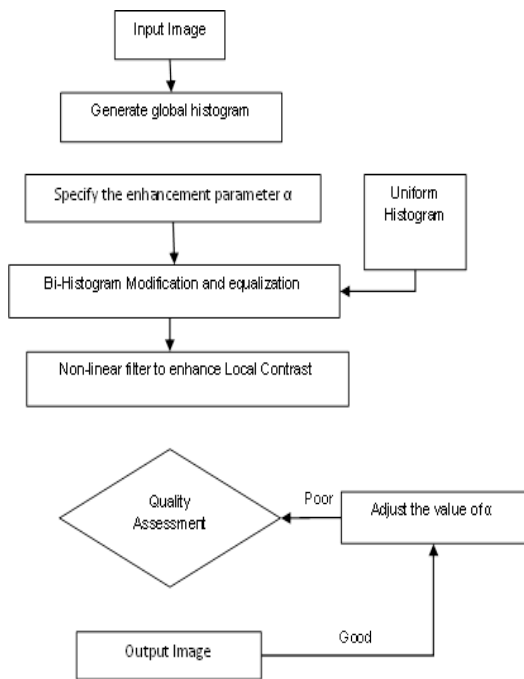


Figure 1. Flowchart of Proposed BHM-ANF

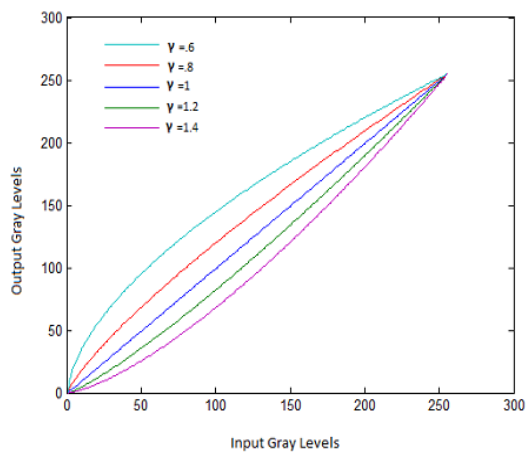


Figure 2. Mapping of Gray Levels for Different Values of γ

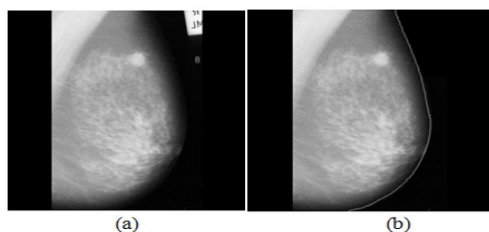


Figure 3. (a) Original Mammogram mdb202 (b) Mammogram with Extracted Breast Border

Table 1. Comparison of Breast Border Extraction Techniques

Author(s)	Methods applied and performance measure achieved	Number of Images	Detection Accuracy
Méndez and Tahoces., (1996)	Intensity Gradient Based	322	89%
Mario et al., (2009)	Region Growing	40	100%
Raba et al., (2005)	Histogram based threshold, Gaussian Filter	320	98%
Ferrari et al., (2000)	Active Contour	84	0.96 completeness and correctness
Proposed	Morphology	322	98.75

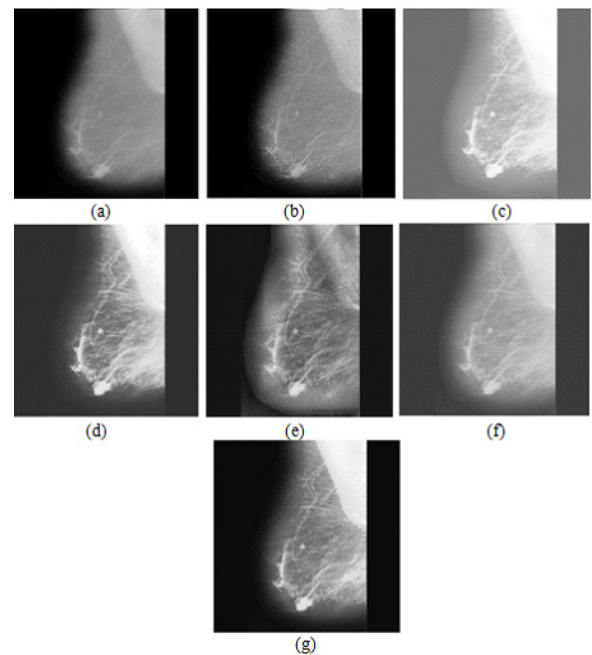


Figure 4. (a), Original Image mdb005; (b), Result of US; (c), Result of HE; (d), Result of BBHE; (e), Result of CLAHE; (f), Result of HM-LCM; (g), Result of BHM-ANF

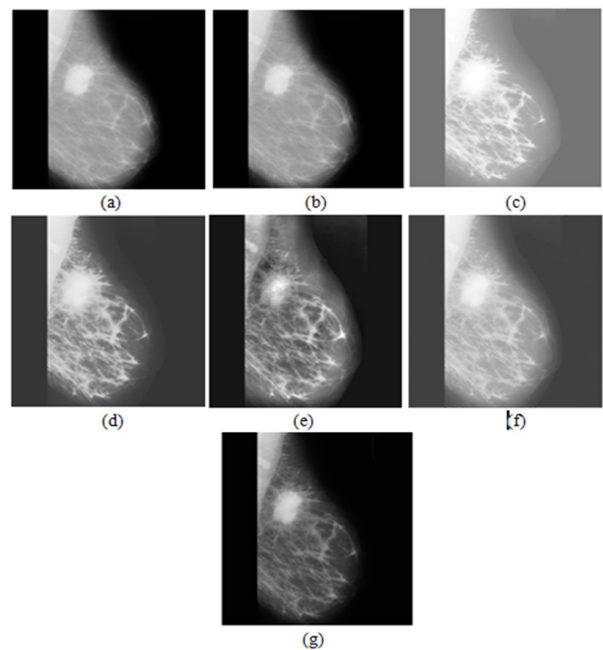


Figure 5. (a), Original Image mdb184; (b), Result of US; (c), Result of HE; (d), Result of BBHE; (e), Result of CLAHE; (f), Result of HM-LCM; (g), Result of BHM-ANF

Table 2. EME and AMBE Values of Enhanced Images with Different Techniques

Original File Name	EME						AMBE						
	Original	HE	BBHE	CLAHE	US	HM-LCM	BHM-ANF	HE	BBHE	CLAHE	US	HM-LCM	BHM-ANF
mdb005	5.141	6.885	13.657	25.542	8.456	15.069	18.912	85.071	34.296	20.126	0.091	48.047	16.054
mdb023	14.652	7.979	14.152	28.389	12.268	15.744	17.652	80.075	23.240	17.984	0.069	82.975	17.153
mdb025	19.433	6.897	14.647	28.376	8.856	16.245	22.433	90.501	33.813	18.624	0.058	50.551	16.560
mdb028	17.610	6.136	12.489	25.840	10.808	13.140	20.610	91.299	32.842	19.065	0.034	88.816	18.441
mdb058	18.813	4.970	14.109	27.187	3.554	14.118	21.813	111.726	30.982	22.185	0.049	62.740	20.554
mdb063	15.469	3.685	12.457	26.197	4.811	12.156	18.469	122.218	28.553	18.064	0.071	91.596	16.705
mdb069	15.463	7.388	15.577	30.435	8.919	18.084	21.663	92.974	31.167	14.094	0.052	91.396	15.771
mdb178	16.561	1.533	9.034	17.266	4.179	5.672	19.561	155.884	24.961	13.724	0.041	71.357	7.913
mdb184	18.968	5.892	12.072	25.073	6.312	15.024	22.908	86.604	31.618	19.738	0.047	79.865	18.405
mdb186	19.826	2.802	10.954	20.240	11.633	7.544	22.826	137.290	22.384	14.285	0.039	46.299	10.382
mdb190	15.282	7.990	18.933	29.666	9.796	17.312	18.282	101.457	34.904	22.476	0.036	63.531	21.757
mdb193	19.830	6.606	12.999	30.325	6.720	16.653	22.830	83.078	28.245	21.073	0.056	70.493	20.844
mdb204	17.417	6.761	12.995	24.711	10.097	17.686	20.417	81.645	28.773	19.865	0.039	80.181	20.746
mdb206	17.412	7.014	16.058	31.767	7.348	15.046	20.412	102.834	25.610	18.957	0.066	49.460	18.634
Average	16.563	5.896	13.581	26.501	8.125	14.250	20.628	101.618	29.385	18.590	0.053	69.808	17.137

visual inspection of a trained radiologist. Figure 3 shows the result of successful breast border extraction for the image mdb28. A Comparative study of different breast

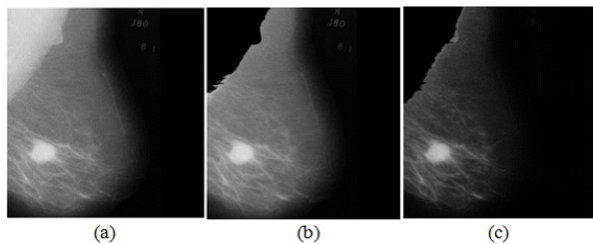


Figure 6. (a), Original Image mdb28, result of Phase II of Pectoral Muscle Removed Image when Applied to; (b), Original Image; (c), Enhanced Image Using BHM-ANF

border extraction method is presented in Table 1. The comparison shows the technique presented in (Mario et al., 2009) is the best over other techniques and the proposed one is the second best. But the technique in (Mario et al., 2009) is experimented only with 40 images whereas the proposed technique is experimented with 322 images with an achievement of 98% accuracy.

Discussion

Performance measure of Contrast Enhancement

A processed image is considered to be enhanced over the original image by visual observation if the desired information can be perceived. In this study, the performance of the proposed method is analyzed based

Table 3. Combined Enhancement Measure Discrete Entropy Values of Enhanced Images with Different Techniques

Original File Name	CEM						Entropy						
	HE	BBHE	CLAHE	US	HM-LCM	BHM-ANF	Original	HE	BBHE	CLAHE	US	HM-LCM	BHM-ANF
mdb005	2.847	2.298	1.486	1.737	2.353	1.317	5.176	3.966	4.124	5.417	5.188	5.433	5.189
mdb023	3.362	2.229	1.500	1.742	3.229	1.505	5.104	4.044	4.564	5.548	5.154	5.607	4.964
mdb025	4.283	2.313	2.252	1.741	3.117	1.234	5.410	3.987	5.009	5.542	5.415	5.562	5.009
mdb028	8.327	3.039	2.233	1.740	5.402	1.204	5.580	4.220	4.907	5.691	5.590	5.651	4.907
mdb058	5.908	2.591	1.753	1.740	3.929	1.369	4.232	3.052	4.122	4.406	4.235	4.396	4.122
mdb063	6.086	2.992	2.177	1.752	4.277	2.084	4.119	2.896	6.998	4.409	4.118	4.163	4.033
mdb069	6.853	3.062	2.017	1.747	4.774	1.941	5.519	4.280	4.868	5.662	5.514	5.629	5.868
mdb178	3.281	2.268	1.824	1.741	2.394	1.341	3.085	2.028	2.985	3.203	3.086	2.924	3.685
mdb184	10.334	3.802	3.092	1.722	8.330	1.286	4.900	3.673	4.618	5.163	4.909	5.101	4.668
mdb186	3.436	2.298	2.190	1.738	3.281	1.607	3.536	2.659	3.481	3.778	3.583	3.441	3.481
mdb190	9.756	3.531	1.830	1.748	6.330	1.568	5.135	4.049	4.574	5.454	5.133	5.374	4.874
mdb193	3.297	2.202	2.173	1.744	2.504	1.418	5.195	3.953	4.995	5.447	5.195	5.314	4.995
mdb204	4.246	2.359	1.945	1.738	5.298	1.021	5.422	4.263	4.587	5.683	5.433	5.599	5.487
mdb206	2.885	2.391	1.318	1.736	2.394	1.449	5.035	3.822	4.722	5.296	5.035	4.947	4.722
Average	5.350	2.670	1.985	1.741	4.115	1.453	4.818	3.635	4.611	5.050	4.828	4.939	4.715

on visual perception and quantitative measures. The performance of the proposed method is compared with the state of the art contrast enhancement techniques like HE, BBHE, CLAHE and US. In this study 14 mammogram images from Mini MIAS dataset are selected to evaluate the performance of the proposed method. These mammograms include images with benign and malignant masses comprises of different types of tissues.

The enhanced versions of the mammogram images mdb005 and mbd184 with different approaches are presented in Figure 4 and Figure 5 respectively. From the figures it is clear that the proposed method performs much better enhancement than HE, BBHE, CLAHE, US and HM-LCM.

In practice several quantitative measures are used to evaluate the performance of contrast enhancement techniques. In this study the quantitative measures used are Measure of Enhancement (EME), Absolute Mean Brightness Error (AMBE), Combined Enhancement Measure (CEM) and Discrete Entropy (H). The performance matrices of EME, AMBE, CEM and H are presented in Table 2 and Table 3.

The EME is defined by the equation (9). A too high score of EME indicate loss of finer details in the enhanced image while a too low score for the same indicate inability to enhance hidden details. Studies show, an optimal score of EME indicates better image contrast enhancement particularly for medical diagnosis purpose. The average EME listed in Table 2 shows that CLAHE has the highest score while HE, US and BBHE have even smaller EME than the original image. The proposed method has an optimal EME score that indicates the proposed method performs better than the existing techniques.

$$EME = \frac{1}{b_1 \times b_2} \sum_{l=1}^{b_1} \sum_{k=1}^{b_2} \left[20 \ln \left(\frac{I_{max,k,l}}{I_{min,k,l}} \right) \right] \quad (9)$$

Where the image I is divided into $b_1 \times b_2$ blocks $I_{max,k,l}$ and $I_{min,k,l}$ are the maximum and minimum intensity values within the blocks respectively.

AMBE is defined as the absolute difference of the mean values of the input and output image. The theoretical background on AMBE suggests that a lower score provides a better enhancement than a higher score. However the visual inspection does not comply that a low AMBE score will always indicate better performance. Table 2 show that HE has the highest AMBE value (101.618) followed by the AMBE value of HM-LCM (69.808) while US (0.053) has the lowest AMBE value which indicate US as the best enhancement method, but visual inspection shows a very poor enhancement by US. The proposed BHM-ANF and CLAHE, both shows optimum AMBE score 17.137 and 18.590 respectively. But BHM-ANF has a smaller value than CLAHE, which indicates BHM-ANF outperforms CLAHE in terms of AMBE.

The Combined Enhancement Measure (CEM) (Singh and Bovis, 2005) is tabulated in Table 3. CEM is a function of three measures viz. Distribution Separation Measure, Target to Background Contrast Enhancement based on

Standard Deviation and Target to Background Contrast Enhancement based on Entropy. A lower value of CEM indicates a better enhancement of edges. The CEM value (1.453) obtained for proposed method over the rest of the methods is found to be smallest while the CEM value (5.350) for HE is highest amongst all the methods. This also indicates that the proposed BHM-ANF outperforms over all other techniques.

The discrete entropy (H) is tabulated in Table 3. The average H of the proposed method has a very close value (4.715) to the average H value (4.818) of the original images. This shows the closeness between the original image and the enhanced image. US also shows a close H value to that of original images, but as we have already mentioned that US results in very poor image enhancement, so we are not considering the value of US. CLAHE has highest average value (5.050) which indicates the deviation from the originality of the images.

Pectoral Muscle Removal

In this study the pectoral muscle removal method is applied to the enhanced images obtained using proposed HM-ANF method. The advantage of using contrast enhanced image is that the contrast between the pectoral muscle and the breast tissue is higher in the contrast enhanced image than that of the original image producing better results. Fig 6 shows the original image (mdb028), (b) and (c) are results of phase II of pectoral muscle removal when applied to the original image and the enhanced image respectively. From the result it is clear that the region growing works more efficiently for enhanced images than the original images. So refinement at phase III of pectoral muscle removal does not play a significant role.

A set of preprocessing steps are proposed to perform breast border extraction, contrast enhancement and pectoral muscle removal. The breast border extraction method proposed here is a very simple technique yet yields promising results with higher accuracy.

The proposed contrast enhancement method gives a flexibility to tune enhancement parameter making it possible to apply in different applications. The method enhances both local and global details, which is very important for a good contrast enhancement method. It is tested over 14 selected mammogram images from Mini Mias dataset. The experimental results shows better contrast enhancement in comparison to the existing methods discussed in the previous sections. In terms of visual inspection as well as in terms of quantitative measures like EME, AMBE, CEM and H. The method works well for different types of mammographic tissues like fatty, dense-glandular and fatty glandular.

In the original work of pectoral muscle removal method discussed here, the original images were taken as the input images, however in this work we chosen enhanced images as input. Choosing enhanced images as input over original images increases the performance of the overall process.

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