Histogram based Contrast Enhancement Method for Mammographic Breast Images

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ABSTRACT
Enhancement of images is applied over all the mammographic images before their diagnosis. The contrast of mammograms is always required to be good so that further investigation of breast cancer images is accurate. Here HE (histogram equalization), HS (histogram specification) and LE (local enhancement) methods are discussed for enhancing and improving the quality of mammographic images and their result and performance are compared with statistical parameter SNR (signal to noise ratio) and RMSE (root mean square error). In histogram techniques, the flexibility of this image processing approach is emphasized to enhance the images. The experimental result indicates that the algorithm can not only enhance image information effectively but also keep the original image luminance well enough fine structure of the image.

Keywords
Contrast enhancement, Mammographic images, Histogram, SNR (signal to noise ratio)

1. INTRODUCTION
Mammographic images do not have sufficient contrast between normal glandular and malignant tissues because of low attenuation between the tissues in the images; particularly in cases of breast cancer images of younger women that have denser breast tissues [1]. The main goal of image enhancement is to process an image so that the resulting image becomes better or more suitable than the original image for a particular application such as detection of abnormality or tumor in medical images. Image enhancement can improve the contrast or brightness of the input image by changing dynamic range of digital image features such as brightness values. Mammographic breast cancer images contain some noise and contrast is also poor due to X-ray quantum absorption. The noise in image acquisition system makes the detection of small and subtle structures more difficult [2]. It has been observed that noise increases with the increase in pixel intensities in images where local contrast and image intensity are interdependent [3]. The contrast enhancement techniques are classified as global, local and adaptive. A quantitative measurement is used to evaluate the performance of the image enhancement in terms of SNR, RMSE etc [4-7]. All of these measurements techniques were commonly used in medical image processing and applications by the radiologists in interpretation of x-ray images [8].

2. CONTRAST ENHANCEMENT
Histogram based methods for image enhancements are mostly based on equalizing the histogram of the image and increasing the dynamic range corresponding to the image [9-13]. Few important histogram methods are discussed below.

2.1 Histogram Processing
The histogram of an image generally is referred as representation of the pixel intensity values. This is drawn by using a graph that shows the number of pixels in an image at each different intensity value found in that image. For an 8-bit grayscale image there are 256 different possible intensities, and the histogram displays 256 numbers as the distribution of pixels amongst those grayscale values.

The histogram of digital image is the probability of occurrence associated with the gray level in the range 0 to 255, which can be expressed using discrete function:

$$P(r_k)=n_k/MN \qquad (1)$$

$$\sum_{k=0}^{L-1} P(r_k) = 1 \qquad (2)$$

where r_k, the kth gray level; n_k, the number of pixels in the image with that gray level; n, the total number of pixels in the image; and k=0,1,2,3,…….,255. The value of $P(r_k)$ gives an estimate of the probability of occurrence of gray level r_k. The image is scanned in a single pass and a running count of the number of pixels found at each intensity value is kept. This is used to construct a histogram [14].

2.2 Histogram Equalization (HE)
Histogram equalization is used to improve the contrasts in an intensity image. This is normally done for smaller images or images where almost all of the different intensity levels are represented. The equalization begins with the mask being cantered on the upper left pixel. A histogram is calculated for all pixels covered by the mask. The pixel in the centre of the mask will then be written to the resulting image. The mask is then moved one pixel to the right and a new histogram be computed. This is continued for each pixel of each row in the image [15]. When the mask is moved, the pixels that leave the mask and add the ones that enter are subtracted [16].

Let us assume that the 'r' represents the intensity of an input image in the range [0, L-1]: black to white. The intensity mapping takes place as:

$$S = T(r) \qquad 0 \le r \le L-1 \qquad (3)$$

such that $T(r)$ is increases linearly in [0,L-1]. The image intensity level can be viewed as random variable in [0,L-1]. Let $P_r(r)$ and $P_s(s)$ represent the probability density function of r and s. A transformation which is used that would produce the out put image with uniform $P_s(s)$ for an input image with an arbitrary $P_r(r)$. The desired transformation is

$$S = T(r) = (L-1)\int_0^r P_r(w)dw \tag{4}$$

This transformation leads to the r and s uniformly distributed in [0, L-1]. The discrete form of the equalizing transformation is

$$S_k = T(r_k) = (L-1)\sum_{j=0}^{k} P_r(r_j) = \frac{L-1}{MN}\sum_{j=0}^{k} n_j \tag{5}$$

This type of mapping is called histogram equalization.

2.3 Histogram Specification (HS)

Histogram specification is a method which helps in transforming the histogram of one image into the histogram of another image; this can be easily done by recognizing an equally spaced ideal histogram [17]. It is possible to impose an arbitrary histogram on any image, subject to the constraint that single bins may not be split up. The technique can be implemented as:

- The histogram of the image to be transformed is calculated.
- The cumulative sum of the input histogram is now calculated.
- Then the cumulative sum of the histogram of the image to be changed is computed.
- The pixels are mapped from one bin to another according to the rules of histogram equalization.

The input image has probability density $P_r(r)$. The transformation works so that the probability density of the new image obtained by this transformation is $P_z(z)$. This gives an image with a uniform probability density. The transformation function which can generate an image with uniform density:

$$G(z) = \int_0^z P_z(z)dz = V \tag{6}$$

The inverse process helps to get back the gray level z, of the desired image, by

$$Z = G^{-1}(V) = G^{-1}[T(r)] \tag{7}$$

P(*r*) is represented as the Probability Density Function (PDF) of the input gray level *k*. The Cumulative Density Function (CDF) is defined as $G(Z_k)$. HE equalizes the histogram distribution of input stream into its dynamic range by employing the CDF as a transform function.

2.4 Local Enhancement

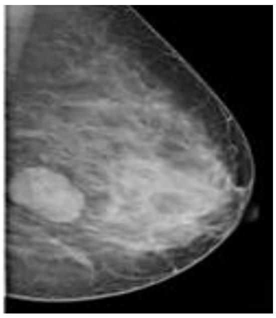
This method is used to enhance small areas in an image. The histogram of the points in the neighborhood is computed and either a histogram equalization or histogram specification transformation function is obtained [18]. This function is used to map the gray level of the pixel centered in the neighborhood. The center of the neighborhood region is then moved to an adjacent pixel location and the procedure is repeated.

We consider two uses of the mean and variance for enhancement purposes. The global mean and variance are measured over an entire image and are useful primarily for gross adjustments of overall intensity and contrast. A much more powerful use of these two measures is in local enhancement, where the local mean and variance are used as the basis for making changes that depend on image characteristics in a predefined region about each pixel in the image.

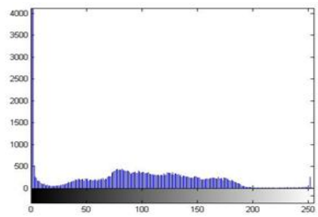
The local mean is a measure of average gray level in neighborhood S_{xy}, and the variance or standard deviation is a measure of contrast in that neighborhood. An important aspect of image processing using the local mean and variance is the flexibility they afford in developing simple, powerful enhancement techniques based on statistical measures that have a close, predictable correspondence with image appearance [19].

3. EXPERIMENTAL RESULTS

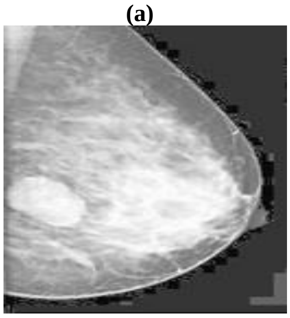
We have used an image database of mammograms developed by our research group in consultation with a senior radiologist. Uniform distribution of the histogram of the output image is limited by discrete computation of the gray-level transformation. The histogram equalization method forces image intensity levels to be redistributed with an equal probability of occurrence which is shown in Fig. 1 (c) and intensity is redistributed by uniform probability density function shown in Fig. 1(e). Local enhancement it is to improve the contrast on an image that has different partial areas, which is shown in Fig. 1(g), for example, an image that need to be improve in dark areas and also in the light areas, then it would be used this algorithm. The clue points of this method are to choose well the values of the relative dispersion to find the optimum pixels that it has to improve. The input image has one white area and another one black that have low contrast. After the local enhancement transformation the output image has more less the same contrast in the white area but has improve the black one contrast. Statistical parameters used in present work for comparison of enhanced images are shown in the table1 by, signal to noise ratio (SNR) and root mean square error (RMSE), where we can see better SNR values in Local enhancement method as compared to HE and HS methods and the contrast of the background is enhanced.



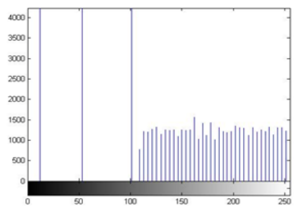
(a)



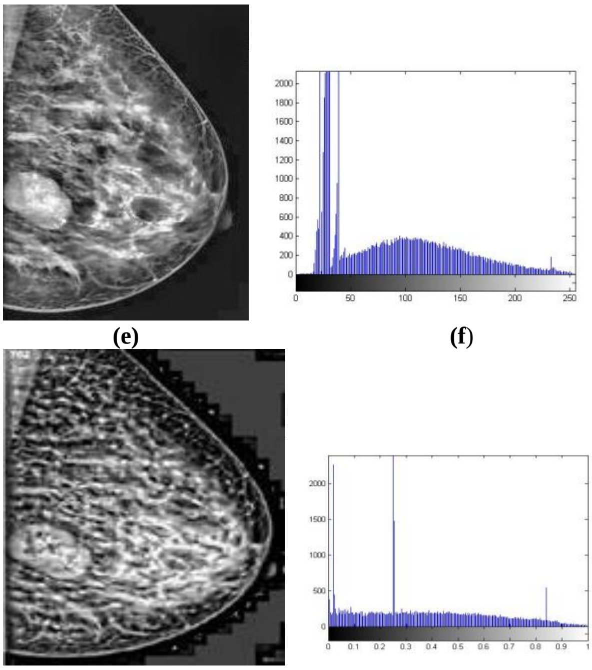
(b)



(c)



(d)



(e) **(f)**

(g) (h)

Fig. 1: Result of histogram based contrast image enhancement (a) Original image (c) histogram equalized image (e) histogram specification based image (g) result of local enhancement of histogram, and their respective histogram are shown in (b), (d), (f), (h).

TABLE-I: COMPARISON OF DIFFERENT ENHANCEMENT METHODS

S.N.	Methods	SNR(dB)	RMSE
1	Histogram Equalization	37.37	31.65
2	Histogram Specification	42.53	36.72
3	Local Enhancement	53.17	42.19

4. CONCLUSION AND FUTURE SCOPE

We have presented a comparative analysis of histogram based method for enhancement of mammographic breast images. Three method of histogram based enhancement techniques i.e. HE, HS and LE are discussed and their result are compared in terms of SNR and RMSE. We get better SNR value in LE method and it improves the quality of images. Future scope includes other histogram technique like Local histogram equalization (LHE), Global histogram equalization (GHE), Adaptive histogram equalization (AHE), Dynamic histogram equalization (DHE) and Contrast limited adaptive histogram equalization (CLAHE).

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