



Visibility improvement and mass segmentation of mammogram images using quantile separated histogram equalisation with local contrast enhancement

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Abstract: In this work, the authors develop a working software-based approach named 'linearly quantile separated histogram equalisation-grey relational analysis' for mammogram image (MI). This approach improves overall contrast (local and global) of given MI and segments breast-region with a specific end goal to acquire better visual elucidation, examination, and grouping of mammogram masses to help radiologists in settling on more precise choices. The fundamental commitment of this work is to demonstrate that results of good quality of breast-region segmentation can be accomplished from basic breast-region segmentation if the input image has good contrast and a better interpretation of hidden details. They have evaluated the proposed strategy for MIAS-MIs. Experimental results have shown that the proposed approach works better than state-of-the-art.

1 Introduction

Presence of the cancerous region (CRg) in the breast is the foremost and most deadly diseases in women, worldwide. As per the available statistics, 12.5% of women are prone to CRg in the breast in their lifespan [1]. In available human CRg in breast detection approaches, mammography is one of the widely accepted approaches. Mammography is used for early detection, diagnostic and screening for CRg in the breast, by detecting essence masses and/or micro-calcifications. The micro-calcifications are nothing but small deposits of calcium in breast tissues and appear as small bright spots on a mammogram [2, 3]. Owing to the small size and elusive nature of micro-calcifications they can be ignored by a radiologist who is examining the mammogram image (MI).

Assessments of incorrect diagnostic of cancers missed by mammography are for the most part around 10–30% [4]. The reason for this much high rate of false rejectance (FR) is based on the grounds that mammogram contains confounded organised background (BG). Hence diagnosing disease tissues utilising advanced mammogram is a period expending errand not withstanding for profoundly talented radiologists. We can improve the visibility of the MI by contrast enhancement (CE) approaches, it might help elucidation by people or computer for CRg detection in the breast. Mammography is a standout amongst the most encouraging cancer control systems since the reason for the growth of cancer is still obscure. Radiology field broadly utilises image enhancement/improvement approaches (in this work we will use the words enhancement and improvement interchangeably), where the subjective nature of images is essential for human translation and finding.

We can find sufficient large approaches available in the literature for CE and image segmentation (SG) for medical images (MeI). Zuiderveld developed a globally accepted approach termed as 'contrast limited adaptive histogram equalisation' (CL-AHE) [5]. The key disadvantage of the CL-AHE is that here equal level of CE takes place in the BG and foreground (FG) of the given input image. This results in the improvement of the contrast of FG achieved on the cost of the appearance of artefacts in the BG. It makes CL-AHE inappropriate for MeIs, where we required very fine details such as in MIs, where the BG region inhomogeneity can lead towards a false acceptance (FA). Although CL-AHE eliminates the noise up to a good extent, we have to make a

trade-off between the accuracy of processed image and increase in the rate of FA due to the appearance of artefacts in the BG. Later Sundaram *et al.* [6] developed an approach for CE for MIs named HM-CL-AHE, which is a fusion of histogram modification and CL-AHE. This approach is able to produce good results, but in some case, it suffers from limitations of CL-AHE. Another few interesting approaches have also developed for the improvement of MeIs. For CE of colour MeIs using Young-Helmholtz transformation and improved non-linear extrapolation approach is developed by Hua [7]; the widely used Haar and wavelet transform are also applied for improvement of MeI [8]. One more approach was developed by Sundaram *et al.* [9], this approach is termed as histogram modified local CE (HM-LCE) and this approach is mainly developed for MIs. This approach modifies input image histogram using a histogram modification function, which is followed by a local CE mechanism.

The widely accepted approaches used for SG of breast-region (BRg) are classified into two main categories (this criterion is based on the region for which the image SG process is applied): (i) BRg-SG and (ii) region of interest SG. The MIs are captured from two different views namely the craniocaudal view and medio-lateral oblique. For SG of a single view, supervised and unsupervised SG algorithms are used. Here, we will only talk about unsupervised algorithms. Single view unsupervised SG is divided into six categories: contour-based SG, pseudo-colour SG, clustering SG, region-based SG, graph SG, and variant-feature transformations. The SG approaches that are based on clustering have been employed by the authors of [10–13]. For better SG of both calcification and mass; region-of-interest-based SG using different views is used by the authors of [14, 15]. A systematic review of widely used MeI SG algorithms has been discussed in [16–18]. For a better explanation of these approaches, one can refer to [16–18].

By using a proper combination of various widely accepted approaches; in [19] Al-Najdawi *et al.* developed an approach for a better visual interpretation of BRg. This approach uses the widely used image improvement approaches to improve visibility of the given MI and then it segments the processed image for better analysis of mammogram masses to assist the observer in making a more accurate decision. In [19], the authors have illustrated that for getting a good quality of BRg-SG results; the combination of median filter and CL-AHE is the best choice.

Here, we propose an approach named linearly quantile separated histogram equalisation-grey relational analysis (LQSHE-GRA). The proposed approach works better than state-of-the-art approaches. Also, this approach is computationally efficient than many other state-of-the-arts.

The organisation of this work is as follows: Section 2 covers the basic problems associated with the conventional histogram equalisation (HE) method. Section 3 describes completely the proposed approach LQSHE-GRA. Section 4 covers some experimental results that are mainly for checking the effectiveness of the proposed approach. Section 5 contains a short discussion on developed LQSHE-GRA software. The conclusion part is provided in Section 6. Finally, Section 7 contains an acknowledgement by the authors.

2 Problems with conventional HE method

This section describes the problems associated with the conventional HE method. In our discussion, we have considered a grey image I as two-dimensional arrays. Each element of image I can take values from L discrete grey levels from $\{I_0, I_1, \dots, I_k, \dots, I_{L-1}\}$.

2.1 Over enhancement problem

In the case of HE, the transformation function $f(\cdot)$ is given as

$$f(I_k) = I_0 + (I_{L-1} - I_0)C[I_k], \quad k = 0, 1, \dots, L-1. \quad (1)$$

Here $C[\cdot]$ is the cumulative distribution function (CDF). Now the increment in level transformation function is given by

$$f(I_k) - f(I_{k-1}) = (I_{L-1} - I_0)C[I_k] - \{(I_{L-1} - I_0)C[I_{k-1}]\}, \quad (2)$$

$$\Delta f(I_k) = (I_{L-1} - I_0)\text{pmf}[I_k], \quad (3)$$

where pmf is the probability mass function of the occurrence of grey level of the images. Based on the above equation, we can simply say

$$\Delta f(I_k) \propto \text{pmf}[I_k]. \quad (4)$$

From (4) it is clear that $\Delta f(I_k)$ is proportional to the probability value $P[I_k]$. Hence, grey levels of high probabilities will be assigned more weights. In other words, grey levels with higher frequencies dominate the less frequent grey level, due to this, image regions with high probabilities are over enhanced and other less probable regions are less enhanced, this leads to losing important visual details present in the image.

2.2 Mean-shift problem

Another problem with histogram equalised images is that the mean brightness of these images is the middle grey level regardless of the mean brightness of input image. We know that the

conventional HE method claims that the processed image will have a uniform histogram. Mathematically probability mass function (pmf) of histogram equalised image will be given as

$$\text{pmf}(I_k) = \frac{1}{I_{L-1} - I_0}, \quad k = 0, 1, \dots, L-1, \quad (5)$$

so mean brightness of histogram equalised image will be given as

$$E[Y] = \sum_{k=I_0}^{I_{L-1}} \text{pmf}(I_k) \cdot I_k = \sum_{k=I_0}^{I_{L-1}} \frac{1}{I_{L-1} - I_0} \cdot I_k, \quad (6)$$

this is further written as

$$E[Y] = \frac{I_{L-1} + I_0}{2}. \quad (7)$$

The above equation clearly shows that the mean brightness of the histogram equalised image is the middle grey level. Also, this is regardless of the mean brightness of the input image.

3 Proposed method (enhancement and breast region SG)

The overall working of our approach is broadly categorised into two parts: global and local contrast of given mamographic image analysis society (MIAS)-MI is enhanced using first part; this part improves the overall visibility of the given image and improves efficiency for further post-processing. Second part segments the enhanced image and produces BRg segmented image with the location of breast cancer.

3.1 Mammogram enhancement using LQSHE-GRA

The LQSHE-GRA approach uses two-step processing, global and local contrast of given MIAS-MI is enhanced using the first part; this part improves the overall visibility of given image and improves efficiency for further post-processing. Fig. 1 shows the block diagram of the proposed approach LQSHE-GRA.

3.1.1 Linearly quantile-based HE: For global CE of given MI, we are using 'linearly quantile-based HE' approach [20]. This method is capable of dealing with the two main problems of the conventional HE method. The effective mechanism used by this approach is to sub-divide histogram of a given image into two or more sub-histograms, where SG is based on quantile values. In this approach, the entire spectrum of intensity levels will always be utilised. In the proposed work, we have applied this approach for overall CE of the MIAS-MI. A short description of this method is as follows:

The quantile values are the data points which divide the sample data into equal proportion and these values can be calculated with

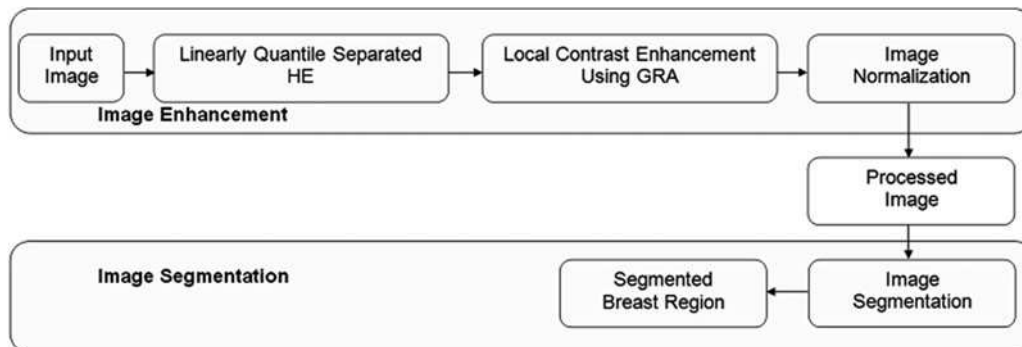


Fig. 1 Flowchart of the proposed approach LQSHE-GRA

the help of probability distribution of the pixel intensities. The q -quantiles provide ' q ' different values, which divide intensity distribution into q equal proportion.

For a random variable I , the k th, q -quantile value is a value i_k for which

$$Q[I] = P[I \leq i_k] = \frac{k}{q}, \quad k = 0, 1, 2, \dots, q. \quad (8)$$

The histogram of the input image having intensity range $[I_0, I_{L-1}]$ and denoted by $H(I)$. Now, we divide the input histogram $H(I)$ into q -sub-histograms using q -quantile values; $H_1 = [h_0, h_1]$, $H_2 = [h_1, h_2]$, ..., $H_q = [h_{q-1}, h_q]$, such that

$$P[I \in h_k] = P[h_{k-1} \leq I \leq h_k] = \frac{1}{q}, \quad k = 0, 1, 2, \dots, q, \quad (9)$$

where $h_0 = I_0$, $h_q = I_{L-1}$, and $h_k \in I_0, I_1, \dots, I_{L-1}$, $\forall k = 0, 1, \dots, q$ and L is total no. of grey levels. Let the total probability of sub-histogram H_k is denoted by p_k and defined as

$$p_k = \sum_{h \in [h_{k-1}, h_k]} P[I = h], \quad i = 0, 1, \dots, L-1. \quad (10)$$

Then, for sub-histogram H_k , the normalised probability mass function (PMF) of pixel intensities will be

$$P_k[I_i] = \frac{P[I_i]}{p_k}, \quad (11)$$

and the CDF will be as follows:

$$C_k[I_i] = \sum_{h=h_{k-1}}^{I_i} \frac{P[I_j = h]}{p_k}. \quad (12)$$

The histogram transformation function for H_k will be

$$f_k(I_i) = h_{k-1} + (h_k - h_{k-1})C_k[I_i], \quad k = 1, 2, 3, \dots, q. \quad (13)$$

Let I' be the processed image, and can be represented as the union of all processed sub-histograms, i.e.

$$I' = \bigcup_{k=1}^q f_k(I_i). \quad (14)$$

Histogram weighting module. Now, for sub-histograms, $H_k(i)$, we replace the PMF of the input image $P(j)$ by the weighted PMF $P_w(j)$ defined as

$$P_w(j) = P_{\max} \left(\frac{P(j) - P_{\min}}{P_{\max} - P_{\min}} \right)^{\beta} + \beta, \quad (15)$$

where β is a sufficiently small value and it is added in (15) so that the resultant cdf is strictly monotonically increasing. Empirically, it is found that for best results the choice of β should be $P_{\max} \cdot |I_M - I_G| / (I_{\max} - I_{\min})$, where I_M , I_G , $I_{\max}$, and $I_{\min}$ are mean intensity, middle grey level, maximum, and the minimum grey levels of the given input image I , respectively. The above arrangement gives the higher weights to less frequent intensities and provides lesser weights to the intensities with high frequencies. Thus, these weights are able to reduce the difference between the intensity levels and hence the intensity distribution became closer to uniform intensity distribution.

Now, we require the normalisation of the resultant $P_w(j)$

$$P_{wn}(k) = \frac{P_w(k)}{\sum_{j=0}^{L-1} P_w(j)}, \quad 0 \leq k \leq L-1, \quad (16)$$

where $P_{wn}(k)$ is the normalised histogram.

Histogram equalisation module. In this step, we initiate with $P_{wn}(k)$, which we calculate in the last step and then apply the histogram equalisation on each of the sub-histogram separately.

3.1.2 Grey relational analysis for local CE (LCE): In the case of global CE, we have used the complete grey level distribution of the entire image. These strategies (global CE) can modify the average brightness of the processed image to centre grey level and consequently giving a washed out impact [21]. There are circumstances (e.g. MIAS-MI), where we are intrigued to discover neighbourhood (local) information provided by an image. To deal with these drawbacks, we require local CE-based approaches. These approaches do not have much impact on the global transformation function, as contrast transformation function is derived from the grey level distribution of the neighbourhood of every pixel of the image. An exemplary local CE strategy proposed by Beghdadi and Negrata [22] depends on the way that the human discernment component (visual system) is exceptionally sensible to the different forms that are contained in the image. Beghdadi suggested the edge detector operator to develop the local contrast. In the proposed approach for local CE, we are changing a few parameters of the strategy exhibited in [23].

3.1.3 Image normalisation: For image average brightness preservation, we apply image normalisation. It is calculated as

$$g(x, y) = (\bar{I}_1 / \bar{I}_p) f(x, y), \quad (17)$$

where $\bar{I}_1$ and $\bar{I}_p$ are average brightness of input image and processed image, respectively.

3.2 SG of breast region using proposed SG method

In order to locate the CRg in the contrast enhanced image, we suggest BRg-SG. We observed that for efficient SG, proper contrast is more important as compared to any other essence, i.e. if the contrast of the image is good then simpler BRg-SG approaches may produce good results. Here we are using the Otsu approach [24] for BRg-SG on the enhanced image. Otsu's approach is followed by a binary erosion operation [25].

Fig. 2 shows the comparison of SG results in between the proposed approach and [19]. Fig. 2 shows that the approach proposed in [19] and the proposed approach are able to segment BRg in the image effectively. However, Section 4.2 shows that the LQSHE-GRA approach is capable of dealing with the mean-shift problem more accurately than in [19].

4 Quantitative evaluation of proposed method

Performance evaluation of the proposed approach with some other HE-based approaches is performed in this section. Java programming language [26] is used by us for implementation of HE, HM-LCE, HM-CL-AHE, and LQSHE-GRA algorithms. Fig. 3 shows the effectiveness of the LQSHE-GRA approach in visual improvement of CRg of the given MI patch.

Fig. 3 shows that the LQSHE-GRA approach works better than state-of-the-art in enhancing the contrast of a given mammogram patch. Here, the result for an image patch (that has a region affected by cancer and clear BG) is shown; the region affected by cancer is marked by (i) and the clear BG is marked by (ii). A careful examination of Fig. 3a reveals that not much information about the CRg is provided by the input image patch. By utilising HE, we are able to enhance the visibility in the MI but this improvement is performed at the cost of drastic

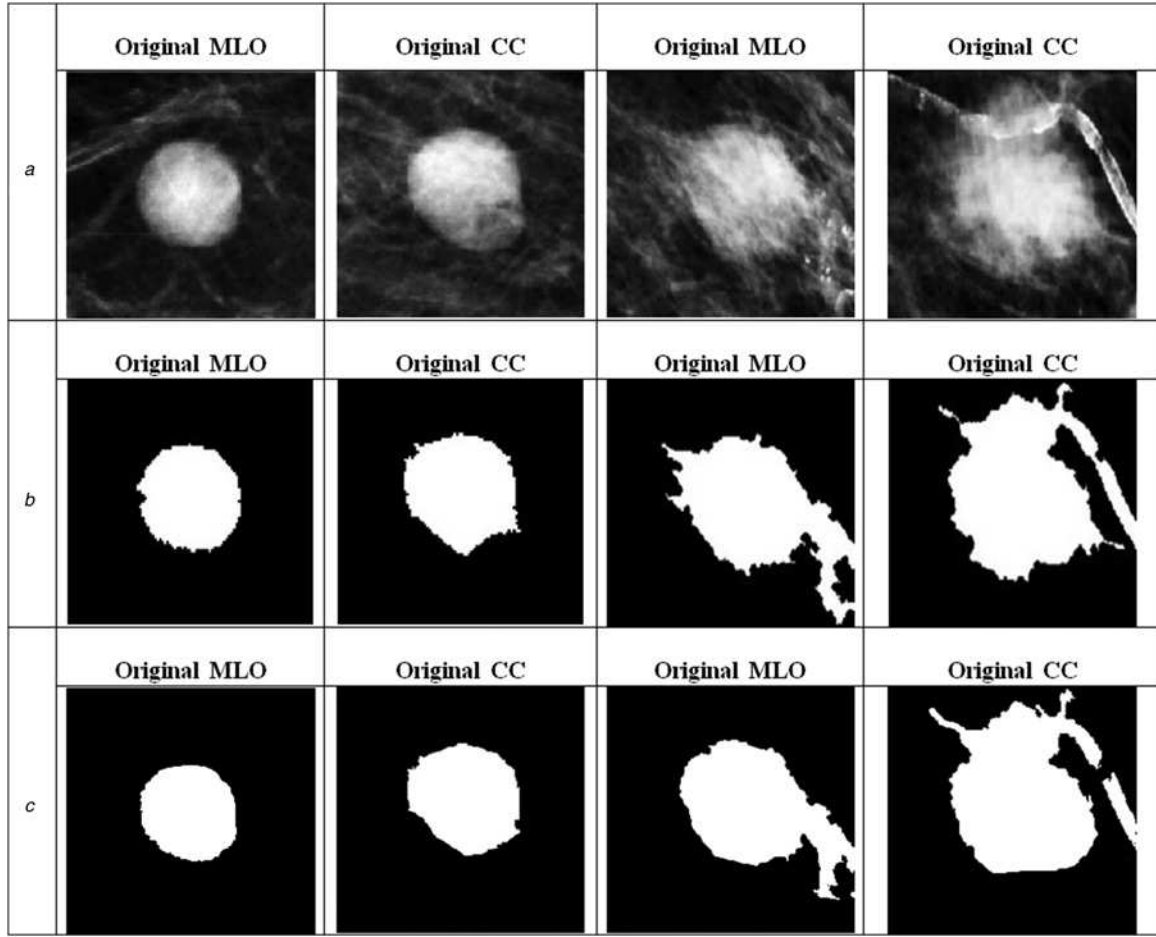


Fig. 2 BRg-SG result comparison in between the proposed approach and [19]

a Given image

b SG of BRg performed by [19]

c SG of BRg performed by the proposed approach. The image set is taken from the work of Najdawi *et al.* [19]

modification in average brightness of histogram equalised image [27]. Other approaches such as CL-AHE-Median, CL-AHE, and HM-CL-AHE are capable of dealing with the mean-shift problem but results of these approaches lead to equal level of CE at FG (part of MI that contains information about micro-calcification) and BG (part of the image that does not contain mammogram); this leads to noise amplification in some regions that are visually important and also introduces artefact (rise of FA) in BG of processed image. Some forms of bad results are produced by the HM-LCE approach in the BG part of the MI patch. The LQSHE-GRA approach produces excellent results than state-of-the-art; as this approach neither improves BG and FG at equal grey nor it over improves contrast in the processed image.

4.1 Statistical observation for CRg SG

Based on our performance evaluation on all 322 MIAS-MIs, we observe that for $q \in [1, 6]$ the proposed approach gives its best performance. However, for $q > 6$, the proposed approach performs proper CE with sufficient average brightness preservation. We observe that for BRg-SG; $q \in [1, 6]$ the proposed approach shows 100% accuracy and for $q > 6$ the proposed approach is near about 85% accurate. Hence, on the premises of average results, the proposed approach is more than 92.5% accurate.

To evaluate the efficiency of SG algorithm, we are using S and $\tilde{S}$ measures. These are performance evaluation of statistical measures [19, 28, 29]. Let A means a person is suffering from CRg in breast and B means a person is diagnosed sick. Also, $\tilde{A}$ means a person is healthy and $\tilde{B}$ means a person is diagnosed healthy. Then true

acceptance (TA): $A \cap B$, FA: $\tilde{A} \cap B$, true rejectance (TR): $\tilde{A} \cap \tilde{B}$, FR: $A \cap \tilde{B}$. The following equations show the S and $\tilde{S}$ measures

$$S = \frac{\text{card}\{TA\}}{\text{card}\{TA\} + \text{card}\{FR\}}, \quad (18)$$

$$\tilde{S} = \frac{\text{card}\{TR\}}{\text{card}\{TR\} + \text{card}\{FA\}}, \quad (19)$$

where $\text{card}\{X\}$ means the total number of elements of set X . Based on the experiments performed on all MIAS-MIs (for $q \in [1, 6]$), the results showed an S of 96.87% and a $\tilde{S}$ of 97.87%, with TA ($A \cap B$) is 93, FA ($\tilde{A} \cap B$) is 5, TR ($\tilde{A} \cap \tilde{B}$) is 221 and FR ($A \cap \tilde{B}$) is 3.

4.2 Image quality assessment

The effective verification of the proposed approach is performed in this section. For this, we have used the MIAS-MI database. The absolute mean brightness error (AMBE), peak signal to noise ratio (PSNR), and structure similarity index measure (SSIM) are used by us for performance evaluation of the proposed LQSHE-GRA approach with state-of-the-art. In Table 1, we are showing the mean values of AMBE, PSNR, and SSIM by each approach.

On the premise of Table 1 (mean values of AMBE, PSNR, and SSIM for all test images), we observe that the proposed approach produces greater average PSNR values than the state-of-the-art. However, the state-of-the-art approaches are unable to minimise the average brightness modify in between input image and

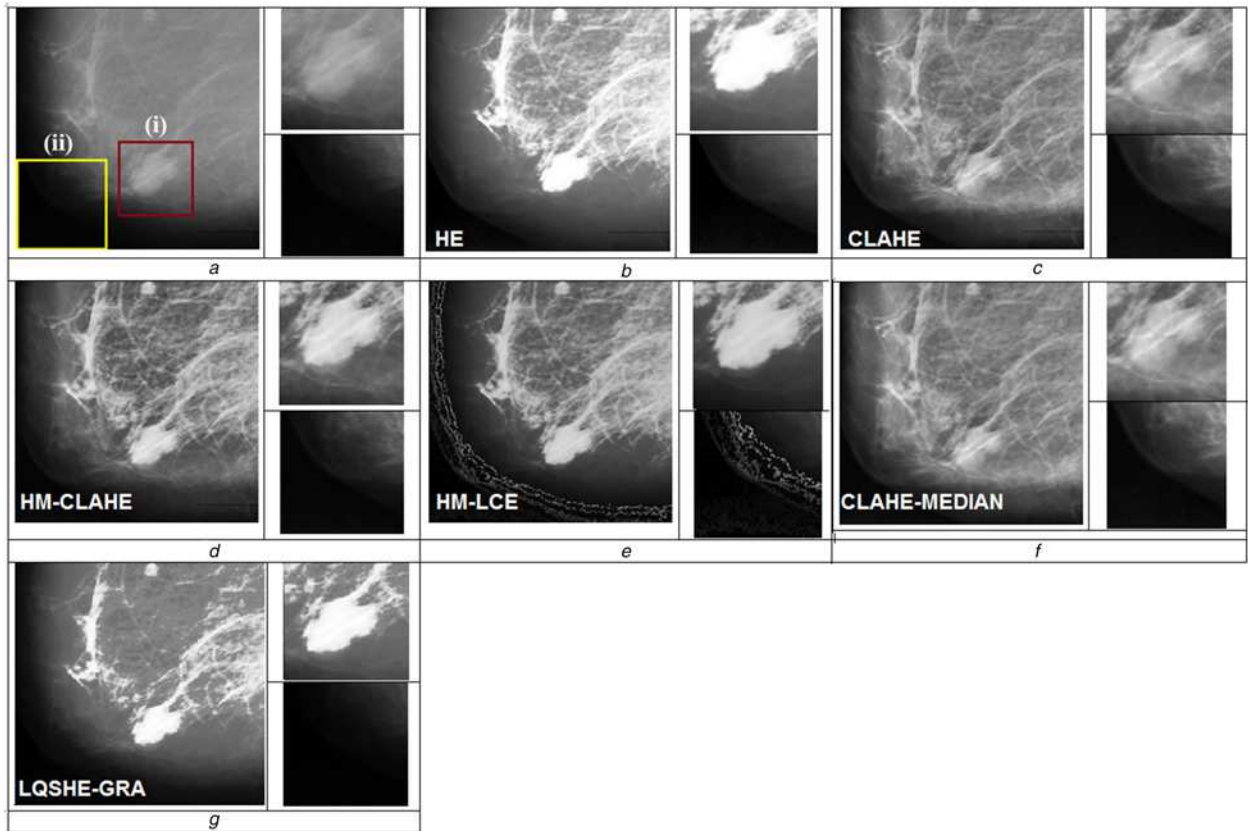


Fig. 3 Results for an image patch in this figure

a is original MI patch

Table 1 Average results of PSNR, AMBE, and SSIM

Methods	Average PSNR	Average AMBE	Average SSIM
HE	5.299	126.872	0.619
CL-AHE	18.900	21.856	0.976
HM-CL-AHE	13.000	50.398	0.874
HM-LCE	13.407	47.015	0.885
CL-AHE-Median	18.907	21.837	0.976
LQSHE-GRA	26.394	1.259	0.992

processed image (AMBE is used to measure average brightness preservation [30, 31]). By examining the last row of Table 1, which indicates average SSIM values; we understand that the proposed approach can keep up average SSIM more precisely than HE [5, 6, 9, 19]. By this, we arrive at a conclusion that LQSHE-GRA is a decent approach for CE (as a higher value of PSNR demonstrates better CE [32]) with most extreme average brightness preservation (fewer AMBE values indicate maximum average brightness preservation [20]); likewise the proposed strategy does not influence SSIM of the input image.

5 LQSHE-GRA software

A simple description of the developed LQSHE-GRA software is shown in this section. This software is best suited for SG and improvement of given MIAS-MI. Fig. 4 shows a basic working model of the developed software.

We have developed software (LQSHE-GRA software) that implements the proposed approach. This software is developed for the radiologist to perform early detection of CRg from the given MI. This software is easy to operate and it is developed in the 'java programming language' [26] without using any other application programming interface [33]. After selection of the

given image, the examining person can adjust values of the parameters (such as q [20]; b , p and a [22]); after fixing the value of parameters, results generated by the proposed approach can be seen in the different 'tabbed panes'.

In [19], the authors have shown that by merging two or more image improvement algorithms overall performance of SG can be improved. However, in such a case, a robust BRg-SG approach is required. Three major operations [determination of (a) region of interest boundary, (b) roundness of object and (c) mass analysis] are performed in [19] for mass analysis. In the proposed work, we have shown (Figs. 2 and 3) that to get good BRg-SG, the simplest BRg-SG algorithm is enough for enhanced MI (if the processed image is having good contrast).

5.1 Computational complexity of the proposed method

The time complexity of the LQSHE-GRA approach at each stage is shown in Table 2 (we are considering image size as $n_1 \times n_2$ and the image is having L discrete grey levels) :

Here, A is the area of the kernel whose size is $d_1 \times d_2$; and this kernel is used for binary erosion operator. Hence, the total computational time required to execute $n_1 \times n_2$ instructions is $\mathcal{O}(n_1 n_2 \cdot A) + \mathcal{O}(L^2)$.

We consider the developed software as one of our main contribution to this work. This software gives a practical scenario for the proposed approach. We have proved (in Fig. 2) that to get good SG, the simplest BRg-SG approaches can be applied to the processed image (that have good visibility and fine details) of the image. Fig. 3 demonstrates that the proposed approach gives good CE in the given MI also it does not enhance BG and FG at the equivalent level. The proposed LQSHE-GRA software is designed in such a way that it works for all kinds of MIAS-MIs (those formats are supported by the implemented programming language [34]) and this software can be generally utilised for

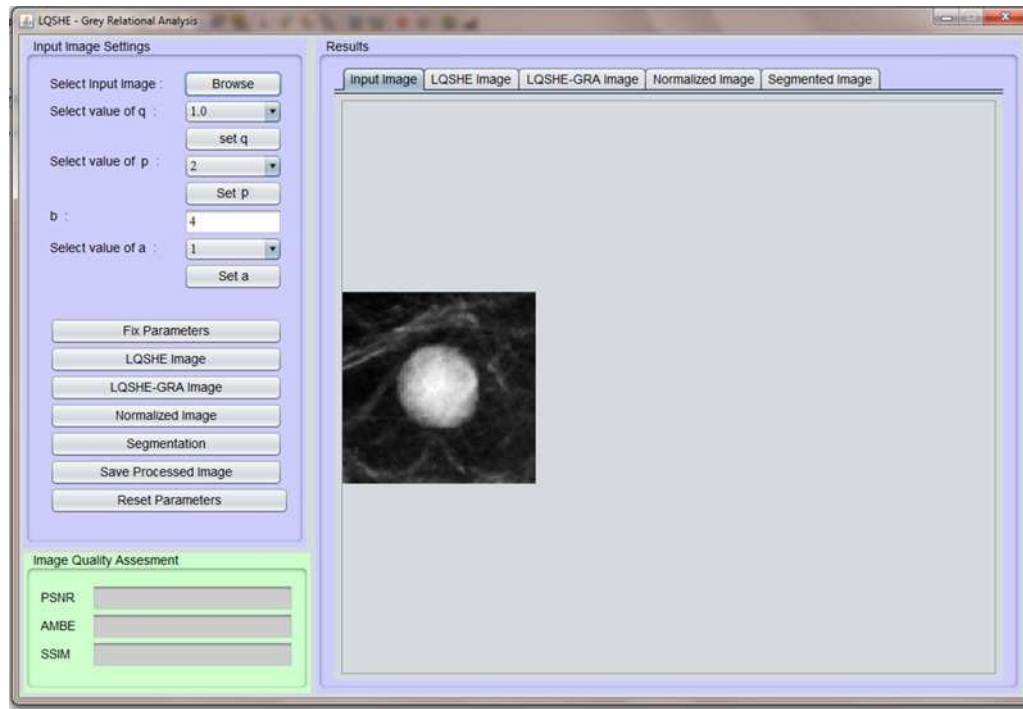


Fig. 4 Snapshot of the developed LQSHE-GRA software

Table 2 Computational complexity of the proposed method at different stages

S.No.	Operation	Computational complexity
1	linearly quantile segmented histogram equalisation	$O(L) + O(n_1 n_2)$
2	grey relational analysis (for constant patch size)	$O(n_1 n_2)$
3	image normalisation	$O(n_1 n_2)$
4	breast region SG	$O(L^2) + O(n_1 n_2 \cdot A)$

MIAS-MI BRg-SG. In the future, we will improve the working of this software by providing extra MeI pre- and post-processing approaches also this will work for unsupervised SG and colour medical image processing.

6 Conclusion

A software supported approach for MI improvement and BRg-SG, which improves micro-calcification recognition in the given MI is exhibited. Our approach gives a superior visibility improvement on MIs with most extreme average brightness preservation, it aides in the discovery of cancerous area with comparatively less FA rate. The proposed approach is a two-stage process; At first, it improves the contrast of the MIAS-MI utilising linearly quantile segmented HE and after that utilises GRA for local CE; in the second step it utilises the BRg-SG approach to segment the enhanced image. The local CE approach ensures the absence of artefact in the processed image and hence reduces the FA rate. Our claims are likewise bolstered by the trial results performed on all MIs.

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