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Wavelet based contrast limited histogram equalization for contrast enhancement of digital mammography

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WAVELET BASED CONTRAST LIMITED HISTOGRAM

EQUALIZATION FOR CONTRAST

ENHANCEMENT OF DIGITAL MAMMOGRAPHY

by

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ABSTRACT

Mammography has been the most efficient tool for screening of micro-calcification and cancer tissues; however, the raw images produced by mammography systems are usually of poor contrast. In order to use these raw images for early diagnosis; their contrast, sharpness and noise need to be enhanced. Among these important enhancement parameters contrast enhancement is critical. A novel algorithm is introduced which blends wavelet transforms with Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement. In this algorithm, the input image is decomposed to its low frequency and high frequency components in wavelet domain. Decomposed coefficients from different bands are then manipulated. Manipulation of decomposed images consists of applying the modified CLAHE algorithm. The new algorithm was tested on a number of mammogram images. To gauge the potential of the new algorithm, the results were compared with results of CLAHE algorithm. The comparison showed that the proposed algorithm produces improved contrast.

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1. INTRODUCTION

Mammography is an effective tool used presently for the screening of breast cancer. For early diagnostics, radiologists need to detect micro-calcifications and cancer tissues in the mammograms. The main challenge in mammography is: the raw images out of mammography imaging systems are of low contrast, making micro-calcifications and cancer tissues hard to discern. As a result it becomes difficult to diagnose correctly. In addition the micro-calcifications are often found in low contrast regions of the breast, and hence it becomes even harder to distinguish from other tissues. Therefore it is essential to enhance these images in terms of contrast, sharpness and noise without any artifacts. These enhancements lead to improved efficiency of diagnosis for radiologists.

In the enhancement parameters listed above, contrast enhancement is the most critical step. There has been a lot of development in the field of contrast enhancement. Many algorithms have been developed over the years; Contrast Limited Adaptive Histogram Equalization (CLAHE) is one of them. A new contrast enhancement algorithm is being proposed. This algorithm Wavelet based Contrast Limited Adaptive Histogram Equalization (WBCLAHE) blends wavelet transforms with CLAHE to get improved results than CLAHE algorithm.

The basic wavelet based enhancement includes: wavelet decomposition, manipulation of wavelet coefficients and image reconstruction. Wavelet decomposition involves decomposing the image in to its low frequency and high frequency components. The low frequency components contain the contrast information, whereas the high frequency components contain the information related to edges. Therefore it is evident that manipulating low frequency components will lead to contrast enhancement, on the other hand manipulating the high frequency components will result in enhancement of the sharpness.

The CLAHE algorithm consists of dividing the image into number of smaller regions called contextual regions, acquiring histogram for each of these regions, clipping the histogram based on a parameter called clip limit, redistributing the pixels to get histogram equalization and lastly calculating each pixel value by bilinear interpolation of mapping function of neighboring regions. The motivation of the work done towards this paper was to improve the results of CLAHE. In this research the CLAHE algorithm was modified before applying it. The modification involved omission of background from the calculations of the histogram and bilinear interpolation. This helped in reducing the artifacts in output of the CLAHE.

In the WBCLAHE algorithm, an input image is first decomposed into its low frequency and high frequency components using wavelet transforms. The components are then modified to get desired enhancement. This modification includes manipulating the low frequency components using CLAHE for contrast enhancement and multiplying the high frequency components with a scalar to enhance the details or edges. Once the coefficients have been modified the output image is then reconstructed to get better results compared to CLAHE in terms of contrast and sharpness. The WBCLAHE was then tested on number of mammogram images. In order to scale the effectiveness of this algorithm, the results were compared to CLAHE results. The comparison showed that WBCLAHE gave improved results than CLAHE in terms of not only contrast but also sharpness.

2. BACKGROUND

2.1. X-RAYS

William Roentgen discovered X-rays in 1895. [1] After this X-rays were widely used in medical and industrial field. In the medical field, X-rays have been used for both diagnosis and therapeutic purposes for over a century. X-rays find major use in medical imaging, some applications of X-rays in medical imaging are [1]:

Radiography: Single projection imaging for chest, skull, etc.

Mammography: Single projection imaging for breast.

Fluoroscopy: Single projection imaging for displaying continuous x-ray images as a video.

Angiography: Single projection imaging with series of images to view body's blood vessels.

Computed tomography: Multiple projections imaging system to view anatomical cross sections.

Bone Mineral Densitometry: Multiple projections imaging to measure the density of minerals per cubic centimeter of bones.

2.2. MAMMOGRAPHY

Mammography is an application of X-rays which is widely used for viewing anatomical structure of breast. Among all the radiographic examinations, technically mammography is the most difficult one. Mammography can be divided into three basic categories: screening, diagnosis and surveillance. Screening is for detection of breast cancer before a lesion is palpable. Diagnostic mammography is for the cases which have symptoms found or the cases which are suspicious for breast cancer. Diagnostic mammography is also done as a further step of screening to determine previously nonpalpable cancer. Surveillance mammography is the one which does follow up of cases that have been detected with cancer. [2] [27]

As breast cancer arises in glandular tissues, mammography's goal should be to image this glandular tissue. This image should be having high amount of contrast and details (sharpness) while keeping the radiation dose below the acceptable limits. [2] Mammography can be done in two major ways: Screen Film Mammography and Digital Mammography. They both have their pros and cons. Digital mammography is further divided among two sub types of Digitized Screen Film Mammography (Digitized SFM) and Full Field Digital Mammography (FFDM).[1]

2.2.1. Screen Film Mammography. The objectives behind screen film mammography are to produce images with consistently good quality parameters with the lowest radiation dose to the patient. The quality parameters include high-contrast, high-resolution and low-noise. Over the years there have been significant technological improvements in mammographic screen film imaging system. Before 1970's direct-exposure X-ray films were used. This type was also known as industrial type of X-ray films. [2]The problem associated with these films was, they often required long exposure times. It caused blurring of image due to the motion and also resulted in high radiation exposure to the patient. During this period, films were processed manually in tanks or film processors. This processing would take long time.

The current screen film mammography technology involves screen film combinations which have improved characteristics designed especially for mammography. Along with the improvements in screen and film combinations, there have been improvements in film processing as well. Because of increased quality images obtained with screen-film mammography, the mortality rate for breast cancer has been reduced. Because of this reason SFM systems are considered the standard of reference in diagnosing breast cancer. But approximately 10%-20% of the breast cancers detected at the stage of breast self-examination or physical examination are not visible to SFM. Also very less percent of the lesions (almost 4% to 5%) detected with SFM were found to be malignant. [3] This high number of false-positives is most undesirable because, false positives lead to unnecessary biopsies and also psychological stress to the patients involved.

The image forming system can be easily explained using Figure 2.1 below. The X-rays are generated in X-ray tube. These X-rays get attenuated once they enter the breast. Breast has tissues having different attenuation coefficients leading to different attenuation of X-rays. These attenuated X-ray photons then pass through the grid and then interact with image receptor. A latent image on the film is formed after photons are absorbed by the film. The last task before the film becomes usable for the diagnosis is film processing.

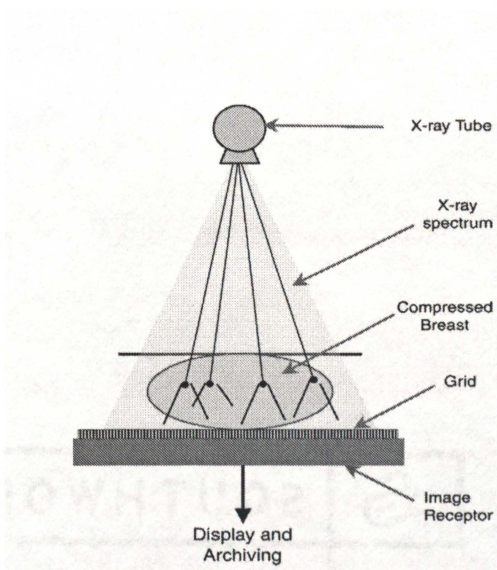


Figure 2.1. Typical set up for screen film mammography [4]

The screen film mammography has its own advantages and disadvantages; some of the advantages [5] are as follows:

1. The high contrast images from SFM allow the subtle differences among soft tissue densities to be visualized.
2. The images have high spatial resolution of the order of 20 lines per mm, this resolution is good enough to display microcalcifications.
3. Multiple image receptor sizes are used. This enables imaging of different sized breasts.

Although now a days digital mammography is being used because of various disadvantages associated with SFM. The most significant disadvantage is SFM has limited dynamic range. The other important disadvantage is, SFM has high false-positive diagnosis rate. Figure 2.2 shows limited dynamic range of screen-film and digital mammography.

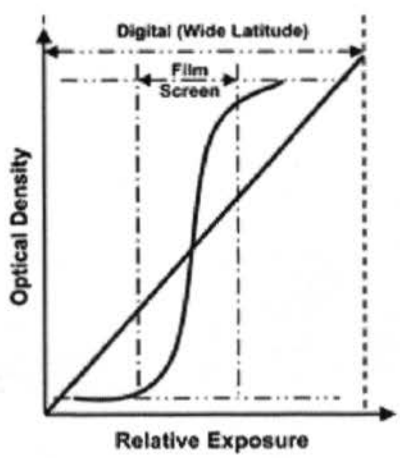


Figure 2.2. Comparison of dynamic range between SFM and digital mammography [6]

It can be easily seen that the dynamic range of digital system is much wider than that of screen film system. For the best results, optimization between dynamic range and image quality parameters (contrast, resolution and noise) is must; also one has to compromise between resolution and efficiency.

In a film screen system, film acts as the only medium for image acquisition, display and a medium of storage. All of these steps contribute to the image quality; any change in these steps changes the quality. The limitations of the screen film mammography can be demonstrated from the Figure 2.3 below.

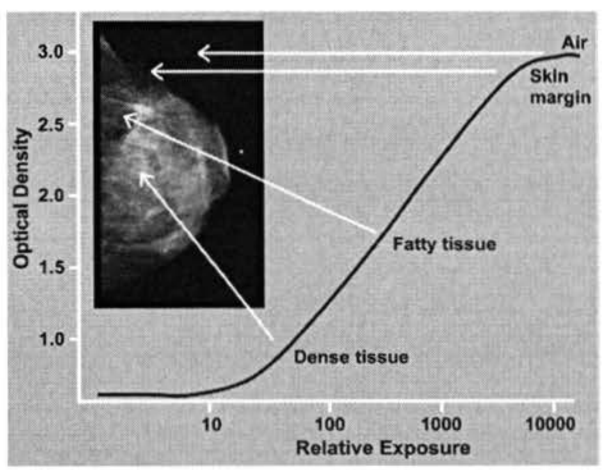


Figure 2.3. Different regions of the breast image are represented with the characteristic response of a mammographic film [4]

The radiograph in the Figure 2.3 is with the imaging system optimized for the dense part of the breast, all the other tissues fall on the on the upper optical density value on the film response curve (Relative exposure vs. optical density), making them impossible to visualize. Some technical factors such as film processing, developing and image artifacts add up to the limitations list for the use of SFM. Digital mammography is a potential alternative to overcome the limitations of screen film mammography. When compared with SFM, digital mammography is better at early breast cancer detection and lesion characterization.

2.2.2. Digital Mammography. Digital mammograms are further classified into 2 ways: digitized SFM and full-field digital mammograms. Digitized SFM is simply a conventional screen film digitalized to get digital mammogram. On the other hand full-field digital mammogram (FFDM) can be obtained using digital detector instead of screen-film combination.

The FFDM system [4] [7] [8] can be divided among two system types, namely direct systems and indirect systems. The indirect system works in two steps. First the attenuated X-rays are absorbed by the scintillator to convert X-rays to visible light; this visible light is then detected by an array of photodiodes or charge-coupled devices (CCDs). For digital mammography application Cesium Iodide (CsI) can be used as the scintillator. In the direct capture process, the X-ray photons are directly captured by the photoconductor and then absorbed X-rays are converted to the digital signal. [9]. Photo conductor such as amorphous selenium (a-Se) can be used for the mammography application. In the indirect system once the visible light is generated by the scintillator might get scattered or spread to give mitigated resolution, this does not happen in the case of direct system. Although the resolution of direct capture has a limitation, resolution is limited by pixel size and not to the thickness of photoconductor.

2.2.3. Imaging Physics. The physics of radiography can easily be explained by explaining attenuation of an object with a structure of interest in it. To make an analogy one can relate the object to the breast making background as normal tissues and structure of interest as microcalcification, tumor or some normal aspect of breast anatomy. So now lets consider that there is a mono-energetic X-ray beam transmitted on the object described above. The set up can be easily demonstrated by Figure 2.4.

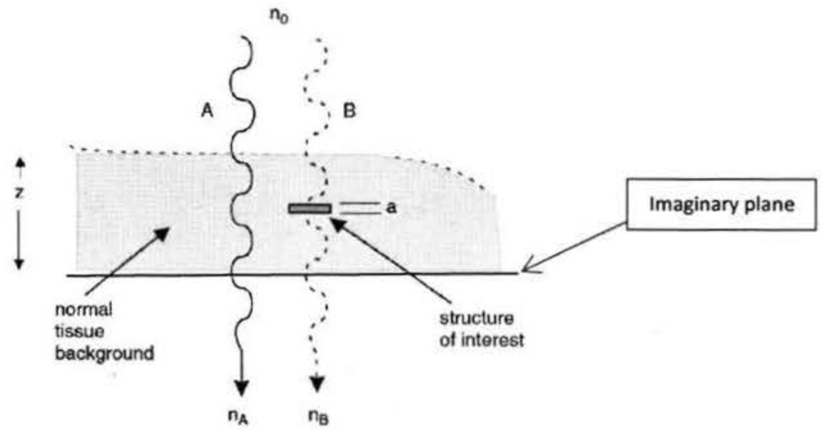


Figure 2.4. Schematic diagram showing the breast and two photon paths, path A passing through normal tissue and path B passes through normal tissues and the structure of interest [10]

It can be seen that there are two paths with which X-rays can transmit through the breast. In the first case, some number of photons transmitted through path A and some number of photons do though path B. In the first case the number of photons at an imaginary plane after the breast can be calculated by simple lamberts law. The number is given by [1]:

$$n_A = n_0 e^{-\mu Z} \qquad (1)$$

where, n_0 is the mean number of photons incident on the breast,

Z is the thickness which photons have to travel inside the breast and

μ is the X-ray attenuation coefficient of breast tissues.

Note that, in this attenuation, scattering is ignored. This can be done by using an anti-scattering grid.

Now for case two that is photons traveling through path B: Photons attenuate with two materials; normal tissue background and structure of interest i.e. microcalcification or tumor. The number of photons reaching the imaginary plane right after the breast can be given by [10],

$$n_B = n_0 e^{-((\mu_1(Z-a))+\mu_2 a)} \tag{2}$$

where, μ_1 is the linear attenuation coefficient of breast tissues,

μ_2 is the linear attenuation coefficient of the structure of interest,

Z is the thickness of breast and

a is the thickness of structure of interest.

The presence of the structure influenced difference in the signal produced (in a digital system) by the X-rays. This difference can be given by: $n_A - n_B$. The contrast occurred by this difference in number of photons can be given by:

$$Contrast = \frac{n_A - n_B}{n_A + n_B} \tag{3}$$

Substituting equations (1) and (2) in equation (3), we get:

$$Contrast = \frac{1 - e^{-(\mu_1-\mu_2)a}}{1 + e^{-(\mu_1-\mu_2)a}} \tag{4}$$

This contrast allows a viewer to differentiate between different components in the X-ray image. In the case above, because of this contrast one will be able to differentiate between the tissue background and tumor (structure of interest).

2.2.4. Advantages of Digital Mammography. A digital mammogram can be manipulated in many ways in order to make them more discernable and improve quality in terms of contrast, sharpness and reduced noise. In addition to the quality, a radiologist can alter the digital mammogram to change its orientation, magnification and brightness as desired. According to patient's point of view there is not much difference, although in screen film mammography a patient gets more radiation dose than in the digital mammography. [4]

A digital mammogram can be viewed by using high luminance computer monitor, as well as it can be printed as a film. Digital mammograms are more storage friendly, they can be stored electronically. This makes them very easy for retrieval and also makes it able to be used remotely, facilitating distant screening and consultation for mammography. Because of many advances in digital detectors over the years, digital mammograms have acquired the potential to detect breast cancer, microcalcifications and tumors more efficiently compared to screen film mammography. Digital mammograms result in reduced number of false positive diagnosis, with fewer doses to the patient. Also, to eliminate structural noises from the image flat field correction can be used, image can also be processed to remove random noise. [4]

Unlike screen film mammography, in digital mammography, the basic steps of imaging i.e. image acquisition, displaying and storing are independent of each other. This independence gives a scope of improvement and optimization in each of the above processes independently. Screen film mammography has a short dynamic range (40:1), whereas digital mammography as wider dynamic range (1000:1), in addition image can be manipulated. Better dynamic range and ability to be post-process puts digital mammography ahead in the comparison with screen film mammography. [11] Digital mammography gives fairly improved visibility of lesion which increases the efficiency of diagnosis and fewer false positives.

To summarize the advantages of digital mammography, it can be said that digital mammography:

- gives less radiation dose to the patient,

- has its data in digital form which can be manipulated to improve the image quality,
- provides the facility of controlling brightness and contrast for the display image,
- is very easy for storage and retrieve for screening and
- can be processed to reduce noise.

2.3. CONTRAST ENAHANCEMENT FOR DIGITAL MAMMOGRAPHY

The raw images out of the digital mammography system are very crude, and need to be enhanced in terms of contrast, sharpness and noise. Among these, contrast is a critical parameter which needs to be enhanced significantly. The raw images have very poor contrast, which makes it hard to differentiate between the different anatomical parts of breast and the tumor or microcalcification.

The purpose of contrast enhancement is enhancing the image features against its background, making it easy to visualize the image properties and features to an open eye. In digital X-ray mammography the contrast is caused by the radiation reaching the detector as discussed in article 2.2.3. As contrast is dependent on radiation, it can be stated that, good contrast involves more radiation and hence more dose to the patient. The patient is supposed to have low exposure or less dose, this implies less radiation and hence less contrast; although appropriate image processing can overcome this limitation. Therefore digital mammography allows mammography of a patient without additional exposure, with the aid of contrast enhancement.

2.3.1. Indirect Contrast Enhancement. In indirect contrast enhancement, the image contrast is enhanced with modification of the histogram or low frequency image instead of enhancing contrast directly. There are many popular methods of indirect contrast enhancement of digital images, they are discussed below.

2.3.1.1. Contrast stretching. Contrast stretching is one the basic contrast enhancement tools. The range of intensity values is uniformly stretched over the available grayscales. This expands the full intensity range of an image from the acquisition medium to the maximum possible for that bit. If $\boldsymbol{f}$ is the original image and '$\boldsymbol{A}$' & '$\boldsymbol{B}$' are lower and upper limits of the desired stretching respectively, while '$\boldsymbol{C}$' &'$\boldsymbol{D}$' are the maximum and minimum gray values of the original image respectively. Mathematically contrast stretching is given by:

$$f'(x,y) = A + \frac{B - A}{D - C} * [f(x,y) - C] \tag{5}$$

where, x and y give the spatial coordinates

$f'$is output image of contrast stretching.

Contrast stretching is more of a global contrast enhancement. For better results, local contrast enhancement is more suitable, therefore contrast stretching is not widely used. Contrast stretching can be understood with the help of Figure 2.5.

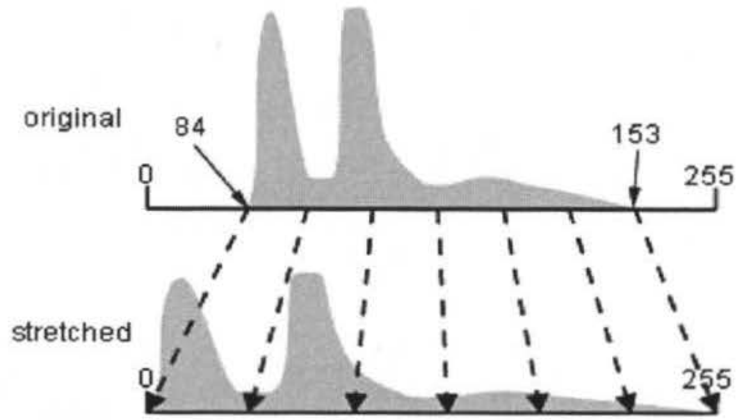


Figure 2.5. Contrast stretching [11]

2.3.1.2. Histogram equalization. Histogram equalization is one more of the basic contrast enhancement technique. In histogram equalization, the histogram is equalized by distribution of pixels over the entire intensity levels, resulting in increased dynamic range of the image histogram. Generally, having the histogram as flat as possible gives better contrast. Histogram equalization is a globally operating contrast enhancement technique; therefore many modifications in this technique are done over the time. As it operates globally, details outside the denser parts of the breast are lost.

The few of the famous modifications in histogram equalization are: bi-histogram equalization [12], minimum mean brightness error histogram equalization [13], recursive mean separate histogram equalization [15] and partially overlapped sub-block histogram equalization [14] [11], etc.

2.3.1.3. Adaptive histogram equalization. As histogram equalization had a limitation of being global operator over the image, adaptive histogram equalization kind of takes care of this limitation. Adaptive histogram equalization works on local neighborhood, each pixel value is modified based on its neighbor. For each pixel under process, a local window is selected. These pixels cover different range of gray values, depending on the location of that region in the image. These local windows are then enhanced using histogram equalization separately. Contrast can also be altered by changing the slope of the transform function which processes the input image pixels to get output pixel values. The drawback of adaptive histogram equalization is it can add to the noises by significant amount in the regions with dense tissues or with background. [9]

2.3.1.4. Contrast limited adaptive histogram equalization. Even though adaptive histogram equalization gives better contrast, it does not work the best in few regions, e.g. dense breast tissues or background. To remedy that, contrast limited adaptive histogram is adopted. It divides the image in number of contextual regions which are user specified and uses contrast limit or clip limit, which controls maximum number of pixels with same gray value in a region of interest. Basically a local histogram is acquired for each contextual region and then this histogram is clipped at the clip limit. The clipped pixels from the histogram are then redistributed among all the bins of histogram to achieve histogram equalization. After that a mapping function is calculated for each pixel depending on the neighboring regions, this mapping function is then used with bilinear interpolation to get the final pixel value of the output image. CLAHE algorithm has many parameters to control in order to get contrast as desired. CLAHE gives improved contrast to match the human visual system although its region based operation might create artifacts at the borders of regions. [10] [16]

2.3.2. Direct Contrast Enhancement. In direct contrast enhancement, first contrast measure criterion is established later the image is enhanced to improve image contrast. Establishing a suitable contrast measure is the key step of enhancement for direct contrast enhancement. Some of the direct contrast enhancement techniques are discussed below:

2.3.2.1. Optimal adaptive neighborhood contrast enhancement. In this method, neighbor consisting of a square of coefficients surrounds the center of a given coefficient to calculate the local contrast. The contrast measure in this method [17] is defined as:

$$C = \frac{|p - a|}{|p + a|} \qquad where\ 0 \leq C \leq 1 \tag{6}$$

where, 'p' is the average density of the center and

'a' is the average density of the surround.

Each pixel value is transformed to get new pixel value using a suitable contrast enhancement function. The enhanced contrast can be obtained by replacing old pixel values with new pixel values.

2.3.2.2. Adaptive fuzzy logic contrast enhancement. This method uses fuzzy entropy principle to enhance contrast both globally and locally. Fuzzy entropy principle transforms an image in fuzzy domain to compute fuzzy entropy, this measures the local histogram. On the other hand, histogram of an image provides the global contrast. Finally the output image is obtained by defuzzification to transform the enhanced mammogram from fuzzy domain to spatial domain.

2.3.3. Multiscale Contrast Enhancement. Multiscale contrast enhancement enables tuning the contrast of certain frequency bands i.e. contrast enhancement can be done at different scales. With the help of multiscale processing it is possible to enhance the micro-calcifications and masses in a range of scales. Some of well-known methods of multiscale contrast enhancement are discussed below:

2.3.3.1. Multiscale wavelet based enhancement. Wavelet based multiscale processing is a very commonly used multiscale contrast enhancement techniques. This approach was first introduced by Laine et al to digital mammography in 1994 [18]. A wavelet transform basically decomposes the input image into its high frequency and low frequency components. These components can be modified locally or globally using suitable enhancement functions. The low frequency coefficients usually carry the contrast information while the high frequency coefficients (Horizontal details, vertical details and diagonal details) contain the edge information or detail information. Therefore it is evident that for enhancement of contrast, the low frequency components must be modified. On the other hand, for enhancement of sharpness and noise, high frequency coefficients should be modified. [19] [18] [20].Once the coefficients have been modified, the output image is reconstructed from the modified coefficient using wavelet inverse transform. Wavelet multiscale approach can be used for enhancement of more than one quality parameters, like adaptive denoising and contrast enhancement was proposed in [18]. Wavelets are a powerful enhancement tool, which can reveal features that are barely discernable by traditional unprocessed mammograms. [6].

2.3.3.2. Laplacian based enhancement. Multi-scale image contrast amplification (MUSICA^{TM}) is a very well-known technique in contrast enhancement, this method uses Laplacian pyramid. [21] Laplacian pyramid approach was first introduced for image compression. [22] In MUSICA^{TM}, a power law is used with linear lower and upper cutoffs. Lower cutoff was introduced to avoid amplification of noise whereas higher cutoff enhances contrast non-linearly.

3. METHOD

The proposed algorithm WBCLAHE (Wavelet based Contrast Limited Adaptive Histogram Equalization) is primarily for contrast enhancement, but it also enhances sharpness of the mammograms. This algorithm blends wavelet transforms with Contrast Limited Adaptive Histogram Equalization. In any wavelet based image processing, input image is transformed in wavelet domain to decompose it into its high frequency and low frequency coefficients. These components or coefficients are then modified to enhance the quality parameters of the image, and the output image is then reconstructed using the modified coefficients with inverse wavelet transform. In the proposed algorithm similar approach is adopted, the modifications of coefficients include application of CLAHE algorithm on the set of low frequency coefficients and scalar multiplication on high frequency coefficients to achieve the desired goal. The purpose of the blend was to achieve contrast enhancement without increasing the noise which comes with the contrast enhancement.

3.1. WAVELET DECOMPOSITION

Wavelet transforms are based on small waves called wavelets of varying frequency and limited duration. This allows having both spatial information and temporal information. Wavelets were first introduced as new powerful approach to digital signal processing and analysis called multiresolution theory in 1987. [23]

An image is composed of connected regions of similar texture and intensity levels that combine to form objects. If objects are small in size or low in contrast, the analysis usually requires high resolution; on the other hand when they are large in size and or high in contrast then coarse view suffices the requirement. If both the situations are present simultaneously, having several resolutions help in examining the image more efficiently. This is the motivation behind multiresolution processing.

Mathematically, images can be represented as two dimensional arrays of intensity values.[23] These intensities vary all over the image depending on the object; the intensities vary abruptly on the features such as edges of an object etc. When the variation is abrupt it is said to be having high frequency. In an image, it can be stated that, edges and details contribute to high frequency while contrast is termed in low frequency.

Various filters are being used to decompose the image to get separated high frequency and low frequency coefficients. Biorthogonal filter type was used to decompose the input image into its high frequency and low frequency coefficients. Once the image is decomposed the size of the approximation image or any of the set of high frequency coefficients is reduced to half of the original size. If there is an image I of size $(X \times Y)$, once this image is wavelet transformed the size of the sets of coefficients gets reduced to $(\frac{X}{2} \times \frac{Y}{2})$. [23] This wavelet transform of the input image is usually termed as first order wavelet decomposition. If the approximation image is further decomposed using wavelet transforms, the decomposition is 2^{nd} order decomposition. After this decomposition, the size is further reduced to half of the size of approximation image from the first order decomposition. The size of approximation image after 2^{nd} order decomposition is$(\frac{X}{4} \times \frac{Y}{4})$. First order and second order decompositions and the image size reduction can be seen in Figure 3.1.

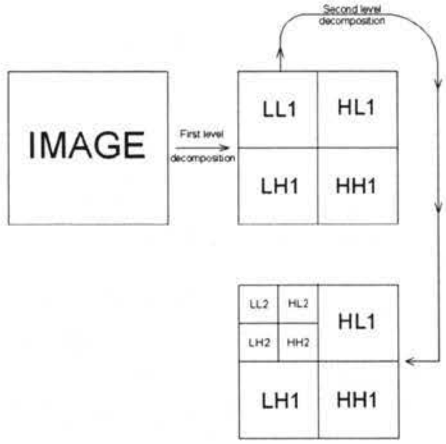


Figure 3.1. First level and second level wavelet decomposition of an image

Figure 3.1 shows an IMAGE of size $(X \times Y)$ which was decomposed in wavelet transform of the first order to get four sets of coefficients $(LL1, HL1, LH1$ & $HH1)$. $(LL1)$ is a set of approximation coefficients or low frequency components, if this set was shown as an image it would look similar to the original image after blurring. The size of $(LL1)$ is reduced to $(\frac{X}{2} \times \frac{Y}{2})$, so are the sizes of other sets of coefficients $(HL1, LH1$ & $HH1)$. These are high frequency components or detail coefficients. $(HL1)$ is the set of horizontal detail coefficients, $(LH1)$ is the set of vertical detail coefficients and $(HH1)$ is the set of diagonal detail coefficients. The low frequency component that is $(LL1)$ or approximation coefficients usually carry the contrast information. Therefore if one desire to enhance the contrast using wavelet transforms approach, one should decompose the image using wavelet transforms, enhance the approximation coefficients and reconstruct the coefficients using inverse wavelet transforms. On the other hand, high frequency components carry the detail information that is edges and noise. In order to use wavelet domain to enhance the sharpness and reduce the noise, one should manipulate high frequency components.

Similarly approximation image from the first order wavelet decomposition can be treated as a separate image, and it can be decomposed again using wavelet transforms.

This decomposition is known as second order wavelet decomposition. Figure 3.1 shows that the approximation coefficient from first order decomposition ($LL1$) was decomposed again in wavelet domain to get another four sets of wavelet coefficients ($LL2, HL2, LH2$ & $HH2$). ($LL2$) is approximation image, and ($HL2, LH2$ & $HH2$) are sets of horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients respectively. The size of these sets are further reduced to $\left(\frac{X}{4} \times \frac{Y}{4}\right)$. This process is called second order wavelet decomposition. Image can be decomposed further to desired level which is limited by the size of the image. These decompositions can be used for image processing, and this approach is what is called multiresolution theory. In this research wavelet decomposition of first order was used, and for decomposition MATLAB inbuilt function was used. The wavelet theory is very big topic of study, only the material with relevance this thesis was discussed in this section.

3.2. CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Contrast limited adaptive histogram equalization (CLAHE) is a well-known contrast enhancement technique. In the case of mammograms, the grayscale distribution is highly localized; it might not be desirable to enhance these low-contrast images by histogram equalization. Usually the mapping curve may include segments with high slopes, meaning that two very close grayscales might be mapped to significantly different grayscales. This limitation is overcome by Contrast Limited Adaptive Histogram Equalization by limiting the contrast allowed through histogram equalization. In CLAHE algorithm, this contrast limited approach is combined with adaptive histogram equalization. [16] [24] [25]

3.2.1 Contextual Regions. CLAHE is formulated based on dividing the input image to number of user assigned, non-overlapping regions of almost equal size. Dividing these "contextual regions" is a major task in the CLAHE algorithm, the selection of appropriate number of contextual regions affects the contrast enhancement of the mammograms or any input image to the CLAHE algorithm. To achieve good statistical estimation: a $\mathbf{512 \times 512}$ image should be divided in 64 equal sized regions, i.e. 8 in each direction. [16] For explanation of the region division, please refer Figure 3.2.

The Figure 3.2 shows a (512×512) image divided among 64 equal sized regions. Based on the location of these regions in an image they are classified into three types: Corner Regions (CR), Border Regions (BR) and Inner Regions (IR). [16] These regions can be observed in the Figure 3.2, the number of each type of region can be noted to be: CR as 4, BR as 24 and remaining 36 are the inner regions (IR).

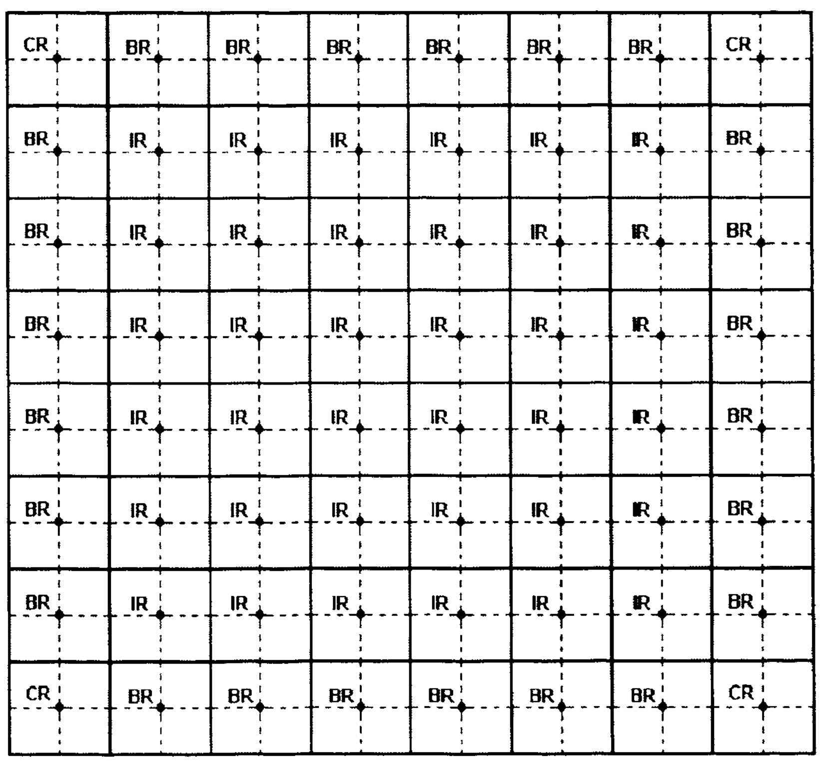


Figure 3.2 (512×512) image divided among 64 contextual regions and classification of regions: IR, BR, CR [16]

The next step after dividing the image into number of regions is to calculate local histogram for each region. Then based on the desired clip limit, a new clipped histogram is obtained. After clipping the histogram, the clipped part of histogram is redistributed in each bin of histogram such that none of the histogram bin height goes above the clip limit. Finally, cumulative distribution functions CDF [26] of the resultant contrast limited histograms are determined for gray scale mapping. Each pixel is mapped by linear interpolation of mappings of the four nearest regions. This calculation of mapping function is discussed further. [16] [25]

3.2.2. Calculation of Mapping Functions. For each region, local histogram is calculated. This is done by determining number of pixels with same grayscales, so basically histogram for each region is a plot of grayscales VS number of pixels. Local histogram can in general be said to be a rough estimate of the grayscale density function. The mapping function can be determined by using an estimate of the CDF.

If total number of pixels in a region is M and the number of grayscales in a region is N, $h_{i,j}(n)$ for $n = 0, 1, 2, \ldots\ldots\ldots, N-1$ is histogram of (i, j) region,then mapping function can be given by:

$$f_{i,j}(n) = \frac{(N-1)}{M} \sum_{k=0}^{n} h_{i,j}(k)\,; where\ n = 1, 2, 3, \ldots, N-1 \tag{7}$$

To limit the contrast, a new variable i.e. clip limit (β) is introduced. This limit is calculated or related to a user declared variable called clip factor (α). The relation is as follows:

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \tag{8}$$

S_{max} is the allowable slope, generally for X-ray images the value for S_{max} is set to be 4. The value of α, lies in a range 0 to 100. When α is 0, the clip limit becomes $\frac{M}{N}$ which results into an identity mapping i.e. no change in pixel values will occur. On the other hand, when clip factor is 100 maximum clip limit is achieved which is $(S_{max} \cdot M/N)$. In this case there will be maximum change in pixel values.

Figure 3.3 shows an explanatory image divided among 9 regions 3 in X-direction and 3 in Y-direction with simulated histograms for each region. Also the clipping and redistribution actions are shown in Figure 3.3.

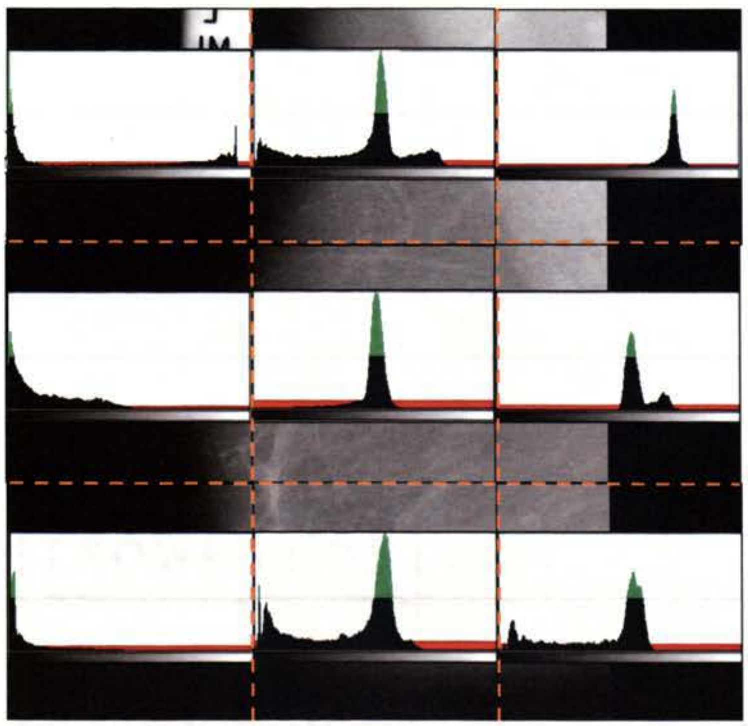


Figure 3.3 An image is divided into nine equal contextual regions and simulated histogram for individual region is processed in order to get clipped histogram

Table 3.1 shows the parameters for making contextual regions and clipping of local histogram.

Table 3.1 Index for Figure 3.3

	Clip Limit
	Clipped part of histogram
	Redistributed pixels from clipped histogram
	Border of contextual region

The histogram is modified based on the desired limit in change of image contrast keeping the maximum number of counts limited by clip limit (β).[16] If there exist any extra pixels for a particular bin, these pixels are equally distributed among the bins with counts less than that of clip limit. While redistributing these pixels, several iterations are carried out with a condition that at no time, the count for any bin goes beyond clip limit.

3.2.3. Combination of Mapping Functions. Every contextual region is subdivided into four quadrants as shown in Figure 3.4. These quadrants are divided because depending on the location of pixel in a region its neighbors will change.

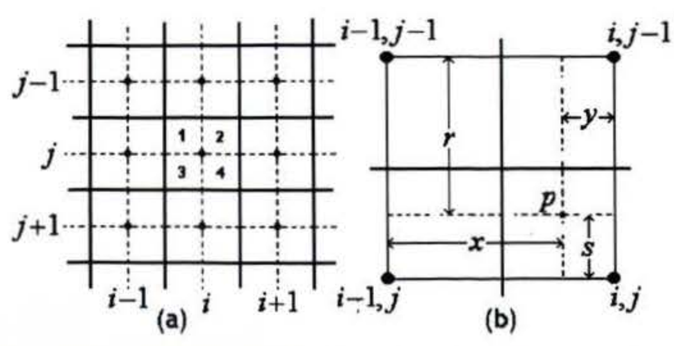


Figure 3.4.Contextual region under calculation (a) Contextual region (i, j) from the group

IR,(b) Neighbors for quadrant 1 for contextual region (i, j) [16]

As a general rule, the new pixel value P_{new} in first quadrant of region (i, j) can be given by:

$$P_{new} = \frac{s}{r+s}\left(\frac{y}{x+y} f_{i-1,j-1}(P_{old}) + \frac{x}{x+y} f_{i,j-1}(P_{old})\right) + \frac{r}{r+s}\left(\frac{y}{x+y} f_{i-1,j}(P_{old}) + \frac{x}{x+y} f_{i,j}(P_{old})\right) \quad (9)$$

Where, (i, j) is the contextual region under operation and $(i-1, j-1)$, $(i, j-1)$, $(i-1, j)$ are its neighbors.

Equation (9) can be used to calculate new pixels in IR regions. But for calculations for CR and BR regions special considerations have to be taken into account because CR and BR are on the corners and borders of the image respectively and hence they have less than 3 neighbors for at least one of their quadrants. If top left corner region is under calculation, it can be observed in Figure 3.2, that first quadrant does not have any neighbors.

Similarly, it can be seen that, all the corner and border contextual regions will have at least one of the quadrants having less than 3 neighbors and hence special manipulation in Equation (9) is needed.

The regions on the border have two quadrants touching the border. These are the regions which share less than 3 neighbors. Figure 3.5 shows right side BR, Figure 3.5 (a) shows region (i, j) with neighbors and Figure 3.5 (b) shows border quadrants 2 and 4 from Figure 3.5 (a).

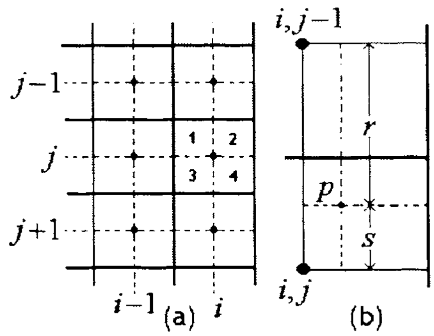


Figure 3.5 Right border region (i, j). (a) Region under calculation and its neighbors (b) Zoomed view to show quadrants 2 and 4 [16]

Equation (9) can be modified to give new pixel values for the pixels in border quadrants of BR group regions:

$$P_{new} = \frac{s}{r+s} f_{i,j-1}(P_{old}) + \frac{r}{r+s} f_{i,j}(P_{old}) \qquad (10)$$

Equation (10) shows the P_{new} value for the pixels lying in the quadrants in the BR group region. There are two border quadrants in every border regions, the location of these two quadrants depends on the location of BR in an image; BR are located at left and right sides also up and bottom borders.

For the regions in CR group, there is one quadrant in each region which had no neighbors. This can be seen in Figure 3.6, Figure 3.6 shows top left CR.

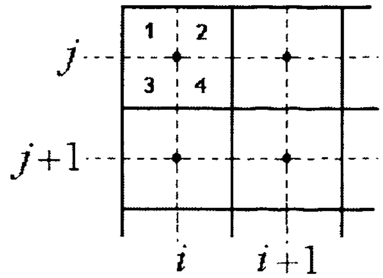


Figure 3.6. Top left corner region and its neighbors [16]

As it can be seen from Figure 3.6 quadrants 2 and 3 can be treated as quadrants in BR because they share a neighbor. Also quadrant 4 can be treated as quadrants in IR as quadrant 4 shares neighbors like IR quadrants. But quadrant 1 in Figure 3.6 does not have any neighbor and hence should be considered separately. Equation (9) can be modified to give P_{new} for pixels in such quadrant of CRs.

$$P_{new} = f_{i,j}(P_{old}) \tag{11}$$

It can be seen that the mapping function for pixels in these quadrants is same as the regional mapping because it does not have any neighboring regions to consider.

In summary of all the operations in CLAHE algorithm, histogram for each contextual region is calculated and then modified using desired clip factor. Grayscale mapping for each region is obtained by Equation (7), and finally determining each pixel value depending on the mappings of the neighboring regions using Equations (9), (10) and (11). For getting the best result CLAHE algorithm was modified before its actual application. In order to avoid the artifacts from contribution of background of breast, background pixels were not included in the calculation of local histogram and the mapping functions. This had to be done because there is no room for additional artifacts to the breast.

3.3. ALGORITHM (WBCLAHE)

The raw images out of mammography imaging systems are of poor contrast. In order to enhance the contrast of these images, a new algorithm was proposed named Wavelet Based Contrast Limited Adaptive Histogram Equalization (WBCLAHE). WBCLAHE uses two of the major approaches in image processing. Firstly the image is decomposed by wavelet transforms. These sets of decomposed coefficients were then manipulated by applying modified CLAHE algorithm on low frequency components, also high frequency components were scalar multiplied to get enhanced sharpness.

The WBCLAHE algorithm can be explained by the Figure 3.7, it also show the path of operation very well. As this algorithm consists of wavelets i.e. multi-resolution theory it is necessary to keep track of the sizes of the images. Figure 3.7 shows the image sizes throughout the flow.

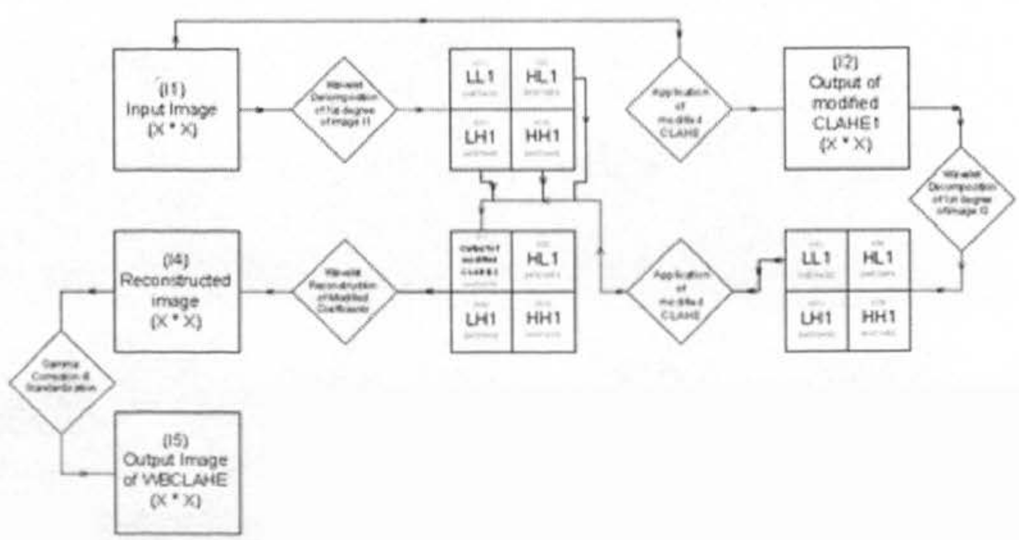


Figure 3.7 Flow diagram for WBCLAHE algorithm

The input image ($I1$-size $(P \times Q)$) was first decomposed in to its wavelet coefficients ($C1, C2, C3, C4$) using wavelet transform (Biorthogonal filter was used). These sets of decomposed coefficients are reduced in size $[(P/2) \times (Q/2)]$ to half of the size of the input image ($I1$). Among these wavelet coefficients, $C1$ is the set of approximation coefficients and $C2, C3$ & $C4$ are the sets of detail coefficients. $C2$ is the set of horizontal detail coefficients, $C3$ is the set of vertical detail coefficients and $C4$ is the set of diagonal detail coefficients.

The modified CLAHE algorithm was also applied on the same input image ($I1$). The modified CLAHE algorithm was basically CLAHE algorithm without the contribution of background of mammogram for the calculation of local histograms for the regions which included the background and also for the calculation of mapping functions. So till this point there were 2 outputs, a contrast enhanced image ($I2$) and sets of wavelet decomposed coefficients ($C1, C2, C3$ & $C4$).

The output image of modified CLAHE-1 that is contrast enhanced image ($I2$) was then decomposed to its low frequency and high frequency components using wavelet transforms. This wavelet transform resulted in wavelet coefficients ($C5, C6, C7$ & $C8$). In these sets of wavelet coefficients, $C5$ was a set of approximation coefficients or low frequency coefficients, ($C6, C7$ & $C8$) were the high frequency components. As low frequency components carry the contrast information, modified CLAHE algorithm (CLAHE-2) was applied on coefficients set ($C5$) to get contrast enhanced image ($I3$). By applying modified CLAHE-2 on the approximation coefficients, only contrast was enhanced not the noise, because most of the noise is in high frequency. The size of image ($I3$) would be half of the size of the original image ($I1$). While applying the modified CLAHE-2 over ($C5$), the set of ($C5$) coefficients were treated just as an image by normalizing the coefficients in the range as ($I1$).

Image ($I3$) and initial high frequency components ($C2, C3$ & $C4$) were put together. Inverse wavelet transform was carried out to reconstruct an enhanced image with ($I3$) as set of approximation coefficients, ($C2$) as set of horizontal detail coefficients, ($C3$) as set of vertical detail coefficients and ($C4$) as the set of diagonal detail coefficients. The initial high frequency components were used because, contrast enhancement algorithms can increase noise too, therefore if compared initial set ($C2, C3$ & $C4$) have less noise than ($C6, C7$ & $C8$). Because of using initial high frequency components the WBCLAHE algorithm helps in suppressing high frequency noise. Before reconstruction of the image ($I4$), the high frequency components ($C2, C3$ & $C4$) were multiplied by a scalar to improve sharpness.

Image ($I4$) was then processed by gamma correction/power law algorithm to enhance the contrast in low intensity range. The result of gamma correction was brought in the desired brightness of 14 bit to get the final output image ($I5$).

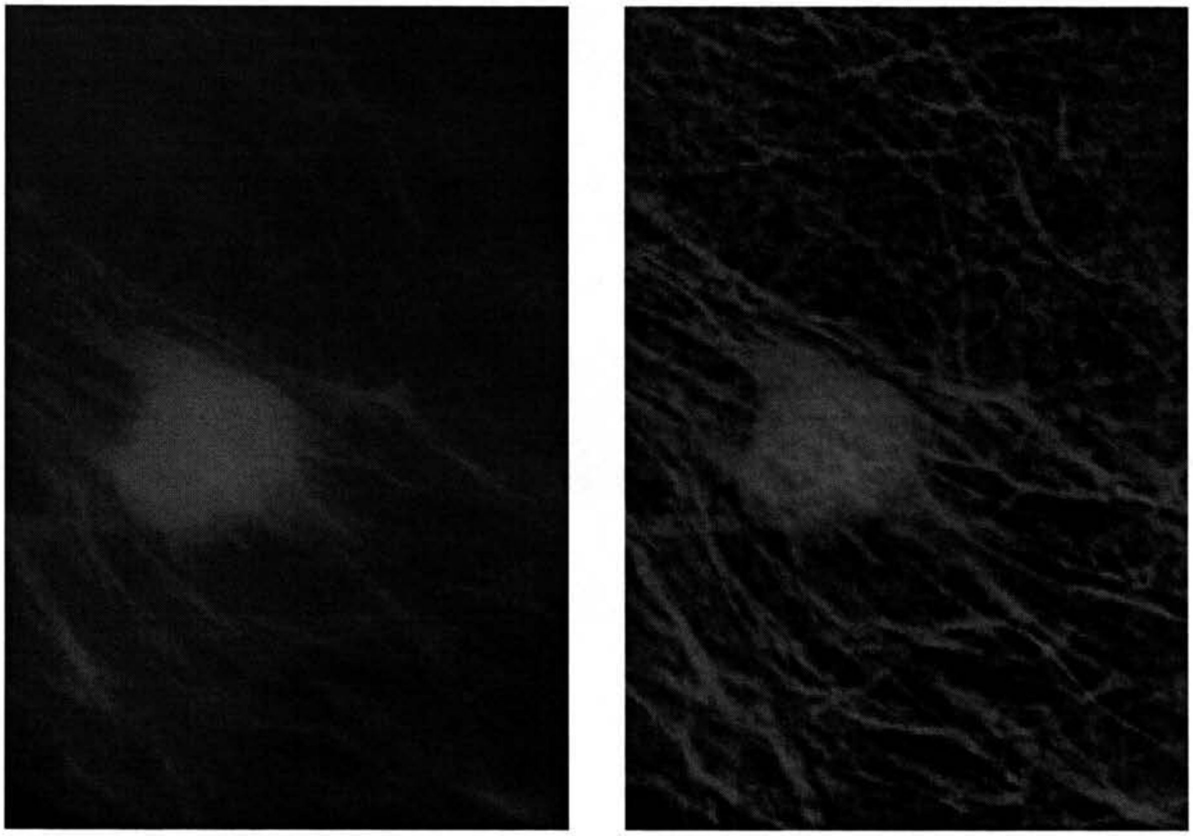
4. RESULT

For testing the performance of new algorithm, WBCLAHE was applied on several mammograms selected from the Mammographic Image Analysis Society (MIAS) database. The images from this data base are digitized to 50 micron pixel edge and reduced to 200 micron pixel edge and padded to make the image of size 1024 $\times$ 1024 pixels. The algorithm was developed in MATLAB R2007b on a core i3 (2GB) RAM machine.

To demonstrate the contrast enhancement capabilities of WBCLAHE algorithm, the input images were cropped to the region of interest from the input images. The region of interest was selected to have fatty tissue with well-defined mass or fatty glandular tissue with calcifications.

Figure 4.1 (a) and (b) shows an original mammogram and enhanced mammogram by WBCLAHE algorithm respectively.

After comparing the Figure 4.1 (a) and (b), it can be easily seen that the contrast was enhanced significantly. Also the lesion and the anatomical structures became more obvious to human visual system in the WBCLAHE. The details in fatty tissue were not discernable before enhancement and after enhancement these details were visible. In addition to the contrast enhancement it can be seen that the sharpness of the image was improved by small quantity.



(a) (b)

Figure 4.1 Result of WBCLAHE (a) Original image (Cropped from the MIAS library) [MIAS] (b) WBCLAHE enhanced image

It can be easily seen that the histogram of enhanced image is more spread out than the histogram of original image. If one has relate contrast to histogram, the relation is found to be- more the histogram is stretched over the available grayscales more is the contrast. Therefore we can say the WBCLAHE enhanced image has better contrast than the input image. The maximum count in an original image histogram is 4760 whereas the maximum count in WBCLAHE enhanced image is 1499. This difference is there because the local histograms were clipped at clip limit and histogram was modified making changes in image histogram.

Figure 4.2 (a) and (b) shows histograms of original cropped mammogram and the WBCLAHE enhanced mammogram, respectively.

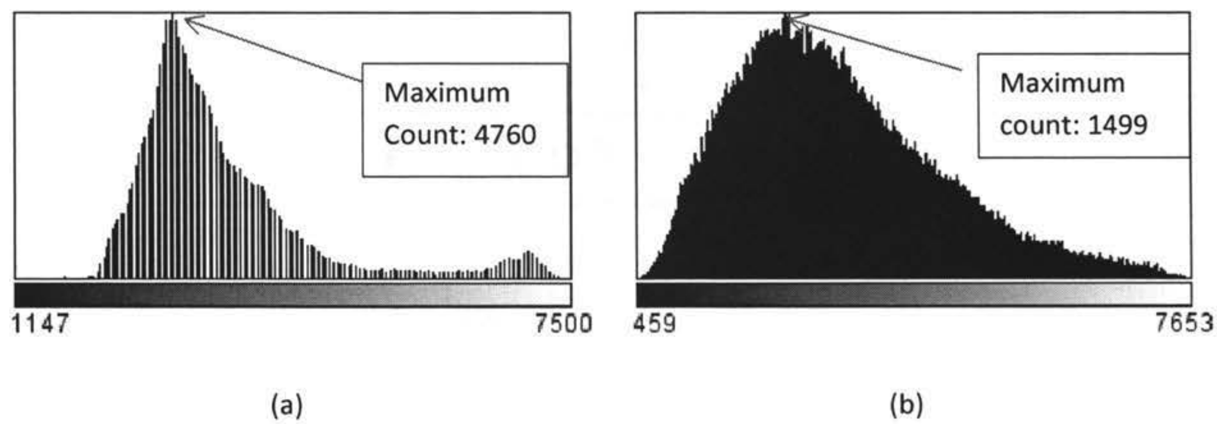
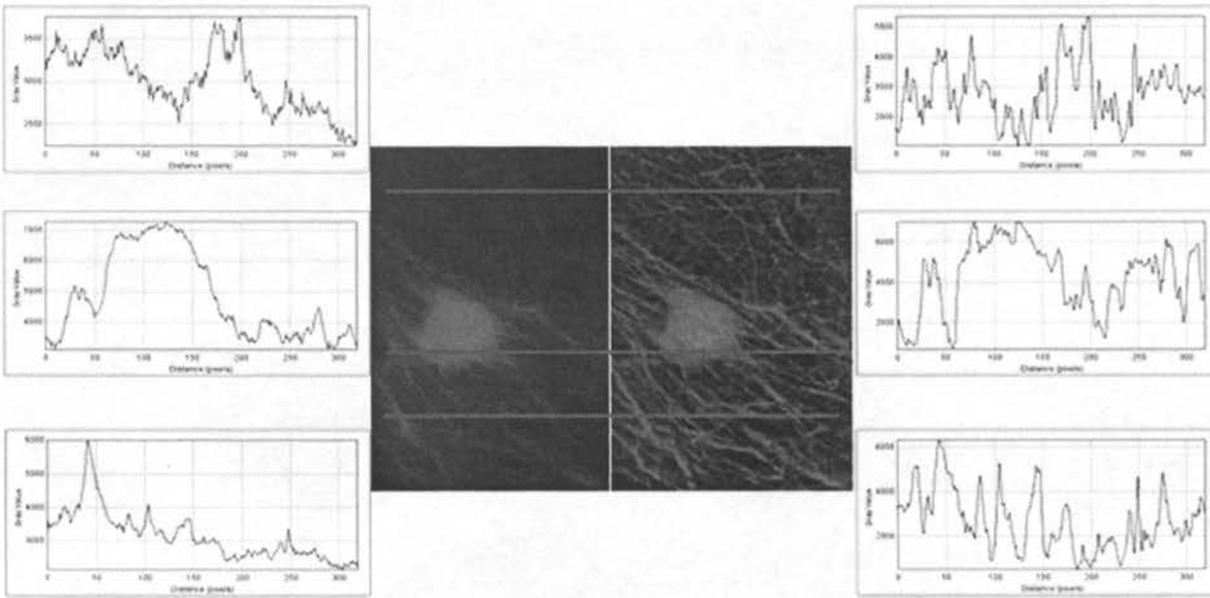


Figure 4.2. WBCLAHE histogram (a) Histogram of original cropped mammogram (b) Histogram of WBCLAHE enhanced mammogram

A horizontal scan line profiles for input image and enhanced image were generated to demonstrate the local contrast enhancement. Three line profiles were generated at different parts of an image. Figure 4.3 shows these line profiles.



(a) (b)

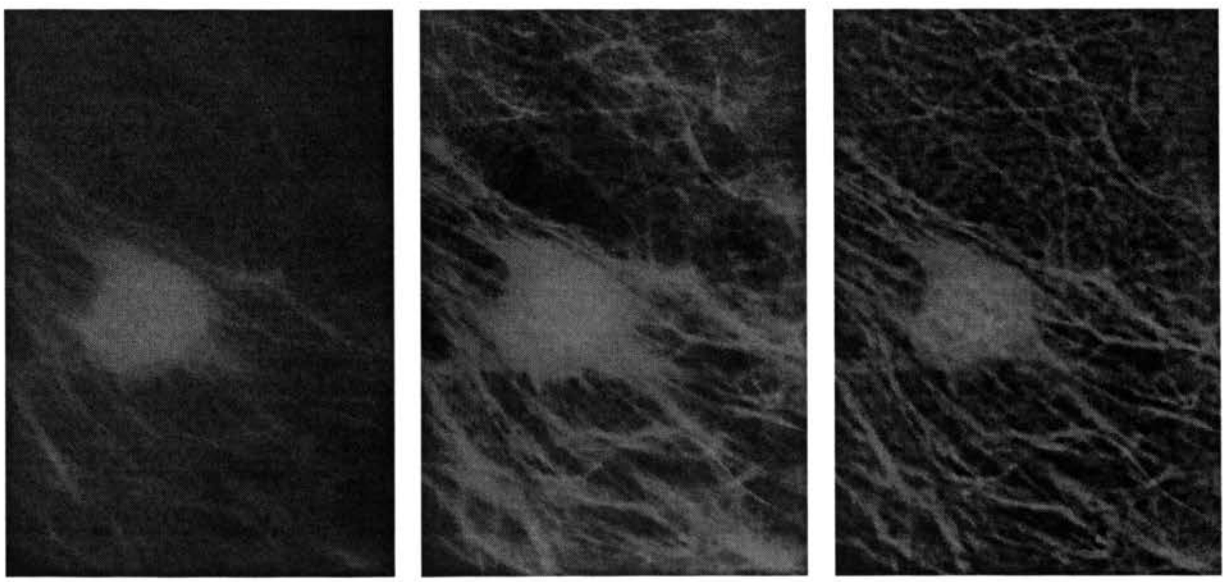
Figure 4.3. Horizontal scan line profiles at red lines for (a) Input mammogram (b) WBCLAHE enhanced image

In Figure 4.3, the red lines are the lines selected for having the scan line profiles. The simplest definition of contrast is the difference between grayscale of object and grayscale of background. If this difference is high, the contrast is high and vice versa. It can be observed that, the variations/differences in grayscales are high in the case of enhanced image profiles than the input image profiles. This proves that the contrast is enhanced.

5. DISCUSSIONS

The proposed algorithm WBCLAHE was designed to improve contrast of digital mammogram by blending a famous algorithm CLAHE (Contrast Limited Adaptive Histogram Equalization) in wavelet domain. [16] It was found that the contrast was enhanced with the use of proposed algorithm. For further validation, the results of WBCLAHE were compared with CLAHE results.

Figure 5.1 (a), (b), (c) shows the input image, result of CLAHE and result of WBCLAH for comparison.



(a) (b) (c)

Figure 5.1. Comparison of CLAHE and WBCLAHE (a) Input image (cropped original mammogram) (b) result of CLAHE (c) result of WBCLAHE

From Figure 5.1 it is obvious that, the result of WBCLAHE is much better than result of CLAHE. Although the contrast has been enhanced in Figure 5.1 (b), there are still some structural details missing. But in the case of WBCLAHE Figure 5.1 (c) it is evident that contrast has been enhanced significantly showing all the structural details. Also the Figure 5.1 (b) shows that the fatty tissue details are not discernable, whereas in Figure 5.1 (c) they are discernable. In terms of sharpness Figure 5.1 (c) looks sharper than Figure 5.1 (b). Therefore it can be said that, WBCLAHE enhances contrast of a digital mammogram better than CLAHE algorithm.

6. CONCLUSION

A new contrast enhancement algorithm "Wavelet Based Contrast Limited Adaptive Histogram Equalization" is proposed. This algorithm blends Contrast Limited Adaptive Histogram Equalization with wavelet transforms to enhance the low frequency coefficients, by doing so only contrast was enhanced without adding any extra noise. This algorithm enhances contrast by enhancing local contrast enhancement by modifying local histograms. The results of WBCLAHE were compared to conventional CLAHE algorithm; the comparison showed that the WBCLAHE resulted in better contrast than CLAHE. Hence the proposed algorithm Wavelet Based Contrast Limited Adaptive Histogram Equalization (WBCLAHE) is a potential algorithm for contrast enhancement of digital mammography. This algorithm can be used for other applications of imaging as well.

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VITA

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