Contrast Improvement of Ultrasound Images of Focal Liver Lesions Using a New Histogram Equalization

Younes Mousania and Salman Karimi

Abstract Contrast improvement is an important issue in the processing of medical images. Due to the difficulty of detecting liver lesions in conventional ultrasound imaging and the low contrast of these images, we tried to provide an indirect optimization technique on the ultrasound images of Focal Liver Lesions database in the space of two-dimensional histogram to improve the quality and the contrast of these images. To prevent undesirable effects due to the adjustment of the histogram images, two techniques are used: CLAHE and RMSHE. By using four effective measurement techniques metrics of EME, PSNR, MSE and AMBE, shows that the proposed method has significant consequences. Furthermore; results of the study revealed that improved outcomes are obtained when the proposed technique is utilized on other standard ultrasound and medical images like mammography.

Keywords Ultrasound image · Contrast enhancement · Histogram equalization CLAHE · RMSHE · EME · PSNR · MSE · AMBE

1 Introduction

The liver is the largest gland of the body with an important role in metabolism and digestion. In this study, focal hepatic lesions and especially hepatic cysts have been investigated with the aim of improving ultrasound images of these lesions. A wide range of liver lesions is presented in differential diagnosis, but in general, these lesions can be classified into two categories of benign and malignant [1]. In order to determine the nature of these masses, one has to consider issues such as age, sex, and the presence of chronic liver disease in the patient [2].

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Liver lesions are accidentally detected and are mostly benign. Benign types originate from the liver tissue, but the malignant type or liver cancers can be of different origins [3]. In addition to pain and swelling in the upper quadrant of the abdomen which is also seen in benign lesions, malignant liver lesions can also cause jaundice, bloody ascites, appetite and weight loss. However, Benign masses, sometimes grow so much that they can cause problems [4]. But in most cases, they do not spread to adjacent tissues and usually do not require treatment, unless the patient has symptoms, in which case removal of the tumor with surgery will improve the symptoms. Although the exact diagnosis of the nature of a liver mass is achieved by sampling and pathologic examination, liver masses can be diagnosed by various diagnostic methods such as clinical, pathological and ultrasonographic methods [5]. Ultrasound imaging has many advantages, the most important of which can be non-invasiveness and the use of non-ionizing radiation, which has led to its wide usage in the diagnosis of various diseases [6].

Benign tumors are usually isolated, but sometimes they may be numerous, such as in the case of liver cysts and multiple liver abscesses. In general, cysts are thin-walled structures that contain liquid. Polycystic liver disease is associated with polycystic kidney disease in half of the cases [7]. Few patients bleed into the cyst, the phenomenon which causes pain in the upper extremity and sudden and severe shoulder pain. Bleeding stops without intervention and the pain declines after a few days. Liver cysts do not interfere with liver function. Cysts are usually found by ultrasound or computerized tomography (CT scan), and the simple type is always benign. Only those who experience symptoms are in need of treatment. Removing the fluid from the cyst with a needle simply is not enough because the cyst will be filled in again within a few days. The best and the easiest treatment is to remove a large part of the cyst's wall. This surgery can usually be done through laparoscopy and has a therapeutic effect in almost all patients [8].

Digital image processing techniques are used to raise the quality level of ultrasound images as well as to increase the accuracy of diagnosis of liver lesions. Image contrast improvement 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 methods and indirect methods [9].

2 Optimal Methods of Direct Contrast

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 improve the image directly. The direct contrast approach considers both the general and local information of the image, hence it can be improved 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 this way the local contrast is measured [10].

3 Optimal Methods of Indirect Contrast

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 are 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:

- Methods that modify the up and down frequency components of the image [11]
- Methods based on Conversion [11, 12]
- Methods based on histogram modification [13, 14]
- Methods based on Soft calculation [15].

The proposed algorithm and techniques presented in this paper are based on histogram correction methods. In Fig. 1, an ultrasound image of Focal Liver Lesions 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

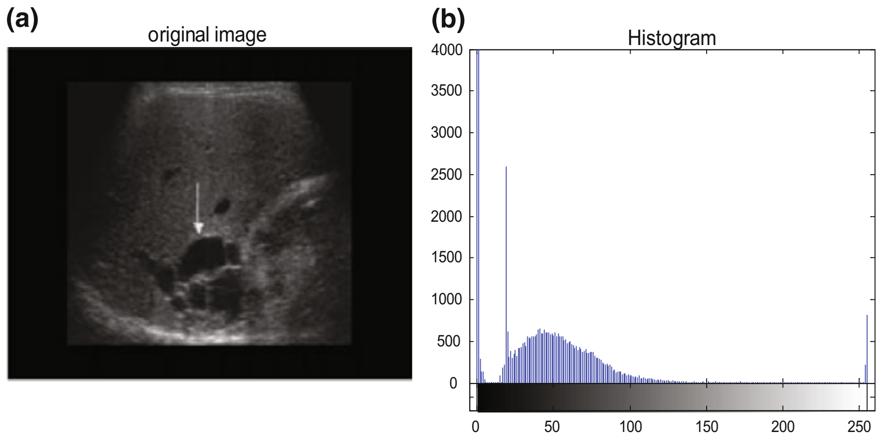

Fig. 1 **a** Original ultrasound image. **b** Histogram image

distribution 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 level [16]. 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 [17].

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 [18]. 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 [19]. At the same time, the contrast of the image is improved equally, which results in an output contrast image with high quality [20]. 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, 24].

3.3 Recursive Mean-Separate Histogram Equalization (RMSHE)

One of the first suggestions to overcome the drawbacks of the HE method is to preserve the brightness of the equalized bi-histogram (BBHE). This 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 Recursive Mean-Separate Histogram Equalization (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 [23]. Using calculations, it is claimed that with increasing n, the brightness of the output image is preserved more efficiently.

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

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, especially 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:

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

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

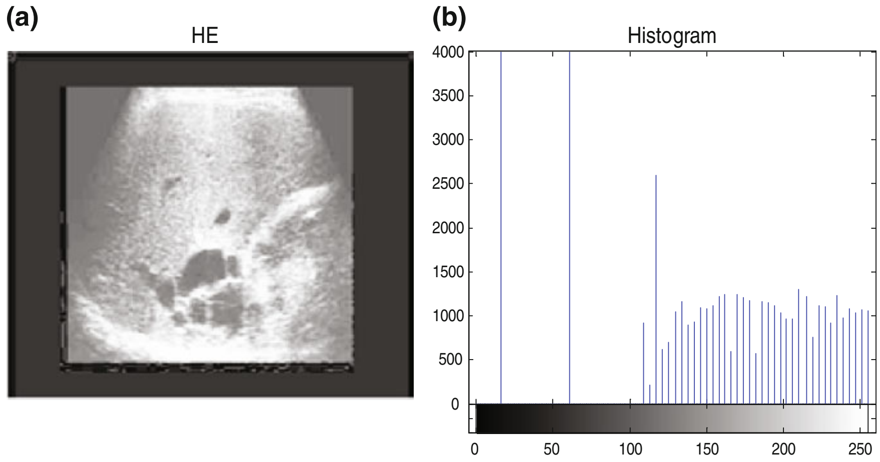

Fig. 2 **a** Contrast enhancement with histogram equalization (HE) technique. **b** Histogram image

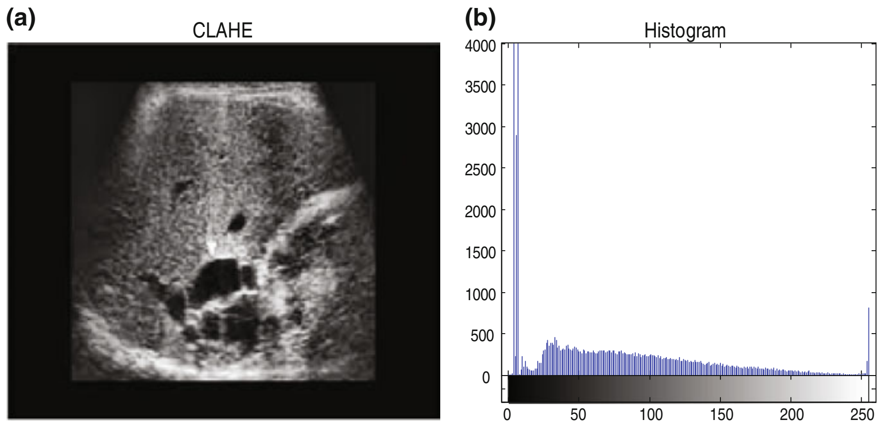

Fig. 3 **a** Contrast enhancement with contrast-limited adaptive histogram equalization (CLAHE) technique. **b** Histogram image

Besides these factors, MSE as the Mean Square Error between the original (i.e. s) and the enhanced (i.e. $\hat{s}$) images is used as illustrated in Eq. (7) (Figs. 2, 3, 4 and 5).

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

In Tables 1, 2, 3 and 4, the results of the Effective Measure of Enhancement (EME), peak signal-to-noise ratio (PSNR), mean squared error (MSE) and absolute

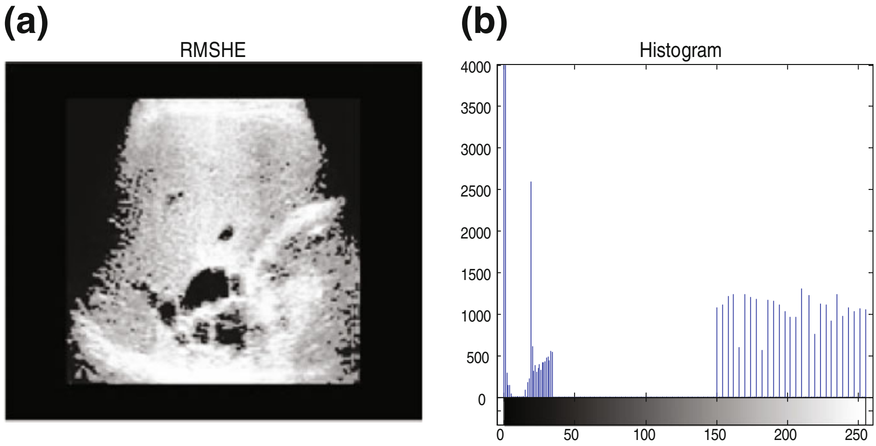

Fig. 4 **a** Contrast enhancement with recursive mean-separate histogram equalization (RMSHE) technique. **b** Histogram image

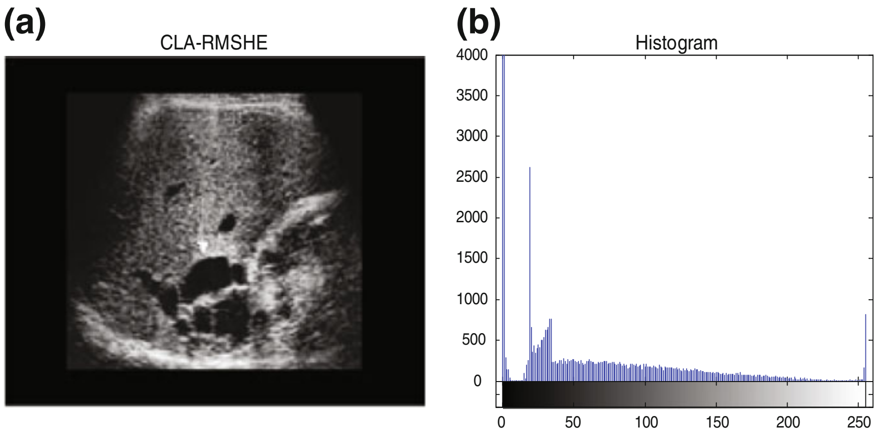

Fig. 5 **a** Contrast enhancement with suggested technique. **b** Histogram image

Table 1 EME values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
Liver cysts 1	2.2486	4.3493	4.6860	6.0966
Liver cysts 2	2.6547	4.0582	5.0975	6.5524
Liver cysts 3	2.3754	3.4284	4.9945	5.4786
Liver cysts 4	1.2882	2.7928	3.4345	4.0855
Liver cysts 5	1.8542	3.4226	4.1450	4.8105
Liver cysts 6	2.2862	4.4173	4.7933	6.2311
Liver cysts 7	2.3452	3.5722	5.2153	6.3751
Liver cysts 8	1.0402	2.6869	3.9929	4.3214

Table 2 PSNR values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
Liver cysts 1	9.5889	16.8176	10.6595	19.8243
Liver cysts 2	7.5803	15.8577	9.0458	18.8056
Liver cysts 3	8.1229	16.4563	9.5785	18.4956
Liver cysts 4	7.8551	17.5952	9.2693	19.4750
Liver cysts 5	8.8437	17.3986	10.1156	20.1406
Liver cysts 6	9.6820	16.7284	10.9549	19.9869
Liver cysts 7	10.5727	16.0937	12.5058	21.7694
Liver cysts 8	7.5767	17.8325	9.2233	21.0033

Table 3 MSE values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
Liver cysts 1	157.8770	109.9894	149.6487	94.6371
Liver cysts 2	174.5568	115.3971	162.2234	99.5821
Liver cysts 3	169.8841	111.9944	157.9591	101.1378
Liver cysts 4	172.1744	105.7949	160.4202	96.3044
Liver cysts 5	163.8707	106.8400	153.7740	93.1521
Liver cysts 6	157.1438	110.4812	147.4545	93.8707
Liver cysts 7	150.2990	114.0433	136.4524	85.8664
Liver cysts 8	174.5882	104.5474	160.7901	89.2194

Table 4 AMBE values for different contrast enhancement techniques

Image	HE	CLAHE	RMSHE	CLA-RMSHE
Liver cysts 1	76.9183	24.6895	50.1574	11.5892
Liver cysts 2	96.1862	28.0400	56.5168	14.3583
Liver cysts 3	91.5083	24.7884	55.0843	15.1228
Liver cysts 4	94.2108	22.4383	55.7983	13.2048
Liver cysts 5	83.0150	21.8273	50.4046	11.4332
Liver cysts 6	77.4449	24.2536	48.7779	10.9278
Liver cysts 7	71.1864	25.6767	39.8442	6.2524
Liver cysts 8	97.3215	23.4840	53.7510	10.2786

mean brightness error (AMBE) are presented which have been obtained by applying the indirect contrast enhancement techniques introduced in this paper and are based on several examples of *Ultrasound Images of Focal Liver Lesions* images extracted from the Ultrasound cases database.

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 verified. By comparing the obtained results of several image samples from the MIAS and Ultrasound cases database, two RMSHE and CLAHE techniques perform better in contrast of mammographic and Ultrasound 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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