Sequential Model for Digital Image Contrast Enhancement

Article · July 2020

DOI: 10.2174/2666255813999200717231942

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International Journal of Software Innovation
Volume 8 • Issue 3 • July-September 2020

Contrast Enhancement Using Optimum Threshold Selection

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ABSTRACT

In the recent era, a boom was observed in the field of information retrieval from images. Digital images with high contrast are sources of abundant information. The gathered information is useful in the precise detection of an object, event, or anomaly captured in an image scene. Existing systems do uniform distribution of intensities and apply intensity histogram equalization. These improve the characteristics of an image in terms of visual appearance. The problem of over enhancement and the increase in noise level produces undesirable visual artefacts. The use of Otsu's single threshold method in existing systems is inefficient for segmenting an image with multiple objects and complex background. Additionally, these are incapable to improve the yield of the maximum entropy and brightness preservation. The aforementioned limitations motivate us to propose an efficient statistical pipelined approach, the Range Limited Double Threshold Weighted Histogram Equalization (RLDTWHE). This approach is an integration of Otsu's double threshold, dynamic range stretching, weighted distribution, adaptive gamma correction, and homomorphic filtering. It provides optimum contrast enhancement by selecting the best appropriate threshold value for image segmentation. The proposed approach is efficient in the enhancement of low contrast medical MRI images and digital natural scene images. It effectively preserves all essential information recorded in an image. Experimental results prove its efficacy in terms of maximum entropy preservation, brightness preservation, contrast enhancement, and retaining the natural appearance of an image.

KEYWORDS

Adaptive Gamma Correction, Automatic Threshold Selection, Histogram Weighting, Homomorphic Filtering, Optimum Contrast Enhancement, Range Stretching

1. INTRODUCTION

Image contrast enhancement is one of the main concerns in the arena of digital image processing. Its main objective is to produce better image quality for correct interpretation.

Study of literature reveals, histogram equalization (HE) is most widely used and popular image contrast enhancement technique, due to its less computation cost and easy implementation. It stretches dynamic range of gray levels, flattens the cumulative density function and successfully achieves overall image contrast enhancement (Gonzalez, & Woods, 2002). But the problem of intensity saturation

DOI: 10.4018/IJSI.2020070107

leads to appearance of undesirable visual artefacts in a processed image. Thus, HE is inefficient in preserving the brightness and providing detailed information recorded in an enhanced image.

To overcome the above said limitations, researcher Kim in 1997 proposed a multiple segmentation-based approach (Kim, 1997). Kim applies Brightness Preserving Bi-Histogram Equalization (BBHE) technique for contrast enhancement of an input image. BBHE completes its task into two steps. At first step, it partitions an input image histogram into two sub histograms on the basis of its mean gray level. At second step, it equalizes each sub histogram independently (Kim, 1997). In this technique Kim proved that the mean brightness of processed image lies between mean brightness of an input image and middle gray level. This technique also reduces the annoying artefacts in the processed image.

Researchers in 1999 proposed another new technique namely Dualistic Sub Image Histogram Equalization (DSIHE). This technique is similar to BBHE except that it uses median rather than mean value. Experimental results in a simulation environment prove that DSIHE is better than BBHE in terms of preservation of average information content of an image (Chen, & Zhang, 1999).

Both techniques are effective in contrast enhancement. BBHE as well as DSIHE faces the problem of brightness shift and intensity saturation artefacts in a processed image.

Researchers Chen et al. in 2003 proposed Recursive Mean Separate Histogram Equalization (RMSHE), an extension of BBHE. In RMSHE, authors suggested, the recursive segmentation of an input image histogram on the basis of local mean. At each step, existing sub-histogram is partitioned into two sub histograms. After r^{th} step, the algorithm yields, 2^r sub histograms, where r is a natural number. The number of recursive steps, r depends upon user's choice. Moreover, the authors claimed that with increase in r, brightness of processed image becomes equal to brightness of an original input image (Chen, & Ramli, 2003). This technique preserves more brightness than BBHE. But it faces the problem of over enhancement at low contrast regions. In addition, it is challenging to find the best value of r.

Researchers Sim et al. in 2007 proposed Recursive Sub Image Histogram Equalization (RSIHE), an extension of DSIHE. This technique is similar to RMSHE except that it does the partitioning of histogram on the basis of its median (Sim, Tso, & Tan, 2007). The authors claimed that, this technique preserves more brightness and information content than DSIHE.

Kim observed that in all previously proposed enhancement techniques (Kim, 1997; Chen, & Zhang, 1999; Chen, & Ramli, 2003; Sim, Tso, & Tan, 2007), an increment in level transformation function is directly proportional to the probability of gray levels. Due to this reason, HE assigns large dynamic range to the high probability gray levels. Thus, high probability gray levels dominate over low probability gray levels. High probability image regions become over enhanced and low probability regions remain less enhanced. This causes a loss of information content present in an image. To resolve this problem, researcher Kim et al. in 2008 proposed Recursively Separated Weighted Histogram Equalization (RSWHE) based approach (Kim, & Chung, 2008). This approach is similar to RMSHE and RSIHE except the use of normalized power law function before applying HE. The power law function assigns slightly higher weights to less frequent gray levels and slightly lower weights to more frequent gray levels (Kim, & Chung, 2008). The author claimed that, the RSWHE technique yields better contrast enhancement and brightness preservation than RMSHE and RSIHE. But the problem of over enhancement in a resultant image still persists. Also, the time complexity increases due to recursive segmentation (Chen, & Ramli, 2003; Sim, Tso, & Tan, 2007; Kim, & Chung, 2008).

A group of researchers, Haung et al. in 2013 proposed an automatic transformation technique namely Adaptive Gamma Correction with Weighted Distribution (AGCWD) (Haung, Cheng, & Chiu, 2013). This technique uses gamma correction. It modifies the probability distribution of luminance pixels. Thus, improves the brightness level of faded images. It uses Hue Saturation Value (HSV) color model. Hence improves the visual quality of color images.

Researcher Zuo proposed a non-recursive approach namely Range Limited Bi-Histogram Equalization (RLBHE) for image contrast enhancement. This technique segments an input image histogram into two parts based on Otsu's single threshold method (Zuo, Chen, & Sui, 2013). The Otsu's method automatically separates the image histogram and minimizes the intra class variance. RLBHE calculates the range of equalization before applying HE. It successfully minimizes the Absolute Mean Brightness Error (AMBE). Range optimization process tries to equate the mean brightness of processed image with original input image (Zuo, Chen, & Sui, 2013). But this technique is inefficient for the segmentation of images with multi objects and complex background.

One more research, Range Limited Bi – Histogram Equalization with Adaptive Gamma Correction (RLBHE with AGC) is a contribution towards contrast enhancement (Gautam, & Tiwari, 2015). It partitions an input image histogram into two parts on the basis of Otsu's single threshold. Then, it calculates the lower and upper bounds for the HE process. This approach keeps a balance between high level visual quality and low computational cost. Its experimental results on a simulator show that, RLBHE with AGC enhances the low contrast images more efficiently in comparison to RLBHE and AGCWD (Gautam, & Tiwari, 2015). But this technique is ineffective in segmenting the multi objective images in complex background.

Other researchers (Xu, Chen et al., 2015) proposed a novel contrast enhancement method namely Range Limited Double Threshold Multi Histogram Equalization (RLDTMHE). This method divides an input image histogram on the basis of double threshold. It calculates range of equalization before applying histogram equalization process. The experimental results show that it gives more clear details and preserves brightness of an image.

Recently Liyun et al. propose an image enhancement technique using entropy-based sub histogram equalization. This method divides an input image histogram into four segments based on entropy values and then adjust the dynamic range of each sub histogram (Zhuang, & Guan, 2018). This method effectively preserves the mean brightness of natural scene digital images. But in case of complex background and multi object images, it may fail to give results with natural appearance due to inappropriate subdivisions. Moreover, this method not provides the control on over enhancement problem.

The extensive study of available literature reveals that the existing techniques address the problems such as mean brightness shifting, domination nature of high frequency histogram bins, and intensity saturation artefacts. Although every method uses a different criterion for segmentation of an input image histogram, but lacks in providing best thresholding technique for segmentation of multi modal histogram of low contrast medical images. The incorrect segmentation and non-optimum thresholding led to challenges such as less entropy preservation, poor contrast enhancement due to raised noise level, over enhancement, undesirable visual artefacts and poor information retrieval from an images with complex background and multiple objects. This motivates us to design a system that can overcome the above said challenges and provide the optimum contrast enhancement.

In this article, we propose an efficient system namely Range Limited Double Threshold Weighted Histogram Equalization with Dynamic Range Stretching (RLDTWHE-DRS). This system is an integration of Otsu's double threshold, dynamic range stretching, weighted distribution, range optimization, adaptive gamma correction and homomorphic filtering.

The system is enriched with the following key features:

- It provides an optimum threshold value for segmentation of all types of low contrast images with complex background and multiple objects;
- It provides the optimum contrast enhancement with minimum noise and undesirable visual artefacts;
- It efficiently controls the problem of over enhancement because it uses the weighted distribution model that effectively dominates the high frequency histogram bins;
- It uses the range optimization process so it provides the maximum mean brightness preservation with better PSNR and contrast;
- This system retains the natural appearance of an image while contrast enhancement process;

- It preserves the maximum entropy during the enhancement process and provides all necessary and recorded information in an image;
- It avoids all unnatural changes that occur in the cumulative density function (CDF) and control the problems such as blurring, noise and over enhancement.

This paper is organized as follows: Section 2 presents the proposed work. Section 3 demonstrates the experimental results. Section 4 shows the comparison of the proposed work with existing systems. Section 5 concludes the proposed work.

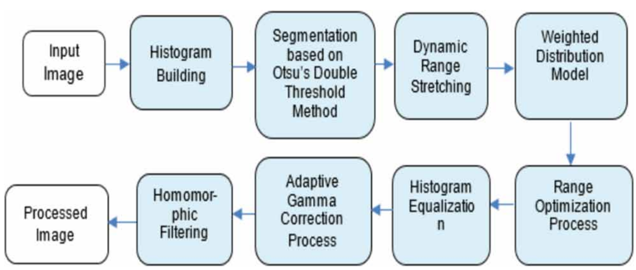
2. PROPOSED WORK

This research aims at improvement in contrast enhancement with less visual artefacts, maximum entropy preservation and minimum over enhancement by finding the optimum threshold value for segmentation of an image.

To achieve the above said objectives, authors propose the 'Range Limited Double Threshold and Weighted Histogram Equalization with Dynamic Range stretching (RLDTWHE-DRS)'. This technique completes its task into five steps. (i) It subdivides an input image histogram into three sub histograms on the basis of Otsu's double thresholds. (ii) Then, it maps each sub histogram to a new dynamic range by the dynamic range stretching process. (iii) It applies weighted distribution model to modify the probabilities of all segmented sub histograms. (iv) Now, the system calculates the new optimal range and then equalizes all sub histograms individually. (v) At the final step, it applies adaptive gamma correction for further global contrast enhancement and homomorphic filtering for local contrast enhancement.

Figure 1 presents the activity flow of the proposed system, RLDTWHE-DRS.

Figure 1. Activity flow RLDTWHE-DRS



2.1. Histogram Building

Histogram of an image is the graphical representation of pixel intensity values of an image. It is a frequency distribution graph which shows the number of pixels in an image at each intensity value (Gonzalez, Woods, 2002). Author uses an inbuilt function of MATLAB tool, imhist () to create a histogram. It expresses an image in the form of 'n' equally spaced bins. Each bin signifies the range of data values.

While histogram building, the system segregates those images which actually needs contrast enhancement. If histogram of an image is concentrated near a narrow range, not flat and not uniformly distributed in a complete range of an image. Then image requires enhancement. From histogram of an image, the system also fetches more information such as which processing operations: addition, logarithms, contrast stretching, histogram equalization, filtering, etc., are applicable for a particular image. Histogram is also useful in deciding the appropriate threshold value for converting a gray scale image into binary image. The main purpose of converting an image into binary is to mark the pixels that belongs to foreground region with a single intensity and background regions with different intensities.

2.2. Segmentation Based on Otsu's Double Threshold Method

In computer vision, image segmentation plays an important role for analyzing an image by converting it into multiple segments or regions. Image thresholding is one of the simplest method to separate regions which are higher than set threshold. Researchers apply two techniques for thresholding: (i) global thresholding and (ii) adaptive thresholding. Global thresholding gives better results because adaptive thresholding may face the problem of local optima and hence not appropriate for multimodal histogram.

Otsu's Double Threshold method performs automatic global thresholding on the basis of shape of a histogram. This algorithm exhaustively searches an optimum threshold value. The threshold value separates an input image histogram and maximizes the inter class variance among three classes of pixels: foreground, background and target. It efficiently removes the segmentation difficulty for density histogram having more than two or three peaks. It minimizes the background noise and extracts the useful information.

Assume T_1 and T_2 are Otsu's double thresholds that segments an input image *I* into three sub images foreground denoted as I_f, background denoted as I_b and target denoted as I_t. Equation (1) computes global thresholds $X\left(T_1, T_2\right)$ of all three classes by maximizing their inter-class variance. Here $E\left(I_f\right), E\left(I_b\right)$ and $E\left(I_t\right)$ are the average brightness of sub images I_f, I_b, and I_t, respectively. $E\left(I\right)$ is the mean brightness of the whole input image *I*. S_f, S_b, and S_t are Probability Density Function (PDF) of sub images I_f, I_b, and I_t, respectively. The minimum gray level I_0 of an input image is 0 and maximum gray level I_{L-1} value is 255:

$$X\left(T_1, T_2\right) = \underset{I_0 < T_1 < T_2 < I_{L-1}}{ArgMax} \left\{ S_f\left(E\left(I_f\right) - E\left(I\right)\right)^2 + S_b\left(E\left(I_b\right) - E\left(I\right)\right)^2 + S_t\left(E\left(I_t\right) - E\left(I\right)\right)^2 \right\} \tag{1}$$

Otsu's double threshold method separates the target region from its foreground and background on the basis of thresholds T_1 and T_2. Thus, it provides more realistic results than Otsu's single threshold method.

2.3. Dynamic Range Stretching

Histogram Equalization fails to enhance the small range sub histograms. The dynamic range stretching overcomes this problem. It stretches the actual gray level range of an input image sub histograms to its maximum extent. It assigns a new gray level range to each sub-histogram. Therefore, it minimizes the dominating nature of high frequency histogram bins.

Let the gray level range of an original input image histogram is [I_0, I_{L-1}]. Let T_1 and T_2 are the Otsu's double thresholds as calculated using equation (1). T_1 and T_2 divide the input image histogram into three sub histograms. The range of first sub histogram is [I_0, T_1], the range of second sub histogram is [$T_1 + 1, T_2$], and the range of third sub histogram is [$T_2 + 1, I_{L-1}$].

The dynamic range of input image sub histogram i is given by Equation (2). Here, l_i is the lowest and m_i is the highest intensity value present in the i^{th} sub histogram:

$$S_i = m_i - l_i \qquad i = 1,2,3 \tag{2}$$

The range stretching factor CF_i for gray level range distribution of i^{th} sub histogram is given in Equation (3). Here, S_i denotes the dynamic range of i^{th} input image sub histogram and N is the total number of pixels contained in the i^{th} sub histogram:

$$CF_i = S_i * \log_{10} N \tag{3}$$

The range stretching function R_i depends on the total number of pixels contained in the respective sub-histograms (Ibrahim, & Kong, 2007). This function was proposed by Ibrahim et al. in 2007 as given in Equation (4). Here, n is 3, which shows total number of sub histograms:

$$R_i = 255 * \frac{CF_i}{\sum_{i=1}^{n} CF_i} \tag{4}$$

The dynamic range of i^{th} processed image sub histogram is given as [P_i, Q_i]. The range of first processed image sub histogram after range stretching is [*0,* R_1]. For i > 1, P_i and Q_i can be calculated as per equations (5) and (6) respectively:

$$P_i = 1 + \left(\sum_{k=1}^{i-1} R_k \right) \qquad i = 2,3 \tag{5}$$

$$Q_i = \sum_{k=1}^{i} R_k \qquad i = 2,3 \tag{6}$$

2.4. Weighted Distribution Model

The histogram weighted module applies normalized power law function and modifies the probabilities of sub histograms. It assigns slightly higher weights to less frequent gray levels and lower weights to more frequent gray levels. It computes the P_{max} as per equation (7) and P_{min} as per equation (8). Equation (9) gives the formula for accumulative probability density α_i of i^{th} sub histogram. P(k) is the probability of k^{th} gray level in an input image:

$$P_{max} = \max P\left(k\right) \quad 0 \le k \le L-1 \tag{7}$$

$$P_{min} = \min P\left(k\right) \quad 0 \le k \le L-1 \tag{8}$$

$$\alpha_i = \sum_{k=l_i}^{m_i} P\left(k\right) \tag{9}$$

The weighted distribution module modifies the original Probability Density Function (PDF) P(k) and generates weighted PDF P_w (k) by using equation (10). This equation minimizes the distance between gray level distribution and uniform distribution (Tiwari, & Gupta, 2014):

$$P_w\left(k\right) = P_{max}\left(\frac{P\left(k\right) - P_{min}}{P_{max} - P_{min}}\right)^{\alpha_i} \quad 0 \le k \le L-1 \tag{10}$$

The sum of all modified weighted PDF P_w (k) is no longer one, so normalization of weighted PDF is necessary. The normalization is done using equation (11). Here, P_{w_n} (j) is normalized and weighted PDF in the range of [I_0 , I_{L-1}]:

$$P_{w_n}\left(j\right) = \frac{P_w\left(k\right)}{\sum_{k=I_0}^{I_{L-1}} P_w\left(k\right)} \tag{11}$$

2.5. Range Optimization Process

Otsu's double threshold method does not ensure the preservation of mean brightness. Thus, there is a need to determine a new optimal range I'_0 to I'_{L-1} in place of I_0 to I_{L-1} of an image that preserves the maximum mean brightness and gives high value of Peak Signal to Noise Ratio (PSNR) with less noise.

The mean brightness $E\left(Y\right)$ of a processed image with double thresholds T_1 and T_2 is calculated using Equation (12) and (13). Here, $I_o = 0$ is the lowest gray level and $I_{L-1} = 255$ is the highest gray level of an input gray scale image.

Here, in equation (12), $E_f\left(Y\right)$ denotes the mean brightness of foreground region and P_f denotes the probability of foreground region for the range I_o to T_1, $E_b\left(Y\right)$ denotes the mean brightness of background region and P_b denotes the probability of background region for the range T_1+1 to T_2, $E_t\left(Y\right)$ denotes the mean brightness of target region and P_t denotes the probability of target region for the range T_2+1 to I_{L-1}:

$$E\left(Y\right) = E_f\left(Y\right)P_f + E_b\left(Y\right)P_b + E_t\left(Y\right)P_t \tag{12}$$

By substituting the following values of $E_f\left(Y\right)$, P_f, $E_b\left(Y\right)$, P_b, $E_t\left(Y\right)$, and P_t we get Equation (13):

$$E_f\left(Y\right) = \frac{I_0 + T_1}{2}$$

$$P_f = \left(\sum_{k=I_0}^{T_1} P\left(I_K\right)\right)$$

$$E_b\left(Y\right) = \frac{T_1 + 1 + T_2}{2}$$

$$P_b = \left(\sum_{k=T_1+1}^{T_2} P\left(I_K\right) \right)$$

$$E_t\left(Y\right) = \frac{T_2 + 1 + I_{L-1}}{2}$$

$$P_t = \left(\sum_{k=T_2+1}^{I_{L-1}} P\left(I_K\right) \right)$$

For:

$$E\left(Y\right) = \frac{I_0 + T_1}{2} \left(\sum_{k=I_0}^{T_1} P\left(I_K\right) \right) + \frac{T_1 + 1 + T_2}{2} \left(\sum_{k=T_1+1}^{T_2} P\left(I_K\right) \right) + \frac{T_2 + 1 + I_{L-1}}{2} \left(\sum_{k=T_2+1}^{I_{L-1}} P\left(I_K\right) \right) \tag{13}$$

For maximum brightness preservation, the mean brightness of an input image $E\left(I\right)$ and the mean brightness of a processed image $E\left(Y\right)$ should be same. Equation (14) presents the mathematical formula for this condition. I_m is the mean of an input image:

$$E\left(Y\right) \approx E\left(I\right) = I_m = \sum_{k=I_0}^{I_{L-1}} I_K P\left(I_K\right) \tag{14}$$

The sum of probabilities of foreground, background and target region is always 1. So we can write $P_t = 1 - \left(P_f + P_b\right)$. Thus:

$$E\left(Y\right) = \frac{I_0 + T_1}{2} P_f + \frac{T_1 + 1 + T_2}{2} P_b + \frac{T_2 + 1 + I_{L-1}}{2} \left(1 - P_f - P_b\right) \tag{15}$$

Substituting the value of E(Y) from equation (15) into equation (14), we get Equation (16):

$$\frac{I'_0 + T_1}{2} P_f + \frac{T_1 + 1 + T_2}{2} P_b + \frac{T_2 + 1 + I'_{L-1}}{2} \left(1 - P_f - P_b\right) \approx I_m \tag{16}$$

In Equation (16), T_1 and T_2 are Otsu's double thresholds. P_f, P_b, and I_m are easily computed from an input image. Thus, to satisfy the mean brightness equality condition of input and processed images, the new values of I'_0 and I'_{L-1} are used in place of I_0 and I_{L-1}, respectively. Here $0 \le I'_0 \le T_1$ and $T_2 \le I'_{L-1} \le I_{L-1}$. The new optimal range of processed image I'_0 to I'_{L-1} is computed using equation (16) ensure for maximum brightness preservation with better PSNR and less noise.

2.6. Histogram Equalization

This step applies conventional histogram equalization process on each sub histogram independently. In this process, transfer function, f maps the k^{th} intensity value X_k to new output level f(X_k), where $k \in [I'_0, I'_{L-1}]$, grey level or new optimal range of an image. Equation (17), (18) and (19) give the final transformation functions $f_f\left(X_k\right)$, $f_b\left(X_k\right)$ and $f_t\left(X_k\right)$ for each sub histogram respectively

[19]. Here, T_1 and T_2 are the Otsu's double thresholds. $C_{wf}\left(X_k\right)$, $C_{wb}\left(X_k\right)$, and $C_{wt}\left(X_k\right)$ are the Cumulative Density Functions (CDFs) of each sub histogram respectively:

$$f_f\left(X_k\right) = I'_0 + \left(T_1 - I_0\right) * C_{w_n f}\left(X_k\right), \quad \left(k = I'_0, 1, 2 \ldots\ T_1\right) \tag{17}$$

$$f_b\left(X_k\right) = \left(T_1 + 1\right) + \left(T_2 - \left(T_1 + 1\right)\right) * C_{w_n b}\left(X_k\right), \left(k = \ T_1 + 1, T_1 + 2 \ldots T_2\right) \tag{18}$$

$$f_t\left(X_k\right) = \left(T_2 + 1\right) + \left(I'_{L-1} - \left(T_2 + 1\right)\right) * C_{w_n t}\left(X_k\right), \left(k = \ T_2 + 1, T_2 + 2 \ldots I'_{L-1}\right) \tag{19}$$

On the basis of above transformation functions, the final processed image is an integration of all three equalized sub images. The processed image Y is given in Equation (20):

$$Y = f_f\left(X_k\right) \cup f_b\left(X_k\right) \cup f_t\left(X_k\right) \tag{20}$$

Equation (21) presents the formula for calculating the normalized CDF function $C_{w_n}\left(X_k\right)$ of a whole image w.r.t. to Equation (11):

$$C_{w_n}\left(X_k\right) = \sum_{k=I'_0}^{I'_{L-1}} P_{w_n}\left(k\right) \tag{21}$$

2.7. Adaptive Gamma Correction Process

Adaptive gamma correction method is an automatic transformation technique. This technique is useful in improving the brightness of low contrast medical images and natural scene digital images. It increases the low intensity values and avoids the significant decrement in high intensity values. It maintains the balance between low computational cost and high level of visual quality.

Equation (22) formulates the adaptive gamma correction method. l symbolizes the intensity and $l_{\max}$ represents the maximum intensity of an input image, γ is the varying adaptive gamma parameter defined in Equation (23):

$$T\left(l\right) = l_{max}\left(\frac{l}{l_{max}}\right)^{\gamma} \tag{22}$$

where:

$$\gamma = 1 - C_{w_n}\left(l\right) \tag{23}$$

It is clear from the above Equations (17), (18) and (19) that slight change in CDF causes harsh change in intensity value of a processed image (Haung, Cheng, & Chiu, 2013). AGC method is important to avoid all such unnatural changes by using Equations (22) and (23) that occur in CDF function.

2.8. Homomorphic Filtering

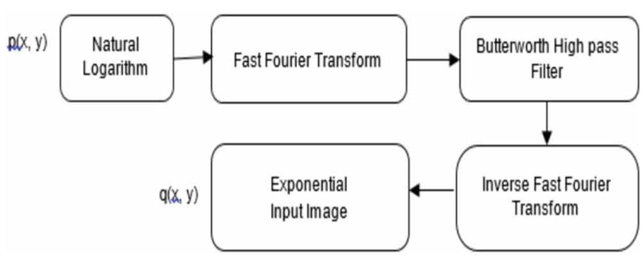
For poor contrast and complex background images such as Medical Magnetic Resonance Imaging (MRI), only AGC is not sufficient for contrast enhancement. So, there is a need to apply homomorphic filtering.

Homomorphic filtering reduces noise from visually important areas of the enhanced image. Thus, successful in contrast enhancement and restoration of the degraded images having uneven illumination. It is advantageous in attenuating the lower frequencies or the background brightness and amplifying the higher frequencies or the brightness of the details. This technique is based on the illumination reflectance model (Agarwal, Tiwari, & Lamba, 2014). The model is represented by multiplication of two components: illumination $i\left(x,y\right)$ and reflectance $r\left(x,y\right)$. Equation (24) gives the function $p\left(x,y\right)$ for original input image in terms of illumination and reflectance:

$$p\left(x,y\right) = i\left(x,y\right) * r\left(x,y\right) \tag{24}$$

In this model, the intensity of illumination component $i\left(x,y\right)$ changes slower than the reflectance component $r\left(x,y\right)$. Therefore, $i\left(x,y\right)$ has lower frequency component than $r\left(x,y\right)$. On the basis of this fact the homomorphic filtering reduces the low frequency component $i\left(x,y\right)$ of an image. In this process image is transformed from spatial to frequency domain using Fourier Transform function. Now, it executes the filtering process in frequency domain. Figure 2 demonstrates the sequential flow of steps involved in homomorhic filtering.

Figure 2. Homomorphic filtering



2.9. RLDTWHE-DRS Algorithm

Detailed algorithms of the proposed technique RLDTWHE-DRS are given in Algorithm 1, 2, 3 and 4.

3. EXPERIMENTAL RESULTS

This section presents the experiment setup, datasets, performance metrics and experimental results obtained using the proposed technique RLDTWHE-DRS.

Algorithm 1. RLDTWHE-DRS

```
REQUIRE: INPUT IMAGE IM
IM = IMRESIZE (IM, [256 200]);             % RESIZE THE IMAGE IM
IM = RGB2GRAY (IM);                        % CONVERT IMAGE IM INTO GRAY SCALE
N = SIZE (IM, 1) * SIZE (IM, 2);           % CALCULATE TOTAL NUMBER OF PIXELS N
[threshold_value 1, threshold_value 2] = OTSU'S DOUBLE THRESHOLD (IM, N);
[FREQ1] = IMHIST (IM);                     % GENERATE THE HISTOGRAM
PROB = FREQ1. / N;                         % PROB IS THE PROBABILITY OF PIXELS
PMAX = MAX (PROB (:));                     % CALCULATE THE MAXIMUM PROBABILITY
PMIN = MIN (PROB (:));                     % CALCULATE THE MINIMUM PROBABILITY
[PROBW1, PROBW2, PROBW3] = POWERLAW [PROB, PMAX, PMIN, threshold_value 1, threshold_value 2]
% APPLY WEIGHTED DISTRIBUTION MODEL
[FREQ2] = IMHIST (IM_OUT);                 % IM_OUT HISTOGRAM EQUALIZED AND MERGED PROCESSED IMAGE
[PROBW] = FREQ2. / N;
PROBW_SUM = SUM (PROBW);
IM_AGC = AGC_GAMMA (PROBW, PROBW_SUM, IM_OUT); % APPLY GAMMA CORRECTION
IM_AGC = IM2DOUBLE (IM_AGC);               % CONVERT IMAGE IM_AGC INTO DOUBLE FOR APPLYING THE HOMOMORPHIC
                                           FILTERING
IM_FFT = FFT2 (LOG (IM_AGC + .02));        % COMPUTE FFT OF AN IMAGE IM_AGC
F1 = BUTTERHP (IM_FFT, 10, 2);             % APPLY BUTTERWORTH HIGH PASS FILTER
C1 = IM_FFT.* F1;
IM_IFFT = REAL (IFFT2 (C1));               % COMPUTE INVERSE FAST FOURIER TRANSFOM
IM5 = ABS (EXP (IM_IFFT));                 % COMPUTE THE ABSLOLUTE VALUE
IM5_MAX = MAX (IM5 (:));
IM5_HF = IM5 / IM5_MAX;
IMSHOW (IM5_HF);                           % SHOW THE FINAL PROCESSED IMAGE IM5_HF
```

3.1. Experiment Set Up

RLDTWHE-DRS is implemented using Intel core i3 platform with a 2.0 GHz processor and 4 GB memory. The system runs on windows 10 operating system. For simulation a software, MATLAB R2017a is used.

3.2. Data Set

For evaluating efficacy of the proposed system, authors used a dataset of 15 test images extracted from public CVG-UGR database (Computer Vision Group, University of Granada, 2014). These images of Aircraft, MRI Brain, MRI Skull, MRI Knee, Palm bone X-Ray, MRI Spinal, Coconut, Cameraman, House, Girl, Villa, Lady, Tank, Barche and Helicopter, are shown in Figure 3. All images vary in average brightness and contrast. The dimensions of gray scale images are 256 x 256.

3.3. Performance Metrics

This sub section presents the evaluation metrics for the image quality.

3.3.1. Entropy

Entropy in bits measures the richness of information present in an image. Higher value of entropy indicates that the image contains detailed information (Huynh, Le, et al., 2014). Equation (25) gives

Algorithm 2. Image segmentation using Otsu's double threshold method

```
INPUT: GRAY SCALE INPUT IMAGE IM AND NUMBER OF PIXELS N
IM = RESHAPE (IM, [ ], 1);                    % RESHAPE THE IMAGE IM INTO SIZE 51200X1
FREQ = HIST (IM, 0:255);
IND = 0:255;
RESULT1 = ZEROS (SIZE ([1 256]) ;
RESULT2 = ZEROS (SIZE ([1 256]) ;
I ← 0;
J ← 0;
while I ≤ 255 do
    while J ≤ 255 do
        [Weightl Varl] = Functioncal (1, I);
        [Weightu Varu] = Functioncal (I+1, J);
        [Weightv Varv] = Functioncal (J+1, 255);
        [Weightf Varf] = Functioncal (1, 255);
        RESULT1 (I+1) = Weightl*(Varl – Varf). ^2) + Weightv*(Varv – Varf). ^2);
      RESULT2 (J+1) = Weightu*(Varu – Varf). ^2) + Weightv*(Varv – Varf). ^2);
    end while
end while
Functioncal CALCULATES THE WEIGHT, MEAN AND VARIANCE
[threshold_value 1] = MAX (RESULT1); % APPLY EQUATION (1)
[threshold_value 2] = MAX (RESULT2);
```

the definition of entropy. Here $P\left(X_K\right)$ is the PDF of k^{th} intensity level and $Ent\left(X_K\right)$ is the entropy of the resultant processed image:

$$Ent\left(X_K\right) = \sum_{k=I_0}^{I_{L-1}} P\left(X_K\right) * log_2 P\left(X_K\right) \tag{25}$$

3.3.2. Peak Signal to Noise Ratio

PSNR is the ratio of maximum power of an input signal to that of power of the corrupting noise. A higher value of PSNR indicates the better quality of reconstruction (Rahman, Liu et al., 2015).

Let N be the total number of pixels in a processed image, $I\left(i,j\right)$ be the input, $o\left(i,j\right)$ be the processed image and MSE is the Mean Square Error as given in Equation (26). Mean Square Error (MSE) is the average of squares of errors between the input image and processed image. It provides a comparison between the true pixel values of an input image and processed image. Equation (27) presents the definition of PSNR. Here, L denotes the maximum intensity value of the processed image. Higher value of PSNR reflects that the processed image contains less amount of noise after the enhancement process so that it matches with the original input image:

Algorithm 3. Adaptive gamma correction process

```
REQUIRE: MERGED HISTOGRAM EQUALIZED PROCESSED IMAGE IM_OUT AND PROBW
IM_AGC = UINT8 (ZEROS (SIZE (IM, 1), SIZE (IM, 2))) ;
CDF = ZEROS (256, 1);        % CREATE ARRAY OF SIZE 256X1
OUT = ZEROS (256, 1);        % CREATE ARRAY OF SIZE 256X1
S = 0;
J ← 1;
while J ≤ 256 do
        S = S + PROBW (J); % CALCULATE THE SUM OF WEIGHTED PROBABILITIES
        CDF (J) = S;
        OUT (J) = ROUND (255 * (J / 255). ^ (1 – CDF (J))); % APPLY EQUATION (24) AND (25)
end while
I ← 1;
J ← 1;
while I ≤ SIZE(IM, 1) do
        while J ≤ SIZE (IM, 2) do
                IM_AGC (I, J) = OUT (IM_OUT (I, J) +1); % CALCULLATE THE GAMMA
                                                          CORRECTED IMAGE
        end while
end while
```

$$MSE = \frac{\sum_i \sum_j \left| I\left(i,j\right) - o\left(i,j\right) \right|^2}{N} \tag{26}$$

$$PSNR = 10 log_{10} \left[\frac{\left(L-1\right)^2}{MSE} \right] \tag{27}$$

3.3.3. Contrast

Contrast measures the average intensities and their dispersion around the central pixel. The definition of contrast of an image is given in equation (28) where r is the width and c is the height of an image. $I_{enh}\left(i,j\right)$ is the pixel intensity at 2D position (i, j). Equation (29) presents a way to convert $C_{contrast}$ into decibel (dB).The decibel conversion is useful for representing the large range of numbers by a convenient and small number so that we can clearly visualize the changes:

$$C_{contrast} = \frac{1}{rc} \sum_{i=1}^{r} \sum_{j=1}^{c} I_{enh}\left(i,j\right)^2 - \left| \frac{1}{rc} \sum_{i=1}^{r} \sum_{j=1}^{c} I_{enh}\left(i,j\right) \right|^2 \tag{28}$$

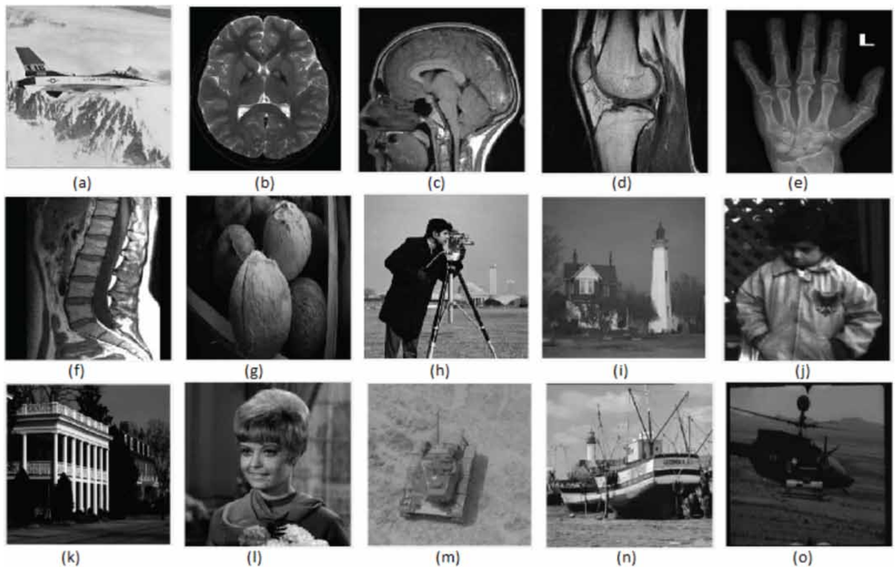
$$C^{*}_{contrast} = 10 \log_{10} C_{contrast} \tag{29}$$

Algorithm 4. Weighted distribution process based on power law function

```
INPUT: START AND END RANGE OF EACH SUB HISTOGRAM, PROB, PMAX AND PMIN
S1 = 0;
J ← 1
while J ≤ threshold_value 1 do
        S1 = S1+PROB (J);
end while
B1 = S1;        % B1 IS THE SUM OF PROBABILITIES OF FIRST SUB HISTOGRAM
S2 = 0;
J ← (threshold_value 1 +1)
while J ≤ threshold_value 2 do
        S2 = S2+PROB (J);
end while
B2 = S2;        % B2 IS THE SUM OF PROBABILITIES OF SECOND SUB HISTOGRAM
S3 = 0;
J ← (threshold_value 2 +1)
while J ≤ 256 do
        S3 = S3+PROB (J);
end while
B3 = S3;        % B3 IS THE SUM OF PROBABILITIES OF THIRD SUB HISTOGRAM
I ← 1
while I ≤ threshold_value 1 do
        PROBW1 (I) = (PMAX*((PROB (I)-PMIN) / (PMAX-PMIN))). ^B1; %APPLY EQUATION (10)
end while
PROBW1 = RESHAPE (PROBW1,threshold_value 1, 1);
I ← (threshold_value 1 +1)
while I ≤ threshold_value 2 do
        PROBW2 (I) = (PMAX*((PROB (I)-PMIN) / (PMAX-PMIN))). ^B2; %APPLY EQUATION (10)
end while
PROBW2 = RESHAPE (PROBW2,threshold_value 2, 1);
I ← (threshold_value 2 +1)
while I ≤ 256 do
        PROBW3 (I) = (PMAX*((PROB (I)-PMIN) / (PMAX-PMIN))). ^B3; %APPLY EQUATION (10)
end while
PROBW2 = RESHAPE (PROBW2,256, 1);
```

Higher value of contrast reflects that the image has better contrast and large dynamic range of gray levels (Tang, & Mat Isa, 2014).

Figure 3. Experimental dataset images: (a) Aircraft; (b) MRI Brain; (c) MRI Skull; (d) MRI Knee; (e) Palm bone X-Ray; (f) MRI Spinal; (g) Coconut; (h) Cameraman; (i) House; (j) Girl; (k) Villa; (l) Lady; (m) Tank; (n) Barche; and (o) Helicopter



3.3.4. Results

The proposed technique executed in the simulation environment on the dataset of 15 low contrast test images.

It yields the average value of entropy = 7.28. This value clearly indicates that the proposed technique accurately preserves the image entropy, as the value matches to the entropy of an original input image.

The technique gives average value of PSNR = 29.25. The value of PSNR reflects that the proposed technique is successful in preserving the brightness of an input image.

The proposed technique yields the average contrast = 39.36. It prevents all the undesirable artefacts.

It also resolves the difficulty arises in segmentation of images with complex background and multiple objects.

4. COMPARITIVE ANALYSIS

In this section, we demonstrate the qualitative as well as quantitative comparison of RLDTWHE-DRS with existing techniques namely GHE (Gonzalez, & Woods, 2002), BBHE (Kim, 1997), DSIHE (Chen, & Zhang, 1999), AGCWD (Haung, Cheng, & Chiu, 2013), RLBHE (Zuo, Chen, & Sui, 2013), RLBHE with AGC (Gautam, & Tiwari, 2015), RLDTMHE (Xu, Chen, et al., 2015) and EASHE (Zhuang, & Guan, 2018). The reason of selecting these techniques for evaluation is that they are mainly based on histogram clipping, histogram segmentation and histogram modification.

A series of experiments are performed to analyze the performance and feasibility of the proposed technique. Figure 4, 5, 6, 7 and 8 presents the comparison of visual quality and statistical analysis of the processed image. Figure 9, 10 and 11 presents the quantitative evaluation of the processed images obtained by RLDTWHE-DRS and existing techniques, in terms of Entropy, PSNR and Contrast.

Figure 4. Visual quality of the aircraft image: (a) Original; (b) GHE; (c) BBHE; (d) DSIHE; (e) AGCWD; (f) RLBHE; (g) RLBHE with AGC; (h) RLDTMHE; (i) EASHE; (j) RLDTWHE-DRS

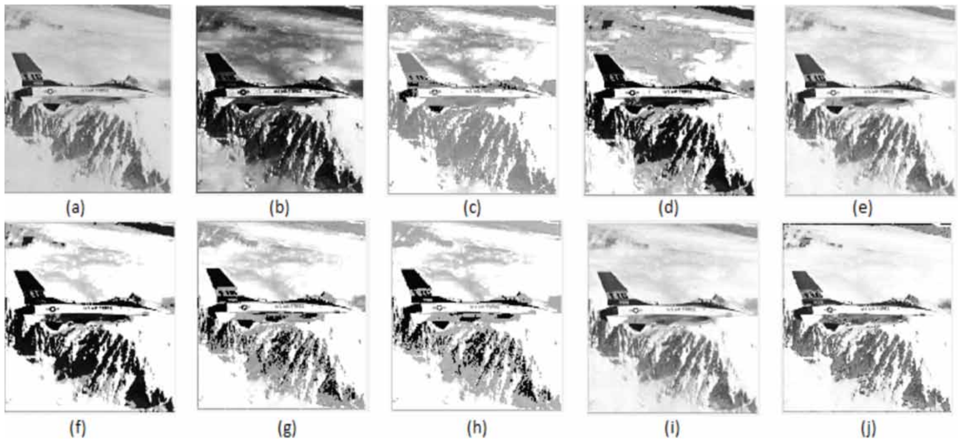


Figure 5. Visual quality of MRI skull image: (a) Original; (b) GHE; (c) BBHE; (d) DSIHE; (e) AGCWD; (f) RLBHE; (g) RLBHE with AGC; (h) RLDTMHE; (i) EASHE; (j) RLDTWHE-DRS

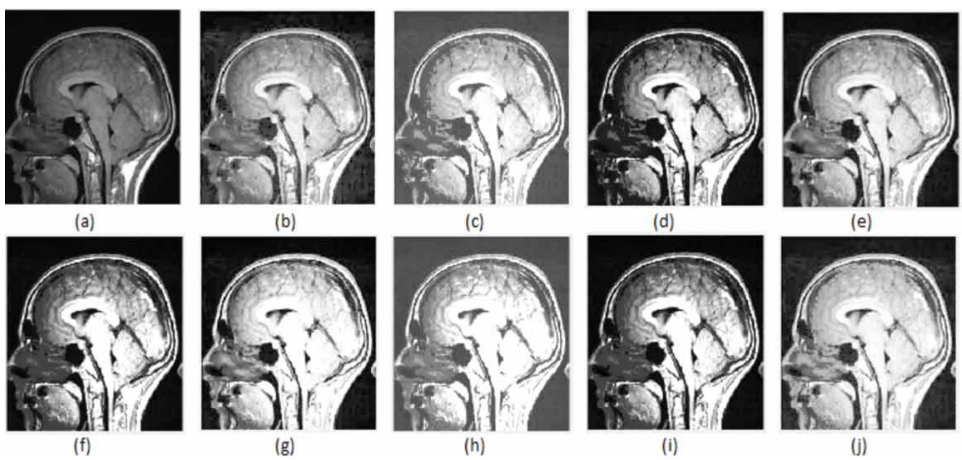
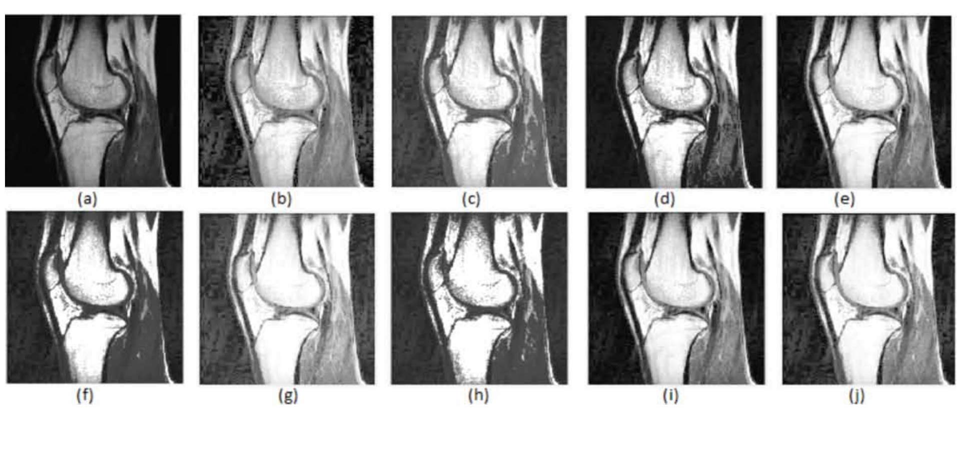


Figure 6. Visual quality of MRI knee image: (a) Original; (b) GHE; (c) BBHE; (d) DSIHE; (e) AGCWD; (f) RLBHE; (g) RLBHE with AGC; (h) RLDTMHE; (i) EASHE; (j) RLDTWHE-DRS



4.1. Qualitative Analysis

The visual quality assessment checks the unnatural look, extra artefacts and over enhancement problems in an image. It evaluates the performance of a technique in terms of contrast enhancement and brightness preservation.

Figures 4-8 (a-j), demonstrate the comparison in visual quality of the aircraft image, low contrast MRI skull image and MRI knee image, Villa image and Barche image respectively. Figures (4a, 5a and 6a, 7a and 8 a) show the original images. The processed images obtained by applying GHE (4b, 5b, 6b, 7b and 8b), BBHE (4c, 5c, 6c, 7c and 8d), DSIHE (4d, 5d, 6d, 7d and 8d), AGCWD (4e, 5e, 6e, 7e and 8e), RLBHE (4f, 5f, 6f, 7f and 8f), RLBHE with AGC (4g, 5g, 6g, 7g and 8g), RLDTMHE (4h, 5h, 6h, 7h and 8h), EASHE (4i, 5i, 6i, 7i and 8i) and the proposed technique RLDTWHE-DRS (4j, 5j, 6j, 7j and 8j).

Figure 4(b-j) shows the experimental results obtained by applying different enhancement techniques on an input aircraft image. The images shown in Figures (4c, 4e, 4g, 4h and 4i) shows the presence of unnatural high intensities in the results yielded by BBHE, AGCWD, RLBHE with AGC, RLDTMHE and EASHE produces the problem of under enhancement and over enhancement. The images obtained by GHE, DSIHE and RLBHE shown in Figures (4b, 4d and 4f) looks like dark due to limited improvement in contrast. Thus, these images do not provide the pleasant look. The processed image as shown in Figure (4j), obtained by applying the proposed technique RLDTWHE-DRS gives more natural look due to selection of best appropriate threshold value.

Figure 5(b-j) shows the simulation results obtained by different enhancement techniques on an input MRI skull image. The existing contrast enhancement techniques as shown in Figures 5(b-i) shows the presence of noise, over enhancement in contrast and blackened effect in an image. The proposed technique RLDTWHE-DRS as shown in Figure 5(j) removes all the anomalies of contrast enhancement. It enhances contrast with maximum brightness preservation.

Figure 6(b-j) shows the comparative enhancement results of MRI Knee image. Figures 6(d), 6(f) and 6(h) shows the presence of black patches of noise. Figures 6(b), 6(c), 6(e), and 6(i) has better quality but produces noise and washed out effects. A close observation of Figure 6(g) reveals that RLBHE with AGC technique produces the brighter output image. While the proposed technique in Figure 6(j) simultaneously enhance the overall contrast of the test image to an optimum level and preserves all necessary details present in the image.

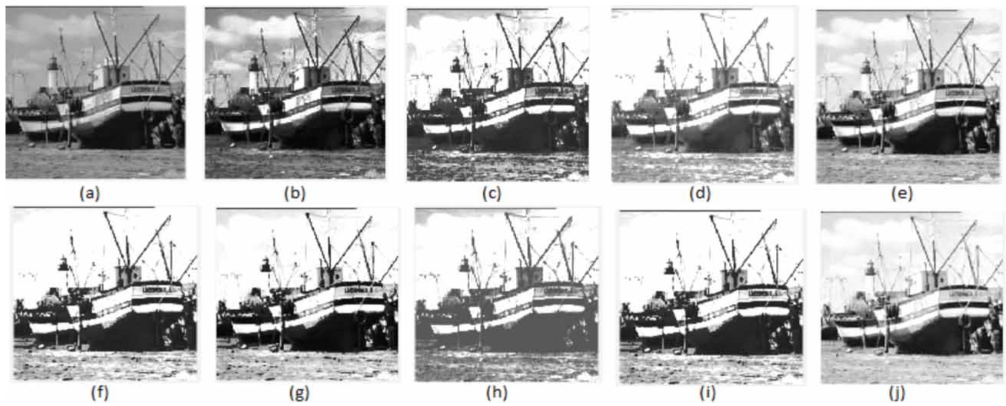
Figure 7(b-j) shows the experimental results obtained by different enhancement techniques on a villa image. Villa image has no clarity. It is difficult to extract all necessary details from this image. It lost its contrast by sharpening the edges. The proposed technique RLDTWHE-DRS as shown

Figure 7. Visual quality of villa image: (a) Original; (b) GHE; (c) BBHE; (d) DSIHE; (e) AGCWD; (f) RLBHE; (g) RLBHE with AGC; (h) RLDTMHE; (i) EASHE; (j) RLDTWHE-DRS

in Figure 7(j) generates the processed image with more clear and natural look as compare to other existing enhancement techniques. It can infer the detailed information.

Figure 8(b-j) shows the simulation results obtained by different enhancement techniques on an input barche image. Figures 8(d), 8(f), 8(g), 8(h) and 8(i) are better in terms of contrast but the

Figure 8. Visual quality of Barche image: (a) Original; (b) GHE; (c) BBHE; (d) DSIHE; (e) AGCWD; (f) RLBHE; (g) RLBHE with AGC; (h) RLDTMHE; (i) EASHE; (j) RLDTWHE-DRS



images lose its natural appearance of clouds. Additionally, it generates blackened effect, sharpened effect and black patches of noise on the ground of a Barche image. The results shown in Figure 8(b) and 8(c) are under and over enhanced leaving no trace of pleasant visual appearance. The result of technique AGCWD in Figure 8(e) is better as compare to others but not preserves the maximum detailed information and produces the mean shift problem. The image shown in Figure 8(j) obtained by the proposed technique displays the clear features of Barche image. There are no extra patches of noise in this image. It does so by efficiently enhancing the contrast. This proves the supremacy of proposed technique in terms of brightness preservation.

The statistical results and visual appearance measurement for the quality of an image clearly indicates that the proposed technique RLDTWHE-DRS outperforms in both factors contrast enhancement and brightness preservation.

4.2. Quantitative Analysis

Visual quality assessment is not sufficient to characterize the contrast enhancement of an image. Thus, quantitative performance evaluation is performed to accurately assess the performance of the proposed algorithm in terms of contrast enhancement and brightness preservation. Figures 9-11 present the quantitative analysis of the proposed system. Values of three parameters (i) Entropy (ii) PSNR and (iii) Contrast of 15 test images demonstrates the performance of various HE methods.

Particularly for medical MRI images, entropy or richness of information content is quite important. Its higher value is desirable. The analysis of results shown in Figure 9, proves that the proposed method preserves the maximum entropy and outperforms over other existing methods. Intensity saturation problem is the main reason for loss of information content in the processed image. The proposed technique effectively avoids the intensity saturation artifacts. Moreover, it minimizes the over enhancement problem.

Figure 10 presents the comparison in the values of PSNR. The experimental results in a simulating environment shows that the proposed technique produces higher PSNR values than existing enhancement techniques. Therefore, it is evident that the proposed technique does not amplify the

Figure 9. Comparison in entropy values

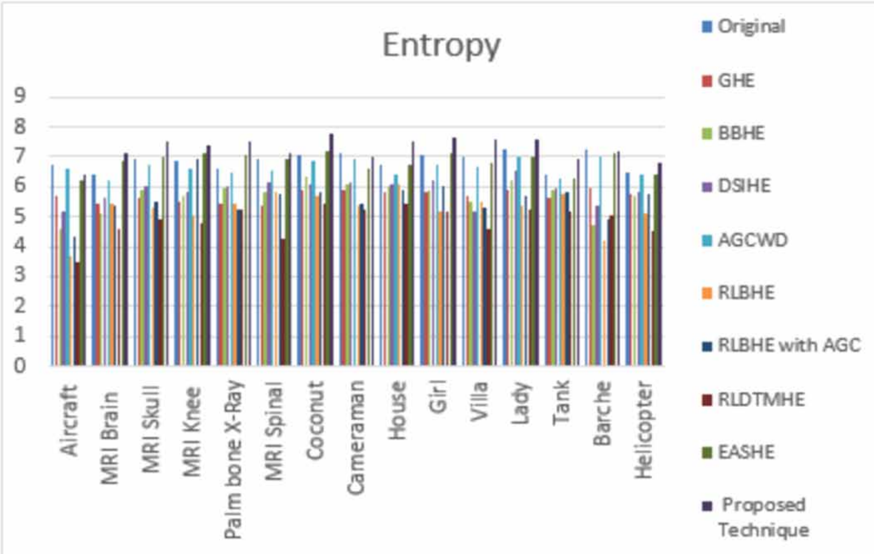
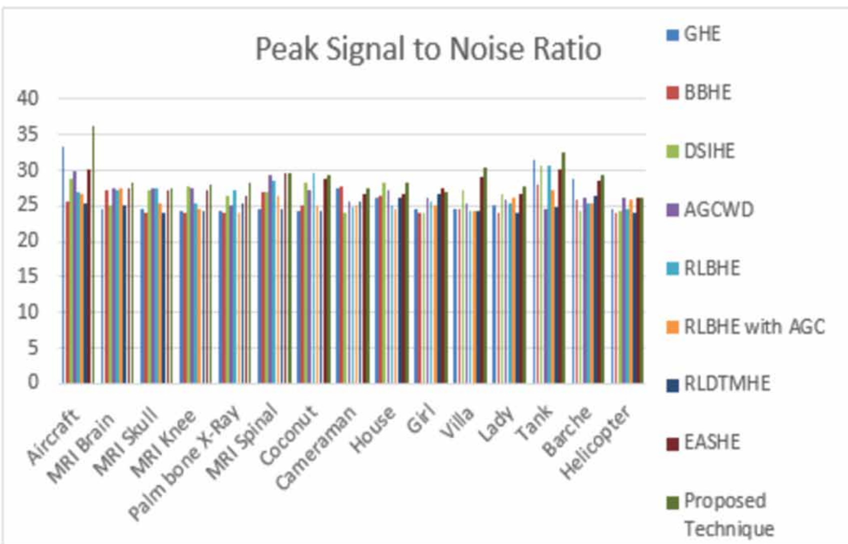


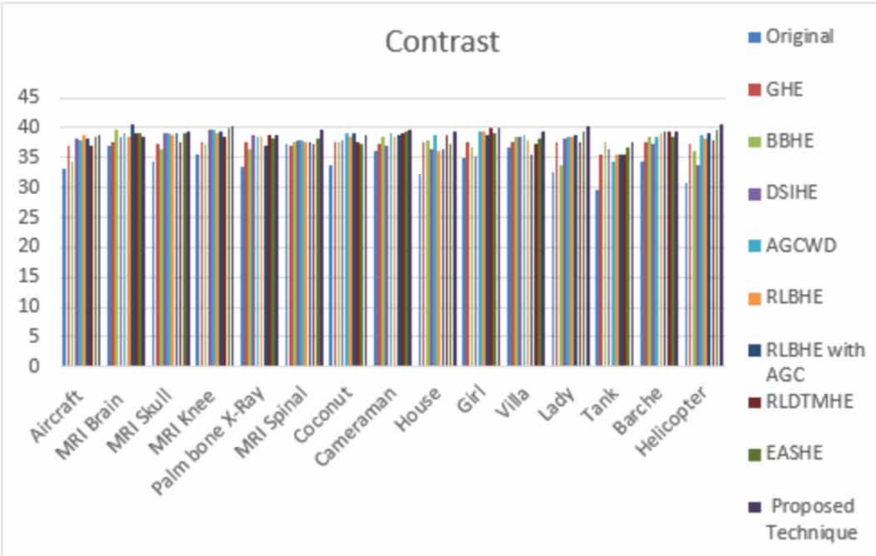
Figure 10. Comparison in PSNR value



noise level during the contrast enhancement process. But it retains the natural appearance of an image by controlling the enhancement rate.

Figure 11 demonstrates the performance measure with respect to image contrast. The BBHE, DSIHE, AGCWD, RLBHE, RLDTMHE and EASHE methods seem to attain the higher contrast, but there is no unrealistic limiting techniques present in these methods. Thus, these techniques produce undesirable visual artifacts. Quantitative analysis of experimental results proves that the proposed technique RLDTWHE-DRS produces an image with a smooth texture and also with a few non-

Figure 11. Comparison in values of contrast



homogeneous regions. All the techniques are alike in terms of contrast enhancement. This proves that enhanced images are not distant from one another in terms of contrast.

Table 1 shows the average results of image Entropy, PSNR and Contrast for 15 test images. On the basis of results of Table 1, it is clear that the proposed technique RLDTWHE-DRS performs well on all low contrast test images. This method provides maximum entropy preservation, well contrast enhancement and efficiently preserves the image brightness more accurately as compare to other methods.

The bold number in the table indicates the best performance.

5. CONCLUSION

This paper proposes a sequential integration of histogram segmentation, dynamic range stretching, histogram weighting, range optimization, histogram equalization, adaptive gamma correction and

Table 1. Average results of entropy, PSNR and contrast for standard low contrast test images

Methods	Entropy	PSNR	Contrast
GHE	5.71	26.19	37.29
BBHE	5.69	25.48	37.16
DSIHE	5.89	26.68	37.51
AGCWD	6.64	26.75	38.52
RLBHE	5.27	26.52	38.21
RLBHE with AGC	5.59	25.56	38.25
RLDTMHE	5.31	25.78	38.11
EASHE	6,85	27.87	38.57
Proposed Technique	7.28	29.25	39.36

homomorphic filtering techniques. The novelty of proposed method is to identify the best suitable threshold for segmentation of an input image histogram. Moreover, the integration of histogram weighted model with dynamic range stretching and range optimization process makes this method superior in terms of preserving the brightness and controlling the enhancement rate. The experimental results over a dataset of 15 low contrast test images, prove that the proposed method enhances the contrast with maximum preservation of entropy, brightness and natural appearance. Furthermore, this method preserves maximum information content during the contrast enhancement process. Thus, it is effective in real time and medical image processing. This method is adaptable, according to characteristics of an image.

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