A Novel Improved Method of RMSHE-Based Technique for Mammography Images Enhancement

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Abstract Contrast improvement is one of the most important steps in medical image enhancement procedures such as mammography. In this paper, a combination of best features related to direct and indirect histogram equalization techniques is proposed in a two dimensional workspace. Using different advantages of these methods, while the proposed algorithm is able to improve the contrast and brightness of mammography images, it could decrease different effects of noises, too. On the other hand, in order to reduce undesirable effects of traditional histogram equalization techniques, an improvement of recursive mean-separate histogram equalization using a fusion of contrast-limited adaptive histogram equalization is proposed, too. Evaluation results using four effective measurement techniques e.g. peak signal-to-noise ratio, **mean squared error**, **absolute mean brightness error** and effective measure of enhancement, shows that the suggested method has significant results in contrast enhancement.

Keywords Contrast-limited adaptive histogram equalization · Recursive mean-separate histogram equalization · Effective measurement enhancement Peak signal-to-noise ratio · Mammographic image · Mean squared error Absolute mean brightness error

1 Introduction

Breast cancer is the second main disease after lung cancer that causes death in women. Breast cancer and fibroids are among the masses that are common among women and if detected on time, the process of recovery and treatment will increase

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substantially [1, 2]. In patients with symptoms that are suspected to have cancer or associated with cysts and other organs, the physician performs mammography. In this method, sound waves are used to create images of various parts of the body, including the breast and X-rays do not play any role. In cases where the breast tissue is very dense or the age is less than 30 years old, the doctor prescribes ultrasound. It should not be forgotten that ultrasound is not a substitute for mammography, but is an adjunct to it.

Ultrasound is currently the best way to diagnose breast cysts, which is similar in appearance to your full masses [3]. Most of women's problems are related to chest pain and swelling in the breasts which leads to inability to do daily works. Breast cancer is the result of an out-of-body growth in abnormal breast cells. In both benign and malignant tumors, there is a rapid and high growth of the cells. The process of increasing cells in benign tumors stops at a definite stage [4]. In malignant tumors, this growth continues unabashedly to an extent that, in the absence of treatment, affects all parts of the body and fails to work. Throw away The most common type of breast cancer is cancer of the origin of ducts, and since this type of tissue is found to be in the upper and lower quarters of the breast, about half of the breast cancers are found in the upper and outer quarters.

It should be noted that in all tumors there is a rapid and high growth of cancer. What is important and the main difference between these two types of tumors is that the process of increasing cells in benign tumors stops at a definite stage, but continues in the non-inhibiting tumors of the malignant tumor. The cell growth in the malignant tumors continues to some extent, which, if not treated, affects all parts of the body and abilities. While this does not happen in benign tumors. No matter how much breast cancer is diagnosed earlier, treatment is easier and more successful. For this reason, women need to know the facts about the disease in order to protect their health.

Mammography is the only sure-tier method by which one can reveal a mass in the chest before being detectable by touch. Mammograms are divided into two main categories according to which direction they are coming from: the craniocaudal taken from the top to the bottom and the mediolateral axis that is taken in half-fold and perverted [5]. The purpose of this work is to examine the chest in different ways in order to better detect lesions.

Micro-calcifications one of the symptoms that are used to detect early breast cancer. Each micro-calcification appears as a bright grain, which has several pixels in digital images and these pixels are brighter with respect to their adjacent pixels [6].

Detection of suspicious areas in a mammogram that includes micro-calcification clusters is usually performed by the radiologist, but it is difficult to determine if a particular cluster is associated with a benign or malignant process [7]. However, because the size and shape of each micro-calcification is different, and also the texture of the mammogram context is heterogeneous, the grains cannot be easily identified individually. In other words, due to the low contrast of the mammographic images, the precise diagnosis of the cancer symptoms such as masses and calcification is difficult for the radiologist. Over time, radiologists have empirically discovered the rules that decide on the appearance of micro-calcification, their dispersal, and other features such as the benign or malignant micro-calcification cluster.

All local features of the original image are extracted by the radiologist's vision system, which is usually not done accurately.

Normally, if the patient's mammogram is suspected of having a micro-calcification cluster, it will be introduced for biopsy (tissue sampling). Different evaluations show that out of all four biopsy surgeries, only one of them is successful. In terms of the factors that endanger the health of the patients, biopsy is not a suitable surgery and it is preferred to avoid this as much as possible [8]. In this way, finding a technique to differentiate between benign and malignant samples in the most accurate way is very helpful in preventing unnecessary biopsies. Hence, relying on image processing techniques in this field is seen necessary to diagnose micro-calcification tissues as the best way as possible. The techniques of the digital image processing are used to enhance the quality of digital mammogram images as well as to increase the detection accuracy of micro calcifications [8, 9]. Improvement of the image contrast is one of the most important requirements used in image processing and vision system applications. In general, methods of the contrast improvement are divided into two major categories: direct method and indirect method [10].

2 Direct Contrast Optimal Methods

In the direct methods, while defining a criterion for measuring the image contrast, attempts are made to improve image contrast by improving this criterion. Creating an appropriate measurement criterion for image contrast is an important stage to improving the image directly. The direct contrast approach considers both the general and local information of the image, hence it can outperform in many applications. In this regard various approaches have been proposed that are based on the phase entropy principle, which transmits the image to the phase domain, and the phase entropy is calculated, and in this manner the local contrast is measured [11].

3 Indirect Contrast Optimal Methods

Improving contrast with the indirect method involves modifying the histogram of the image. In indirect method, the dynamic range of the gray levels of the image is increased to improve contrast. Indirect methods which have been paid more attention in recent years due to direct and knowledge-based representation are categorized into four categories:

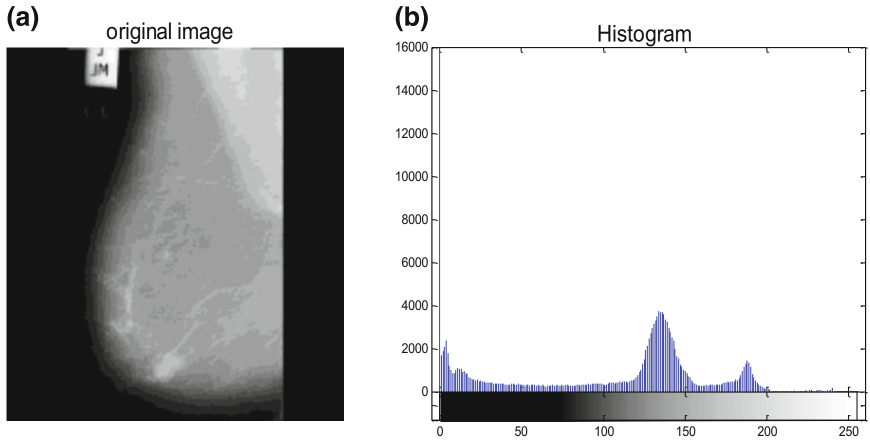

Fig. 1 **a** Original mammography image. **b** Histogram image

- Methods that modify the up and down frequency components of the image [12]
- Methods based on Conversion [12, 13]
- Methods based on histogram modification [14, 15]
- Methods based on Soft calculation [16].

The proposed algorithm and techniques presented in this paper are based on histogram correction methods. In Fig. 1, a mammography image with its histogram is displayed.

3.1 Histogram Equalization (HE)

The main idea of HE is mapping of the values of the input image intensity to the new intensity values through a transformation function created for the cumulative density function (CDF). First, HE converts the histogram of the original image to a plane histogram using an average value that is the average range of gray levels [17]. Therefore, the histogram of the image is divided into two parts based on its average gray level, and the HE algorithm is separately applied on each divided section of the histogram. Secondly, histogram equalization performs the improvement action based on the overall content of the image.

HE is powerful in highlighting the boundaries and edges between different objects, but it may change the local details in these objects, particularly smooth and small areas. The other problem of HE is an abnormal increase and saturation effects of intensity and also it is not appropriate to maintain the brightness of the original image due to the changes in the brightness of the image [18].

3.2 Contrast-Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is a kind of adaptive equalization of the histogram. This method divides the original image into several sub-images without overlapping [19]. The secondary histogram of the images is limited to the value of the improvement per each pixel and then equalization is performed. Details of the image are evidently revealed with respect to the background [20]. At the same time, the contrast of the image is improved equally, which results in an output contrast image with high quality [9]. In this paper, using an adaptive filtering procedure, the histogram of different parts of the partitioned image is calculated and then the histogram balancing is utilized to rearrange the brightness values of the total image. So our proposed method is different from the smoothing of the fundamental histogram, since in this method, as a traditional equation technique, only one histogram is used for the whole image [21].

Consequently, for the purpose of improving the localized image contrast and extracting more details from the image, while significant noise would be generated, the contrasting histogram is equalized.

In order to suppress these deficiencies, a generalization of Adaptive Histogram Equalization (AHE) of a contrast-limited, or concise, which is called CLAHE, is used.

This technique is designed to overcome the problem of noise exacerbation. CLAHE does not deal with the entire image, but deals with pieces that are in small areas of the image [22]. The contrast of each area is improved in such a way that the histogram of the output region corresponds to approximately the histogram expressed by the distribution parameter.

Neighbor sections are combined to eliminate abnormal induced boundaries by using bidirectional interpolations [22]. Utilizing contrast in homogeneous regions, it is possible to avoid any exacerbation of any unwanted noise that may be present in the low contrast image. Besides user friendly, simple calculation and good output in local areas are of the advantages of CLAHE. Additionally, CLAHE has less noise and can maintain the light saturation which normally occurs in the histogram equalization procedures [23–25].

3.3 Recursive Mean-Separate Histogram Equalization (RMSHE)

One of the first suggestions to overcome the drawbacks of the HE method is brightness preserving of the equalized bi-histogram (BBHE).The method preserves the effective amount of image brightness while improving the contrast. Moreover, it divides the histogram into two sub-histograms based on the average amount of the brightness and equalizes each part individually. If X_m denote the mean of the image X and assume that $X_m \in \{X_0, X_1 \ldots X_{L-1}\}$. Based on the mean X_m the input image is divided into two sub level images X_L and X_U. The transform functions for the sub images are defined as

$$F_L(X) = X_0 + (X_m - X_0)C_L(X) \tag{1}$$

$$F_u(X) = X_{m+1} + (X_{L-1} - X_{m+1})C_u(X) \tag{2}$$

According to the above equations, $C_L(X)$ and $C_U(X)$ is the respective cumulative density functions for X_L and X_U.

The output image (Y) of BBHE, is expressed as

$$Y = F_L(X_L) \cup F_u(X_u) \tag{3}$$

Now we introduce a better technique called RMSHE, which in fact performs the same BBHE algorithm as a recursive one. In aforementioned techniques the input image histograms were divided into two parts. However, in this method, instead of dividing the input image one time, the input image divides to 2^n sub-histograms using an optional criterion called n. Then, each of these sub-histograms is equalized in dependently. When $n = 0$, it means that no sub-image is created, which is the same as the HE method [26]. Using calculations, it is claimed that with increasing n, the brightness of the output image is preserved more efficiently.

$$E(Y) = X_m + \left[\frac{XG - X_m}{2^n}\right] \tag{4}$$

In the above relation XG is the average of gray level and X_m is the average of efficiency. When the return level n increases E(Y) suddenly converts to an average of efficiency that is obvious from recent equality.

While RMSHE is a recursive method, it also maintains the scalability of image brightness, which is a very important parameter in image processing. The main advantage of the RMSHE method is to improve brightness with a recursive level assigned to a low contrast image.

4 Proposed Algorithm

In the optimal contrast improvement techniques mentioned in this study, histogram of input image is divided to two or more sub-histogram using different methods and then the histogram equalization (HE) method is performed on each of these sub-histograms independently. Evaluation of medical image's contrast improvement techniques, specially on mammography, shows that RMSHE and CLAHE have the best performance on contrast improvement and brightness reservation. Using these methods on MIAS database shows good developments on EME, PSNR, MSE and AMBE parameters. Also, the RMSHE technique brings the best brightness preservation to the images. Using these results leads us to utilize CLAHE in the equalization of sub histograms. Empirical results show significant improvements on contrast restorations.

However in this paper Effective Measure of Enhancement (EME) and Peak Signal to Noise Ratio (PSNR) are used to evaluate the performance of the algorithms. PSNR is a measure of the deviation of the current image from the original image with respect to the peak value of the gray level. The EME is a quantitative measure of image enhancement.

It is obtained by splitting the image into a number of Blocks and using the equation:

$$\mathrm{EME} = \frac{1}{K_1 K_2}\sum_{L=1}^{K_2}\sum_{k=1}^{K_1} 20\mathrm{Log}\left(\frac{\mathrm{I}_{\max}(K,L)}{\mathrm{I}_{\min}(K,L)}\right) \tag{5}$$

In the above equation, K_1 and K_2 are the numbers of horizontal and vertical blocks of the image and I_{max} (k, L) and I_{min} (k, L) are the maximum and minimum pixel values in a given block, respectively.

Besides EME, in order to improve the confidence of the evaluation results, we use another factor named Absolute Mean Brightness Error (AMBE), which is defined to rate the performance of preserving the original brightness. Smaller values of this parameter are related to the better preservation of image brightness. AMBE is calculated as the absolute difference between original and enhanced images and is given as:

$$AMBE = \left|I(i,j) - \hat{I}(\mathrm{i},\mathrm{j})\right| \tag{6}$$

In this equation, I(i, j) and $\hat{I}(\mathrm{i},\mathrm{j})$ are average intensity of input and enhanced images, respectively which is defined between 0 and ∞.

Besides these factors, MSE as the Mean Square Error between the original (i.e. s) and the enhanced (i.e. ŝ) images is used as illustrated in Eq. (7):

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{J=1}^{N}\left[I(\mathrm{i},\mathrm{j}) - \hat{I}(\mathrm{i},\mathrm{j})\right] \tag{7}$$

In the following, the results of the indirect actions of contrast enhancement techniques introduced in this paper, based on the example of mammographic image are displayed (Figs. 2, 3, 4 and 5).

In Tables 1, 2, 3 and 4, the results of the Effective Measure of Enhancement (EME) and peak signal-to-noise ratio (PSNR), mean squared error (MSE) and absolute mean brightness error (AMBE) are presented which have been obtained by applying the indirect contrast enhancement techniques introduced in this paper are based on several examples of mammogram images extracted from the MIAS (Mammography Image Analysis Society) database.

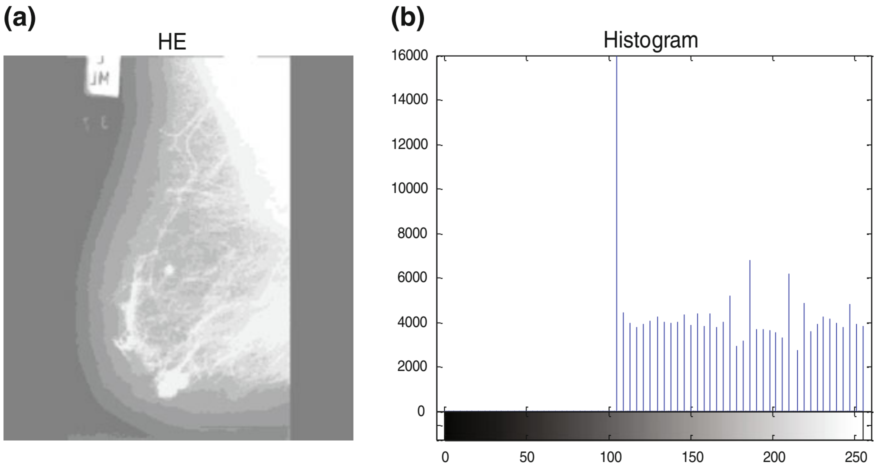

Fig. 2 **a** Contrast enhancement with histogram equalization (HE) technique. **b** Histogram image

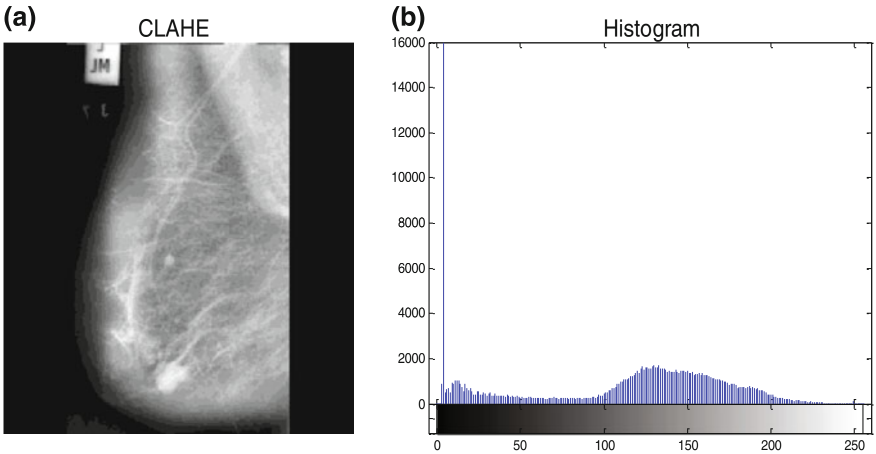

Fig. 3 **a** Contrast enhancement with contrast-limited adaptive histogram equalization (CLAHE) technique. **b** Histogram image

5 Conclusions

In this study, the well-known techniques for improving the image indirect contrast, including HE, CLAHE and RMSHE with their application in low contrast mammographic images were investigated. The traditional HE method significantly changes the image brightness; therefore the details of the image cannot be evidently

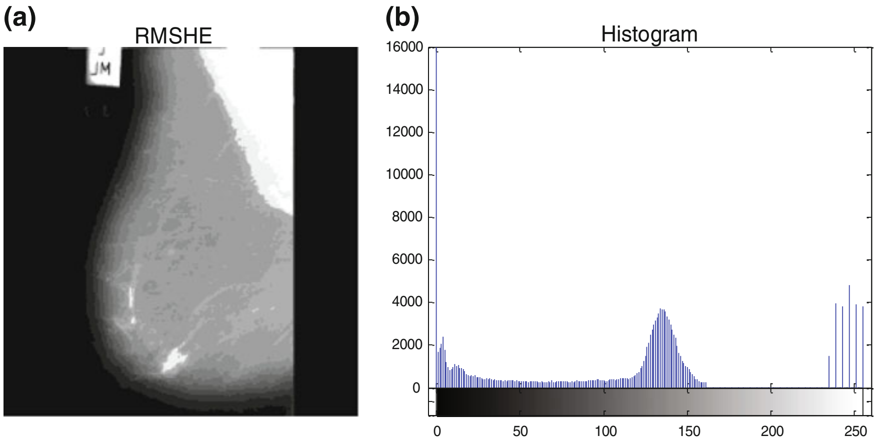

Fig. 4 **a** Contrast enhancement with recursive mean-separate histogram equalization (RMSHE) technique. **b** Histogram image

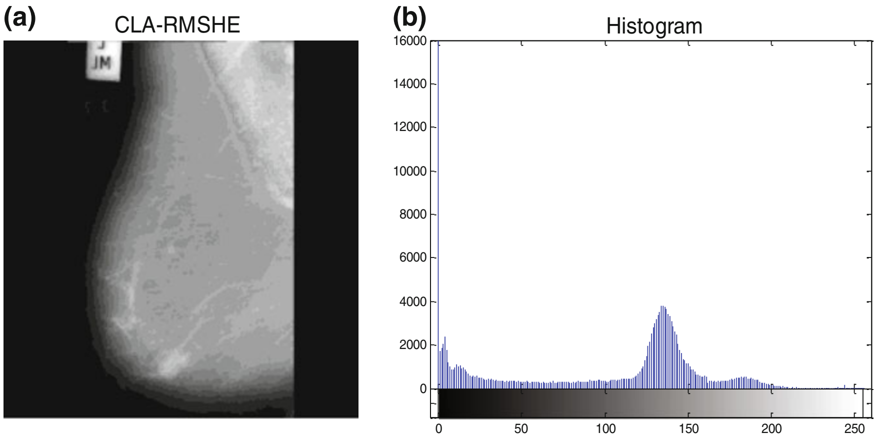

Fig. 5 **a** Contrast enhancement with suggested technique. **b** Histogram image

Table 1 EME values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
mdb009	1.1380	5.1268	7.2849	7.7172
mdb035	0.2818	2.7043	3.8918	4.3630
mdb043	0.2632	2.9431	5.7116	6.1585
mdb057	0.6388	3.3798	4.2820	4.9475
Mdb107	0.5406	3.2968	3.8278	4.5474
Mdb137	0.3705	3.5250	4.5075	5.0512
Mdb145	1.3865	4.6744	6.3660	7.3599
Mdb163	0.5090	3.6073	4.8155	5.2449

Table 2 PSNR values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
mdb009	8.4180	21.2360	18.2825	28.8805
mdb035	4.5880	24.2680	17.7157	29.9343
mdb043	4.2616	25.3344	15.6068	30.7476
mdb057	7.2361	24.5555	19.7264	28.7411
Mdb107	8.4115	21.2360	24.4981	27.7643
Mdb137	6.3530	20.9996	19.8844	24.2115
Mdb145	12.1369	20.9771	34.4241	38.6424
Mdb163	7.6651	22.5691	24.8680	28.9360

Table 3 MSE values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
mdb009	167.3960	74.2731	102.2214	60.1739
mdb035	202.7276	75.7823	105.1597	57.0855
mdb043	206.0635	71.8472	116.8537	54.8107
mdb057	177.5863	74.7005	95.1016	60.5947
Mdb107	167.4504	88.1873	74.9152	63.9247
Mdb137	185.6033	89.2360	94.3532	75.9965
Mdb145	138.9922	89.3364	49.2541	36.9343
Mdb163	173.8180	82.5009	73.5427	63.2929

Table 4 AMBE values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
mdb009	92.8761	6.8134	15.3766	2.4532
mdb035	146.7379	7.4329	12.2321	1.2084
mdb043	153.7188	7.8285	17.2210	0.0738
mdb057	103.9611	4.2711	11.7311	2.7701
Mdb107	88.7582	2.8612	6.8836	4.8524
Mdb137	117.5142	6.0282	11.4282	4.2499
Mdb145	58.1488	4.8354	2.8243	0.4942
Mdb163	96.1106	3.1374	6.9858	3.1002

verified. By comparing the obtained results of several image samples from the MIAS database, two RMSHE and CLAHE techniques perform better in contrast of mammographic images, while the RMSHE technique has the best brightness preservation. Applying the contrast-limited adaptive histogram equalization (CLAHE) to the sub-histograms derived from image decomposition with RMSHE technique, effective improvement results and a better peak signal-to-noise ratio can be achieved for improvement of the image contrast.

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