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Procedia Computer Science 163 (2019) 300–311

Procedia Computer Science

www.elsevier.com/locate/procedia

16th International Learning & Technology Conference 2019

Medical image enhancement based on histogram algorithms

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Abstract

Medical images constitute important information that clinicians need to diagnose and make the suitable treatment decisions. The diagnostic process extremely involves the image visual perception. Unfortunately, the possibility of error existence in perception is not acceptable as it mainly affects the patients' lives. Image enhancement improves the visual quality of image, helps the clinician in his decision and thus saves the patients' lives. Histogram is a common tool for improving contrast in medical imaging. It recovers the lost contrast by redistributing the image brightness values that unfortunately may generate undesirable artifacts. Therefore, researchers developed the histogram-based algorithms to overcome this problem. This paper presents a comprehensive study of many histogram-based algorithms. We utilized the powerful MATLAB package to analyze the enhancement performance of these histogram-based algorithms. Moreover, this paper quantitatively compares the results and thus evaluates their performance by three metric parameters, which are the mean square error, standard deviation, and the peak signal to noise ratio.

Keywords: Histogram; Medical images; Enhancement; Contrast; Metric evaluation parameters; Peak signal to noise ratio

1. Introduction

Radiology is a milestone in disease diagnosis, as it has the ability to obtain a visual representation of the human interior anatomy in forms of radiographs. There are different branches of radiology, each is used for a purpose, and each produces a radiograph of different pixels' intensity distribution. For example, X-rays are mostly used for bone detection because the calcium atoms that make up the human bones have the ability of absorbing the x-rays photons.

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1877-0509
10.1016/j.procs.2019.12.112

While, MRI produces visual imaging of organs, soft tissues, bones and other internal body structures. Therefore, radiographs generated from X-rays are different from those generated from MRI.

In spite of the continuous development of X-rays and MRI acquisition systems, the resultant radiographs still have some uncertainties in representing human parts. In medical image analysis field, any margin of error is not acceptable. In addition, the amounts of image details, quality, and clearness are essential. To meet these requirements, researchers proposed many image enhancement techniques to improve the image perception quality.

Unlike regular still photos, digital radiographs have complex structures and different modalities. Thus, analyzing and processing them require special manipulations to prevent the data loss and to retrieve the attenuated details.

Image histogram is the basis algorithm for numerous spatial domain processing. It provides useful image statistics and it is useful for image enhancement, compression and segmentation. It is simple to calculate in software and even in hardware implementations. Histogram Equalization (HE) generates an image whose intensity levels are equally likely and covers the entire image [2]. The result of this intensity-level equalization is an image with increased dynamic range leading to increase of its contrast [1]. There are different types of histogram equalization algorithms such as Cumulative Histogram Equalization (CHE) [2], Contrast-Limited Adaptive Histogram Equalization (CLAHE) [4, 5, 6], and Quadrant Dynamic Histogram Equalization (QDHE) [3].

The main objective of this research is to find the best contrast enhancement technique for medical images. It describes how to equalize a histogram of medical images and analyzes the four techniques: HE, CHE, CLAHE, and QDHE. In terms of five medical images, it evaluates the response of each technique by three metrics: Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and Standard Deviation (SD). We used the powerful MATLAB package in the implementation of the four algorithms and the response evaluation of each of them.

2. Image histogram processing

Radiology is a milestone in disease diagnosis, as it has the ability to obtain a visual representation of the human interior anatomy. A two-dimensional digital monochromatic image is a binary representation of an array of pixels. Each pixel has a numerical value that represents a grey level.

An image histogram is a graphical representation of the probability distribution of the gray values in a digital image. The visualization of the image's histogram helps in analyzing the frequency of appearance of the different gray levels contained in the image. Equation (1) represents the relation between the histogram and the contrast of the image.

$$Gray-level\ image:\begin{cases} bright & Right-sided\ histogram \\ dark & left-sided\ histogram \\ good\ appearance & well-distributed\ histogram \end{cases} \tag{1}$$

Medical images are commonly 8-bit grayscale images with a gray-level range from zero (black) to 255 (white). Fig. 1. displays three images and their corresponding histograms. The histograms of the bright, dark, and good in appearance images, in sequence, are right-sided, left-sided, and well distributed. Thus, the histogram measures the brightness level of images and reflects either the image has a low or acceptable contrast. As a conclusion, the histogram that covers all the possible values in the gray scale indicates that the image has good contrast and that the details in this image are clear.

2.1. Generating histogram

The histogram of a digital image with L total possible intensity levels in the range [0, 255] is in equation (2).

$$h(r_k) = n_k \tag{2}$$

where n_k is number of pixels with r_k intensity level. It is better working with the normalized histogram that can be obtained by dividing $h(r_k)$ by the total number of pixels in the image, as in equation (3). Histogram of any image is simply the plotting of $P_r(r_k)$ against r_k.

$$p(r_k) = \frac{h(r_k)}{\text{number of rows} \times \text{number of columns}} = \frac{n_k}{MN} : \text{ for } k = 0, 1, 2, \cdots (L-1) \tag{3}$$

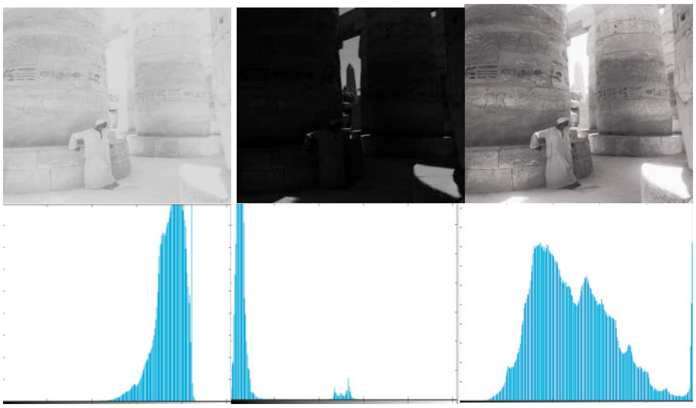

Fig. 1. Image histogram of dark, bright and well-contrast images.

3. Histogram equalization, HE

HE transformation spreads out the image intensity values along the total range [0, 1] leading to an image with a higher contrast. The *HE* transformation function is simply the Cumulative Distribution Function (*CDF*), given in equations (4 and 5).

$$cdf(k) = \sum_{i=0}^{k} P_r(r_i) : k = 0, 1, 2, \ldots, L-1 \tag{4}$$

$$s_k = T(r_k) = floor\left((L-1)\sum_{i=0}^{k} p_i\right) = floor\left(\frac{L-1}{MN}\sum_{i=0}^{k} n_i\right); \quad k = 0, 1, 2, \ldots, (L-1) \tag{5}$$

As an explanatory example, assume an image with intensities in the range [1-8] and it is required to perform the *HE* on the image and scale the processed image in the range [1-20]. The algorithm starts by counting the total number of pixels associated with each pixel intensity. Secondly, the algorithm calculates the probability of each pixel intensity (number of pixels divided by the total number of pixels). Thirdly, the algorithm calculates the *CDF* and then multiply it by 20. Lastly, the algorithm floor round the obtained values (to lower integer values). Both of equation (6) and table (1) represent the procedures of this example. The results show that the processed image includes pixels with increased intensities leading to a higher contrast.

$$Original = \begin{pmatrix} 3 & 2 & 4 & 5 \\ 7 & 7 & 8 & 2 \\ 3 & 1 & 2 & 3 \\ 5 & 4 & 6 & 7 \end{pmatrix} \qquad Processed = \begin{pmatrix} 8 & 5 & 11 & 13 \\ 18 & 18 & 20 & 5 \\ 8 & 1 & 5 & 8 \\ 13 & 11 & 15 & 18 \end{pmatrix} \tag{6}$$

4. Cumulative histogram equalization, CHE

Fig. 2 shows the procedures of the *CHE* algorithm and equation (7) represents its general formula [2].

Table 1. The intermediate results of applying the *HE* algorithm.

Pixel intensity	# of pixels	Probability	Cumulative probability (CP)	CP times 20	Floor rounding
1	1	0.0625	0.0625	1.25	1
3	3	0.1875	0.25	5	5
3	3	0.1875	0.4375	8.75	8
2	2	0.125	0.5625	11.25	11
2	2	0.125	0.6875	13.75	13
1	1	0.0625	0.75	15	15
3	3	0.1875	0.9375	18.75	18
1	1	0.0625	1	20	20
0	0	0	1	20	20
0	0	0	1	20	20

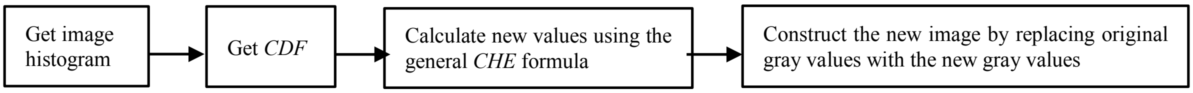

Fig. 2. Stages of cumulative histogram equalization algorithm.

$$eh(k)=\left(round\,(\frac{cdf\,(k)-cdf_{\min}}{MN-cdf_{\min}}\,*(L-1)\right) \tag{7}$$

where CDF_{min} is the minimum *CDF* in the image.

5. Quadratic dynamic histogram equalization, QDHE

This technique produces better brightness preservation with natural looking compared to other existing techniques [3]. Fig. 3 shows the four processes of the *QDHE* algorithm that are histogram partitioning, clipping, gray levels re-distribution and histogram equalization.

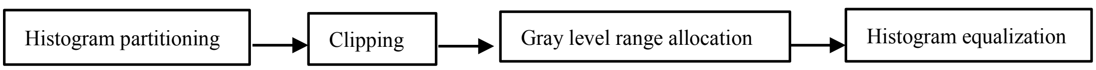

Fig. 3. Procedures of the quadratic dynamic histogram equalization algorithm.

5.1. Histogram partitioning

The *QDHE* is a median-based partition algorithm. Thus, it segments the number of pixels equally in each sub-histogram. Firstly, it divides the original image-histogram into two sub-histograms. Secondly, it uses the medians from the two partitioned sub-histograms as separating points to further division of the two sub-histograms into two smaller sub-histograms per each resulting in four sub-histograms. The minimum and maximum intensity values of the input histogram are set as the limiting separating points while the equation set (8) calculates each other separating point. Fig. 4a shows an image histogram with these separating points.

$$\begin{pmatrix} m_1 = \frac{1}{4}(I_{width} \times I_{height}) \\ m_2 = \frac{1}{2}(I_{width} \times I_{height}) \\ m_3 = \frac{3}{4}(I_{width} \times I_{height}) \end{pmatrix} \tag{8}$$

where m_1, m_2, and m_3 are intensities set to 0.25, 0.5 and 0.75, respectively, for the total number of pixels in the histogram of the input image. I_{width} *and* I_{height} represent the width and height of the input image, respectively.

5.2. Clipping

HE is able to stretch the high-contrast regions and compresses the low-contrast regions of a histogram. Thus, if the object of interest occupies a small portion of the image, then *HE* will not be able to, successfully, enhance it.

The clipped *HE* method overcomes this problem by controlling the enhancement rate and thus preventing the existence of unnatural and over-enhancement in the processed image. It modifies the shape of the input histogram by reducing or increasing the value in the histogram's bins based on a threshold/clipping limit/threshold, T_c that is equal to the average of the image-intensity values. Fig. 4b illustrates the clipping process in which the bins with higher values than T_c take the threshold value itself.

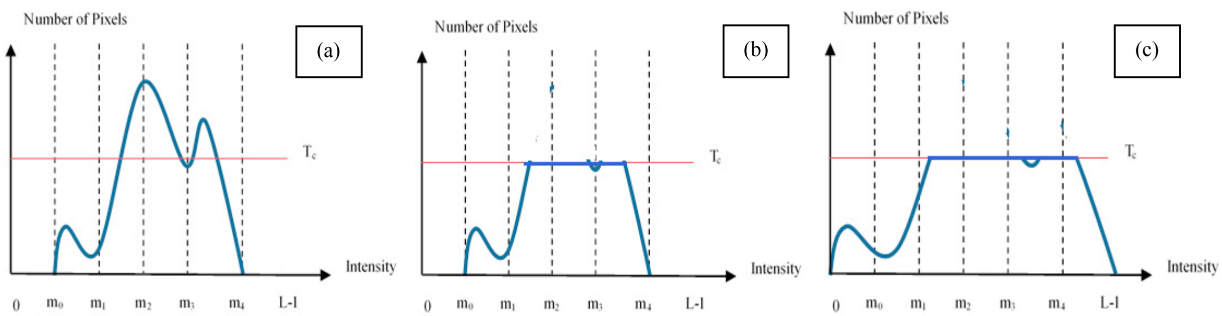

Fig. 4. The procedures of the clipping process.

5.3. New gray level range allocation

To balance the enhancement space for each sub-histogram, equations-set (9) shows the new gray level dynamic range allocation based on the ratio of gray level spans and the total number of pixels in each sub-histogram.

$$\left. \begin{array}{l} span_i = m_{i+1} - m_i \\ range_i = (L-1) \times \dfrac{span_i}{\sum\limits_{k=1}^{4} span_k} \end{array} \right\} \tag{9}$$

where $span_i$ is the dynamic grey level of the i^{th} sub-histogram and $range_i$ is the dynamic level range for i^{th} sub-histogram in the output image. Equation-set (10) represents the new dynamic range $[i_{start},\ i_{end}]$ of the i^{th} sub-histogram. Noting that, the first i_{start} is at the minimum intensity value of the new dynamic range. Fig. 4c shows this stage of process.

$$\left.\begin{aligned} i_{start} &= (i-1)_{end} + 1 \\ i_{end} &= i_{start} + range_i \end{aligned}\right\} \tag{10}$$

5.4. Histogram equalization

The last step of *QDHE* is applying *HE* algorithm for each sub-histogram independently. If the i^{th} histogram is allocated at gray-level range [i_{start} - i_{end}], then the resultant *HE* follows equation (11).

$$y(x) = (i_{start} - i_{end}) \times cdf(X_k) + i_{start} \tag{11}$$

6. Contrast limited adaptive histogram equalization, CLAHE

Reza in [4], states that *CLAHE* produces good results on medical images and its procedures are as follows.

- Divide the image into several almost equal sizes and non-overlapping regions. This partition consequence in three different groups of regions: corner regions (CR), boarder regions (BR), and inner regions (IR). Fig. 5a represents an example of the image partitioning process.
- For each group, calculate the histogram.
- If the clipping level is known, then clip the histogram to that level and then use the clipped histograms to calculate the *CDFs*.
- For each pixel in the image, find its closest four neighboring grid points. Using the intensity value of that pixel as an index, find its mapping at the four grid points based on their $CDFs$.
- Interpolate among these values to get the mapping at the current pixel location. Map this intensity to the range [min: max) and allocate it in the output image.

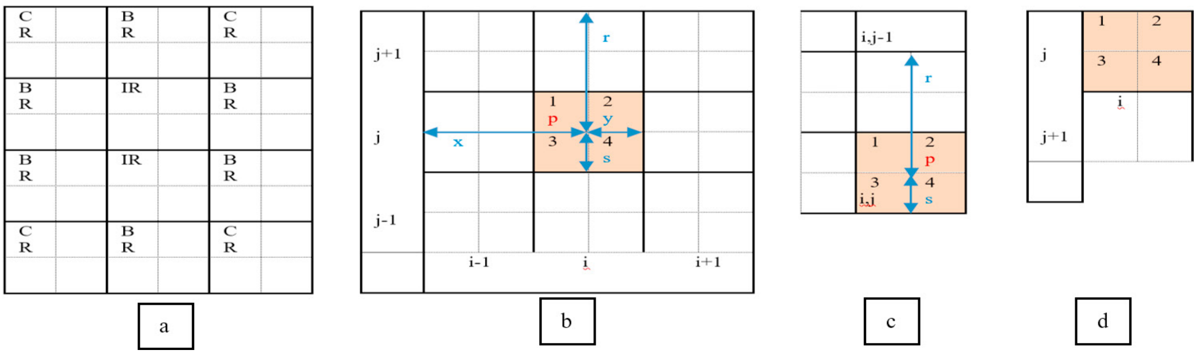

Fig. 5. (a) Three groups of regions in the portioned image, (b) an IR region with its neighboring regions, (c) a BR region with a quadrant 2 pixel of (i, j) region, (d) the top-left corner region and its neighborhood structure.

6.1. Clipping process based on a desired limit for contrast expansion

Clipping the histogram is not simple because the excess after clipping has to be re-distributed among the other bins, which might increase the level of the clipped histogram. Thus, the clipping has to be performed at a level lower than the specified clip level so that after redistribution the maximum histogram level is equal to the clip level. There are many approaches for identifying the point at which the clipping should be performed. Following is an overview of two clipping algorithms.

6.1.1. First approach

Reza in [4] defines a clip limit β as in equation (12).

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{\max} - 1)\right) \tag{12}$$

where M and N are the number of pixels and gray-levels in each region, respectively. The parameter $\propto$ is the clipping factor in percentage. S_{max} represents the limited slope of the transformation function. The clip factor α range is [0-100], thus the slope range, in each mapping, is [1-S_{max}].

6.1.2. Second approach: binary search

Pizer et al. in [6] developed the binary search approach to find the clip value in an automated way. The procedures are as follows.

- Let the specified clip level be *Top* and 0 be the *Bottom*. Thus, $Top = C \;\&\; Bottom = 0$
- While the difference between *Top* and *Bottom* is greater than one, perform the following steps.
- Calculate the *Middle* between *Top* and *Bottom*. Thus, $Middle = (Top + Bottom)/2.$
- Find the sum of excess above *Middle* in each bin of the histogram, S.
- $If\ (Excess + Middle) > C\ then\ top = middle.$
- $If\ (Excess + Middle) < C\ then\ bottom = middle.$
- $If\ (Excess + Middle) = C\ then\ middle\ is\ the\ value\ at\ which\ clipping\ is\ to\ be\ performed.$
- Then break out of the binary search loop.
- Clip the histogram at the value of middle. Thus, $the\ actual\ clipping\ value, P = bottom.$
- Redistribution of each histogram in a way that its height does not exceed the clipping limit. Thus, the modified histogram V is calculated from the original value $V_{orig}\ is$ as in equation (13).

$$V = \begin{cases} (V_{orig} + L) = (V_{orig} + C - P) & \text{if } V_{orig} < P \\ C & \text{if } V_{orig} \geq P \end{cases} \tag{13}$$

6.2. Combination of the regions

The last process is the determination of the *CDF* of the resultant contrast limited histograms. The final image is constructed by mapping all enhanced regions, and by applying bilinear interpolation between the neighbouring pixels whose centres are based on the four nearest IR, two nearest BR, or one nearest CR.

6.2.1. Regions in IR group

The pixel in the 1st quadrant of (i, j) region is mapped based on its vertical and horizontal distances from the centres of $(i, j-1), (i-1, j), \&(i-1, j-1)$ regions, Fig. 5b. If $f_{i,j}$ is the mapping function of pixels in (i, j) region then, the new value p of the pixel that exists in the 1st quadrant of (i, j) region is given by equation (14). Similar procedures are applied to the other pixels in other quadrants of (i, j) region.

$$p_{new} = \frac{s}{r+s}\left(\frac{y}{x+y} f_{i-1,j-1}(p_{old}) + \frac{x}{x+y} f_{i,j-1}(p_{old})\right) + \frac{r}{r+s}\left(\frac{y}{x+y} f_{i-1,j}(p_{old}) + \frac{x}{x+y} f_{i,j}(p_{old})\right) \tag{14}$$

6.2.2. Regions in BR group

Referring to Fig. 5c and for the right-hand boarder of the image, the structure of the pixels in the 1st and 3rd quadrants is the same as that of regions in the IR group but not the same as the pixels in the 2nd and 4th quadrants. Equation (15) represents the new value p of the pixel in the 2nd quadrant of (i, j) region.

$$p_{new} = \frac{s}{r+s} f_{i,j-1}(p_{old}) + \frac{r}{r+s} f_{i,j}(p_{old}) \tag{15}$$

6.2.3. Regions in CR groups

Referring to Fig. 5d and the top-left corner of the image, the 4th quadrant has neighbourhood structure similar to those of IR regions. While, the 2nd and 3rd quadrants have neighbourhood structures similar to those of BR regions. The 1st quadrant in this group has a unique structure as it has no contact with other regions. Its mapping follows equation (16).

$$p_{new} = f_{i,j}(p_{old}) \tag{16}$$

7. Quantitative analysis

In order to explore the successfulness of each histogram method, three metrics are calculated which are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Standard Deviation (SD). *Mean Square Error MSE* measures the noise contained in the image and it can be calculated by equation (17).

$$MSE = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(\mathrm{Img}'(i,j) - \mathrm{Img}(i,j)\right)^2}{MN} \tag{17}$$

where Img' and Img are the enhanced and original images, respectively. *Peak Signal to Noise Ratio PSNR* measures the strength of the information kept in the image in relation to the existing noise and it can be calculated using equation (18).

$$PSNR(dB) = \frac{10\log_{10}(L-1)^2}{MSE} \tag{18}$$

Standard Deviation*, SD,* measures the closeness of the data to their mean and it can be calculated by equation (19).

$$SD = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (f(i,j) - X)^2} \tag{19}$$

Where $f(i, j)$ is the intensity of a pixel at the location $(i, j), X$ is the average of the intensities, and n is the number of pixels.

8. Results

We enhanced five medical images: retina, knee, MRI-brain, MRI-endometria, and mammogram-breast by the four histogram-based algorithms, discussed above [9-12]. In addition, we evaluated each algorithm in each image by the three evaluation metrics. Fig. 6 displays the original images and their enhanced versions. Tables 2, 3, and 4 show the results of the three evaluation metrics for each algorithm and each image. The obtained results are plotted in Figs 7a, b &c.

9. Conclusion

Clinicians can falsely diagnosis medical images due to the unclearness of the images. Therefore, enhancing the images before diagnosis is a crucial step in image processing. Image histogram displays the intensity recurrence in pixels of a digital image. An image with a well-distributed histogram has a high contrast. This paper covered *HE, CHE, QDHE,* and *CLAHE* algorithms and tested them on retina, brain, endometrium, breast and knees images. In addition, it evaluated each of them using *PSNR, SD* and *MSE*.

HE spreads out intensity values along the total range of values in order to achieve higher contrast while *CHE* has a better performance than *HE*. The *QDHE* is a brightness-preserving algorithm that reduces limitations caused by *HE* in contrast enhancement. The *CLAHE* is a recommended technique for images with non-uniform intensity distribution over all areas of the image.

The amount of contrast enhancement for some intensity is directly proportional to the slope of the *CDF* function at that intensity level. Thus, contrast enhancement can be limited by limiting the slope of the *CDF*. Therefore, if we limit the height of the histogram to a certain level we can limit the slope of the *CDF* and hereafter the amount of contrast enhancement.

Results indicated that *SD* is higher in all the enhanced techniques rather than the original images, meaning that all the techniques give better image than the original images. Both of *QDHE* and *CLAHE* gave the least *MSE*. Except for the retina image, *QDHE* gave the highest *PSNR*. The *CLAHE* is the best enhancement technique for the retina images while *QDHE* is the best for brain, endometrium, breast and knees images.

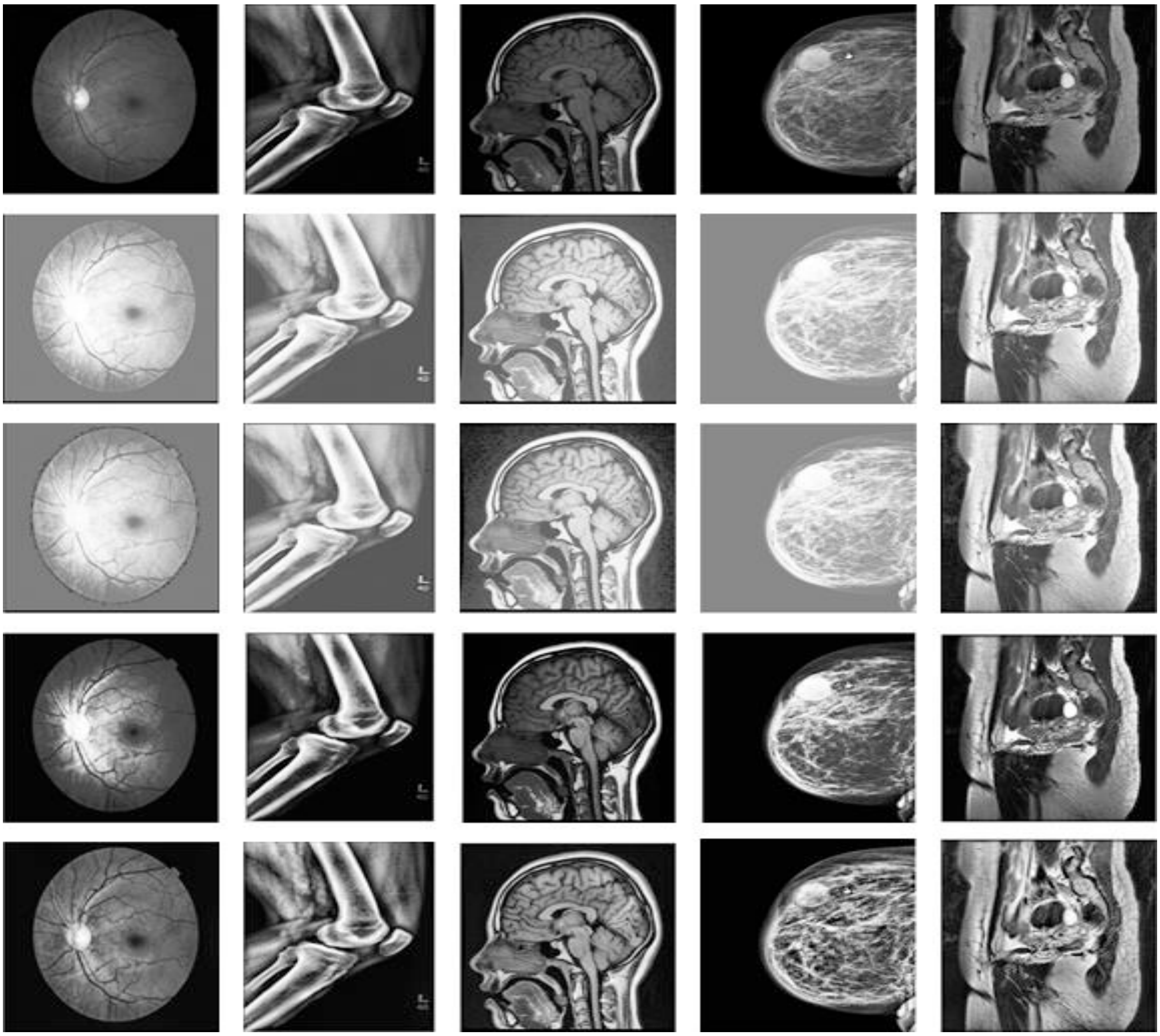

Fig. 6. The 1st (top) row displays the five original medical images, the following rows display the enhanced imaged by the techniques HE, CHE, QDHE, and CLAHE, in sequence.

Table 2. PSNR in dB of each algorithm for each medical image.

Image Type	HE	CHE	QDHE	CLAHE
Retina	6.6611	7.2010	17.4330	21.2357
Knee	9.0325	9.3432	23.6541	16.3653
Brain MRI	7.6048	8.4482	19.8646	14.5745
Endometrium	10.5983	11.0645	18.5760	14.9021
Breast	7.1113	7.3033	19.2915	18.0190
Average	8.20	8.67	19.76384	17.01932

Table 3. MSE of each algorithm for each medical image.

Image Type	HE	CHE	QDHE	CLAHE

Retina	1.4027e+04	1.2387e+04	1.1743e+03	223.0449
Knee	8.1251e+03	7.5641e+03	280.3330	966.1183
Brain MRI	1.1288e+04	9.2952e+03	670.8361	1.2612e+03
Endometrium	5.6656e+03	5.0890e+03	902.5713	1.1520e+03
Breast	1.2646e+04	1.2099e+04	765.4772	770.9151
Average	1.04e+04	9.29e+03	7.59e+02	8.75e+02

Table 4. SD of each algorithm for each medical image.

Image Type	HE	CHE	QDHE	CLAHE
Retina	52.5158	51.8401	60.1603	47.4125
Knee	61.5050	62.0608	68.4751	70.8974
Brain MRI	63.0925	69.3057	60.8605	63.9431
Endometrium	70.9154	72.8752	66.3201	66.6786
Breast	44.8501	44.5951	71.2628	70.8172
Average	58.57576	60.13538	65.41576	63.94976

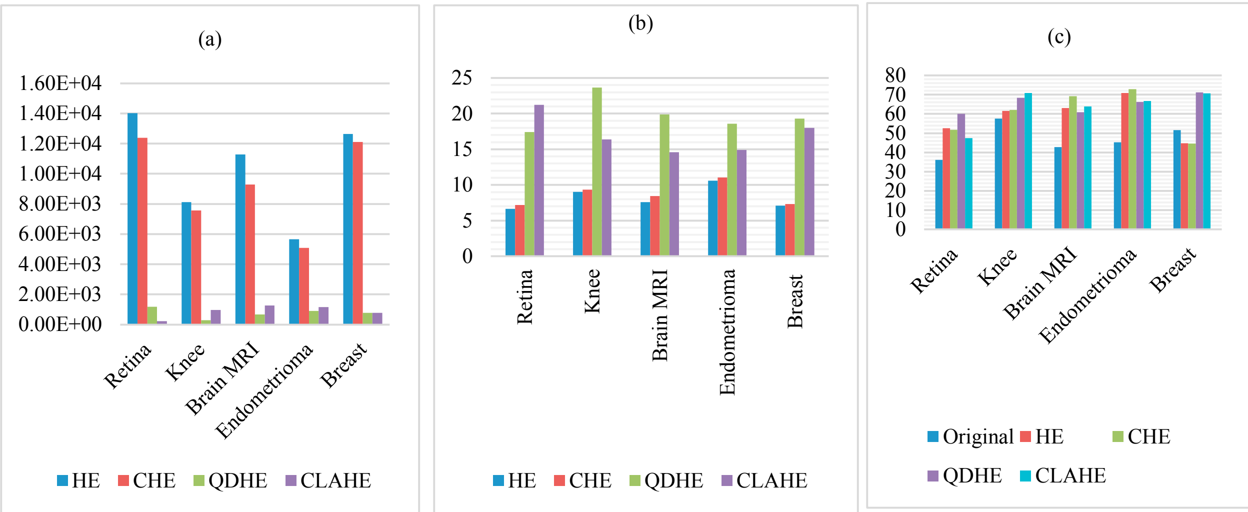

Fig. 7. (a) MSE; (b) PSNR; (c) SD; for each algorithm and for each image.

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