

# An Explorative Survey of Image Enhancement Techniques Used in Mammography

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## Abstract

Breast cancer is the most common disease in women and it remains a leading cause of cancer deaths among women in many parts of the world. Mammography has become indispensable for early detection of breast cancer.

However, interpretation of the resulting images requires sophisticated image enhancement algorithms that enhance visual interpretation and aid the radiologists in the interpretation task. MATLAB software presents several enhancement algorithms which can be used for mammogram enhancement. In this survey, several enhancement techniques for mammographic images are considered.

**Keywords:** Breast cancer, Mammography, Radiologists, Enhancement and Interpretation.

## 1. Introduction

Breast cancer continues to be a significant health problem and it remains a leading cause of cancer deaths among women in many parts of the world [1]. Early detection of breast cancer through periodic screening has noticeably improved the outcome of the disease [2]. Breast image analysis can be performed using mammography, magnetic resonance and ultrasound images. One of the most effective tools for early detection of breast cancer is mammography, which is a screening tool used to examine the human breast utilizing low-dose amplitude X-rays [3].

Mammography is a specific type of imaging that uses a low-dose x-ray system to examine breasts. A mammography exam, called a mammogram, is an X-ray image of the breast that is used to aid in the early detection of breast cancer in women.

It was claimed in [4] that mammography is considered the "gold standard" in the evaluation of the breast from an

imaging perspective and that mammography is essentially the only widely used imaging modality for breast cancer screening. It is effective in reducing breast cancer mortality rates in numerous studies. However, the success of any screening program of asymptomatic women depends on the detection of subtle and small lesions. Improvements over the last decade in the quality of performance and the reporting of mammography studies are the most important advances in breast imaging [5].

## 2. Other Breast Imaging Techniques

Apart from mammography, Ultrasonography (US) also known as ultrasound examination and breast magnetic resonance imaging (MRI) are being offered as diagnostic techniques and as adjuncts to the pre and postoperative workup [6]. Also in [7] it was argued that breast ultrasound and breast magnetic resonance imaging (MRI) are frequently used adjuncts to mammography in today's clinical practice and these techniques enhance the radiologist's ability to detect cancer and assess disease extent, which is crucial in treatment, planning and staging.

Recently, other new modalities like positron emission tomography (PET) and electrical impedance tomography (EIT) are also being offered. However, there is still controversy over the most appropriate use of these new modalities [4].

## 3. Interpretation of Mammograms

Despite the proved value of mammography in revealing and detecting diseases, its efficacy depends on radiologists' interpretations. The radiologist's experience plays a meaningful role in the diagnosis. Until now, no standard

for description of the normal (healthy) breast model has been established. The reference during assessing a mammogram is the image of the other breast or comparison with the previous examinations of the same patient if available [8].

Interpretation of mammograms requires sophisticated image processing methods that enhance visual interpretation and image analysis methods that provide automated or tissue detection and characterisation [9].

In [10], it was ascertained that variability has been noted in the interpretation of mammogram and that the cause of such variability is not well understood; reading of mammograms is a skill that experts developed over time [11]. However, interpretation of mammograms is not easy.

Mammography lesions such as MCs and masses are usually small and have low contrast compared to the contiguous breast tissue. Consequently, these abnormalities are hard to detect.

Mammogram enhancement is the process of manipulating mammogram images to increase their contrast and decrease the noise present in order to aid radiologists in the detection of abnormalities. Image enhancement can improve radiologists' perception of subtle abnormalities and thus aid to make a more accurate diagnosis [12].

## 4. Enhancement of Mammogram

Enhancement of mammograms can be done by different algorithms in MATLAB. Enhancement can be achieved by increasing the contrast of mammograms which have been taken at low-dose X-ray or by sharpening image edges and boundaries. Image enhancement includes gray-level and contrast manipulation, noise reduction, magnification, and so on.

The aim of enhancing mammograms is to eliminate the background noise and improve the image quality for the purpose of determining the region of interests (ROIs) in the image thereby making it easier for Radiologist to read and interpret.

The underlying principle in enhancement of mammogram is to enlarge the intensity difference between objects and background and to produce reliable representations of breast tissue structures.

An effective method for mammogram enhancement must aim to enhance the texture and features of masses. Several approaches have been applied in order to enhance mammograms from various research works. The following sections discuss some of the enhancement techniques applied to mammograms.

### 4.1 Histogram Modeling

A histogram of an image provides information about the intensity distribution of pixels in the image. The simplest

form of a histogram is the plot of occurrence of specific gray-level values of the pixels in the image. The occurrence of gray levels can be provided in terms of the absolute values, i.e. the number of times a specific gray-level has occurred in the image, or the probability values, i.e. the probability of occurrence of a specific gray-level in the image.

The histogram of a digital image with gray levels in the range  $[0, L-1]$  corresponds to a discrete function:

$$h(r_k) = n_k \quad (1)$$

Where  $r_k$  is the  $k^{\text{th}}$  gray level in the image for a total of  $L$  gray values and  $n_k$  is the number of pixels in the image having the intensity  $r_k$  i.e. the number of occurrences of gray level  $r_k$  in the image [13]

If a histogram is expressed in terms of the probability of occurrence of gray-levels, it can be expressed as:

$$p(r_k) = \frac{n_k}{n} \quad (2)$$

Histogram modeling modifies the original histogram into a shape as the image gets enhanced. For example, when the histogram of an image is narrow, it is useful to stretch the low level contrasts. There are different methods of modifying the histogram of a gray level image as discussed in the following sections.

### a. Histogram equalization

Histogram equalization (HE) is a process used to produce a new enhanced image with uniform histogram. The main idea of HE is to re-assign the intensity values of pixels to make the new distribution of intensities uniform to the utmost extent. In this case every pixel is replaced by integral of the histogram of the image in that pixel [14] so as to obtain a histogram as uniform as possible, thereby maximizing the mammogram information.

HE is a method in image preprocessing of contrast adjustment using the image's histogram. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to get better contrast. HE accomplishes this by efficiently spreading out the most frequent intensity values.

Considering that variable  $r$  represents the gray levels of the image, in a continuous function, the transformation resulting from histogram equalization from equation 1, generates a level  $s$  for each pixel with gray level  $r$  in the original image. It is assumed that  $T(r)$  is single valued and monotonically increasing [13].

$$s = T(r) = \sum_{j=0}^k P(r_j) = \sum_{j=0}^k \frac{n_j}{n} \quad (3)$$

Where  $k = 0, 1, 2, \dots, L-1$  and  $P(r)$  corresponds to the probability of occurrence of gray level  $r_k$  in the image, which can be determined by the histogram of the image [15]; [13] Thus  $T(r)$  equalizes the histogram of the given image, having as result a uniform histogram

In mammograms, HE is used to make contrast adjustment so that the image abnormalities will be better visible. [16] used HE technique to rescale mammogram in order to equalize image noise which produced a significant reduction in the variation of the sensitivity of the local feature extraction.

HE is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed [17]

The advantage of this approach is its effectiveness in enhancing the entire image with low contrast. Its drawback is that it cannot enhance the textual information and it works only for the images having one object.

#### **b. Adaptive histogram equalization**

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary HE in that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. In [18] it was ascertained that AHE is appropriate for improving the local contrast of an image and bringing out more details, however, it was argued in [19] that AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification.

Ordinary histogram equalization uses the same transformation derived from the image histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image. However, when the image contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced.

Adaptive histogram equalization (AHE) improves on this by transforming each pixel with a transformation function derived from a neighbourhood region.

#### **c. Contrast limited adaptive histogram equalization**

Contrast limited adaptive histogram equalization (CLAHE) was initially implemented by [20] for enhancing biomedical images and it was considerably a success. The CLAHE method seeks to reduce the noise and edge shadowing effect produced in homogeneous areas and was originally developed for medical imaging.

In [21], it was ascertained that CLAHE technique seeks to reduce the noise produced in homogeneous areas and was originally developed for medical imaging. This method was used in [22] for enhancement to remove the noise in the pre-processing stage of mammograms.

In AHE, there is a possibility of image over-enhancement as noise is enhanced. Nearly uniform regions in the image generate high peaks in the histogram, leading to large values in the final image as a result of integration.

The problem of over-enhancement of image which is a major problem of AHE can be corrected by CLAHE through the limitation of the amount of contrast enhancement at every pixel, which is achieved by clipping the original histogram to a limit [20]. The CLAHE Procedure consists of obtaining a local histogram with the neighbours of every pixel, clipping this histogram to the specified limit, modifying the histogram by redistributing the pixels as given by equation 2.2 and integrating the histogram up to the value of the pixels to obtain the final value [20]. In a nut shell, In CLAHE, a local histogram is calculated and a different gray scale transform is computed at each location, based on the neighbourhood. Because mammograms are images consist of many objects CLAHE is not likely to over enhanced mammograms

#### **d. Histogram matching**

Histogram matching (HM) resembles the processing of histogram of the image in order to be similar to the pre-specified one [15]. The initial step of HM corresponds to the calculation of the histogram of the entire image. Through equation 2.2, the gray levels of the original image  $r_k$  are mapped into corresponding level  $s_k$  based on the histogram of the original image.

A transformation function  $G$  of the given histogram  $p_z(z_i)$  is also computed [13]

$$v_k = G(z_k) = \sum_{i=0}^k p_x(z_k) = s_k \quad (4)$$

$$z_k = G^{-1}(s_k) \quad (5)$$

For equations (4) and (5)  $k = 0, 1, 2, \dots, L-1$  and equation 4 conforms to an approximation of the desired levels of the image with that histogram.

$G^{-1}$  has to be single valued and monotonic, which requires  $G$  to be strictly monotonic.  $z_k$  is then computed for each value of  $s_k$  [13] for each pixel in the original image, if the pixel value is  $r_k$ , it is mapped to its corresponding level  $s_k$ . The final level  $z_k$  is obtained by the inverse transformation function  $G^{-1}$  [13].

The disadvantage of this technique is that the transformation must be designed for each image individually in order to have the desired result [23].

#### e. Contrast stretching

Contrast Stretching also called histogram stretching aims at improving the image by stretching the range of intensity values. Those intensity values are rescaled, usually through the analysis of the image histogram. Generally, contrast stretching is used when the gray level distribution is narrow due to poor illumination, lack of dynamic range in the imaging sensor or others [24]. This technique intends to adjust the histogram to achieve a higher separation between the foreground and the background gray level distribution. However, it is difficult to remove noise whose gray levels are similar to that of the objects' ones, such as the microcalcification ([25]; [26])

A linear rescaling transformation is given by [23] as:

$$y = kx + m \quad (6)$$

Where  $x$  corresponds to the input gray scale image,  $y$  to the output values, and  $k$  and  $m$  corresponds to non-zero transformation parameters. The variation of the values of  $k$  and  $m$  allows increased or decreased contrast [23]

Alternatively, according to [23], a non-linear transformation is represented in equation 2.7, where  $k$  is a factor used to rescale the output image to the range of the input image thus:

$$y = kx^p \quad (7)$$

Other typical transformation is given by [27]:

$$f = \begin{cases} \alpha\beta, & 0 \leq x < a \\ \beta(x-a) + \gamma_a, & a \leq x < b \\ \gamma(x-b) + \gamma_b, & b \leq x < L-1 \end{cases} \quad (8)$$

Where  $L$  is the maximum gray value of the original image, the parameters  $a$  and  $b$  can be obtained through the analysis of the image histogram the slope  $\alpha$ ,  $\beta$ , and  $\gamma$  are usually chosen greater than unity in the region of the stretch [27]. [24] proposed a modified contrast stretching algorithm, in which the image low frequency information is processed by the convectional approach and the high frequency information is processed by the log transformation, thus, the details of the mammogram are more enhanced when compared to the traditional algorithm.

#### 4.2 Fixed neighbourhood statistical enhancement

Fixed Neighbourhood Statistical Enhancement (FNSE), as opposed to the previous ones, uses statistical properties in a pixel neighbourhood to estimate the background and

suppress it; hence it is possible to increase the contrast locally. FNSE has been reported to improve performance for mammograms with no uniform (heterogeneous) background [26].

In [28] FNSE was used to enhance mammograms where the global mean,  $M$ , local mean  $\mu$ , and local standard deviation  $\sigma$  were used to obtain the gray level transformation:

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$$y = \alpha \frac{M}{\sigma} (x - \mu) + \mu \quad 0 < \alpha < 1 \quad (9)$$

Where  $\mu$  is an empirically determined scaling factor. The determination of the local neighbourhood dimensions is the critical step. However, a given neighbourhood size and shape may not be equally effective in enhancing all areas of an image.

#### 4.3 Adaptive neighbourhood contrast enhancement

Adaptive Neighbourhood Contrast Enhancement (ANCE), unlike FNSE adapts the size of the neighbourhood to the local properties. Mammograms have ROIs with some image features, which can vary widely in size and shape, with adaptive neighbourhood, the details can be enhanced without changing the remaining image and without significantly introducing artifacts [26].

ANCE is an automatic segmentation method which starts with the pixel to be processed, that is, the seed. The nearest neighbour to the seed, usually 4-connected or 8-connected are checked to verify if their gray level values are within a specified deviation from the seed gray level. The neighbouring pixels which meet the criterion are labeled as foreground and their neighbours are in turn checked to verify their inclusion. The algorithm stops when the foreground is surrounded by pixels that do not meet the criterion of inclusion, which are called background [29].

ANCE is a region based method which can enhance more anatomical detail without significantly introducing artifacts and can identify calcification more effectively in images of dense breast where contrast between calcifications and breast tissue is quite low [25]. The contrast value of each region can be calculated thus:

$$c = \frac{f - b}{f + b} \quad (10)$$

Where  $f$  and  $b$  are the mean gray level values of the foreground and the background respectively [19].

Contrast can be increased by changing  $f$  or  $b$ . Replacing  $c$  with an increased contrast  $c^1$ , the new value of seed pixel in the contrast enhanced image is obtained as given by [12]:

$$f^1 = b \frac{1+c^1}{1-c^1} \quad (11)$$

Where  $f^1$  is the new foreground value. The new contrast  $c^1$  for the region can be calculated using an analytical function of  $c$  or an empirically determined relationship between  $c$  and  $c^1$ , such as square root, exponential, and logarithm or even an empirically formed plot. This methodology was developed in mammograms using an empirically formed plot in order to correlate  $c$  and  $c^1$  by [23]. More anatomical detail were visible when compare with other enhancements techniques and no significant artifacts were introduced. Thus, the study concluded region based methods can improve the visibility of MC clusters and some anatomic details.

In [29] the effectiveness of this method was analysed having a resultant increasing in the true positive cases. However, false positive cases were also increased.

#### 4.4 Morphology-based processing

Morphological operations used in digital image processing are a way of extracting image components that can be used to express details about a regions shape, its boundaries and its area. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. By choosing the size and shape of the neighbourhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.

In general morphological operations are applied to binary images but there are extensions to the gray-level images.

Dilation and erosion are the two elementary operations in morphological processing; these two operators are inverse of each other [13]. An aggregation of these two represents the rest of the operations. Dilation expands objects, fills holes, and connects disjoint regions. Erosion shrinks objects by eroding the boundaries. Dilation and erosion operations are performed by sliding a structuring element on the image.

Two important factors that determine the performance for the morphology-based processing are the morphological operator and the structuring element. The symbols  $\oplus$ ,  $\ominus$ ,  $\circ$ , and  $\bullet$  denote the four fundamental binary morphological operations: dilation, erosion, opening, and closing

respectively which act on the structuring element [30]. This may result in contrast enhanced mammogram image. This reduces high frequencies in image (i.e. noise). However, a drawback of the mathematical morphology technique is that a part of the noise still remains.

#### a. Dilation

Dilation is generally used to smooth boundaries of regions or bridge very small gaps between neighbouring regions. According to [13], the formal definition of dilation of a set  $A$  by another set  $B$  is denoted  $A \oplus B$  and defined by:

$$A \oplus B = \bigcup_z \left( \hat{B} \right)_z \cap A \neq \emptyset \quad (12)$$

Where  $\hat{B}$  is the reflection of  $B$ , hence, the dilation of  $A$  and  $B$  is the set consisting of all the structuring element origin locations where the reflected  $B$  overlaps at least some portions of  $A$  [13].

This means that dilation of  $A$  and  $B$  is done by reflecting  $B$  and then shifting  $B$  over  $A$  by  $z$ . Then all the displacements of  $B$  are sets such that  $B$  and  $A$  overlap by at least one element, which gives the dilation. Set  $B$  is called the structuring element.

Figure 1, illustrates an example of the effect of dilation of set  $A$  and  $B$ . The center of the structuring element  $B$  is marked by a small black square. In this case, the reflection  $\hat{B}$  is equivalent to  $B$ . Now, if  $B$  is moved within and outside  $A$ , then dilation is given by the set of all points traversed by the center of  $B$ , until  $A$  and  $B$  are overlapped by at least one element. The resultant is shown as the shaded square that is bigger in size than  $A$  as indicated by dashed lines.

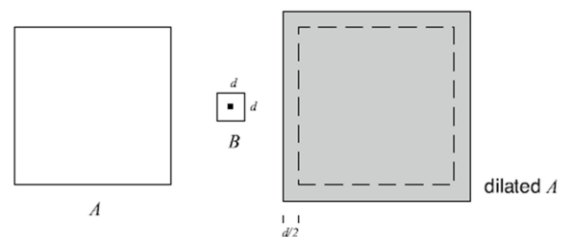


Figure 1: An example of dilation of set  $A$  by set  $B$  [13]

#### b. Erosion

Erosion is the inverse of dilation, meaning that erosion produces an opposite effect of dilation. Erosion can be performed to eliminate irrelevant details, which are smaller than the structuring elements, in other words, the erosion of  $A$  by  $B$  is the set of all points traversed by center of  $B$ , such that is totally contained within  $A$  at all times.

Figure 2 shows an example of set  $A$  and a set  $B$  to illustrate the effect of erosion.

Erosion can be used for removing small unwanted components, such as thread like structures, from an image by using a structuring element (STREL) with an area that is bigger than the unwanted regions.

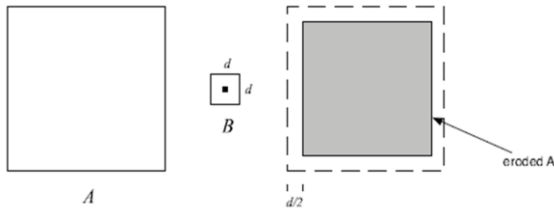


Figure 2: An example of erosion of set  $A$  by set  $B$  [13]

### c. Morphological opening and closing

In digital image processing, the processes of morphological dilation and erosion can be combined together in different ways to make interesting changes in images. Morphological opening and closing denoted by  $\circ$ , and  $\bullet$  respectively are two such operations that are defined by specific combinations of dilation and erosion.

Morphological opening is generally used to smooth region contours and remove thin protrusions in images. The erosion of an object  $A$  by a structuring element  $B$ , followed by the dilation of the resultant image by the same element corresponds to an image opening:

$$A \circ B = (A \ominus B) \oplus B \quad (13)$$

Morphological opening removes regions of an object that are smaller than the structuring element, smooth the edges of the object, and disrupts narrow connections. Similarly, morphological closing adds smoothness to image contours; however, it generally fuses two large regions separated by narrow breaks. This effect is opposite to that caused by morphological opening that breaks the narrow links between two large regions [13].

The dilation of an object  $A$  by a structuring element  $B$ , followed by the erosion of the resultant image by the same structuring element corresponds to an image closing:

$$A \bullet B = (A \oplus B) \ominus B \quad (14)$$

### 4.5 Unsharp Masking

With unsharp masking, a low-pass filtered version of the original image is created and the image values that result are subsequently multiplied by a weighting factor and subtracted from the original image [31]. The final image

preserves much of the detail of the original image, but large structures are presented with less contrast, thereby reducing the dynamic range required to display the image.

In general, unsharp masking involves blending of high frequency components with low frequency components to achieve an effect of sharpening, in which case it will enhance local contrast by suppressing the overall brightness range of the image, or blurring effect, depending on the proportion of the components involved.

According to [32], if  $A$  represents the source image, and  $B$  is the image obtained by applying a local averaging (low-pass filter) to image  $A$ , then the unsharp masking can be represented by the formula:

$$C = \gamma \cdot (A - B) + B = \gamma \cdot A + (1 - \gamma) \cdot B \quad (15)$$

If  $\gamma \in (0, 1)$  is smoothing the image (a blurring effect). Whereas if  $\gamma > 1$  the effect is sharpening the details (emphasis on high frequencies).

With unsharp masking, the sharpness of the borders of mass lesions is enhanced; unsharp masking is a flexible and powerful way to increase sharpness, especially in scanned images. However, it is easy to create unwanted and conspicuous edge effects, or increase image noise. Unsharp masking sharpens edges by subtracting a portion of a Laplacian filtered component from an original image. In [33], this technique was justified to be an approximation of a deblurring process. An extension of this technique was studied in [34] in the context of chest radiographs. However, unsharp masking technique was limited by its linear and single scale nature, and is less effective for images containing diverse features typically found in mammography.

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## 5. Conclusion and Future Work

In this paper various image enhancement techniques available in MATLAB for enhancing mammograms have been discussed; several works have made use of CLAHE for the enhancement of mammograms. It can be concluded that CLAHE perform well for biomedical images due to the following reasons.

- i. CLAHE was originally implemented for biomedical images

- ii. CLAHE performs two-in-one operation of noise reduction and contrast adjustment.
- iii. It prevents edge shadowing effects in an image
- iv. CLAHE prevents over-amplification of noise in homogeneous areas of the images as opposed other enhancement algorithms.

Further work will aim toward enhancing mammograms using the aforementioned techniques and comparing the results obtain by the techniques in order to ascertain which one of the techniques really performs well for mammograms.

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