A project report on

IMAGE ENHANCEMENT USING ENTROPY MAXIMIZATION

Submitted in partial fulfillment of the requirement for the award of degree of

Master of Technology
In
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CERTIFICATE

This is to certify that **Charu Krishna (2K14/ISY/18)** has carried out the major project entitled "**Image Enhancement Using Entropy Maximization**" in partial fulfillment of the requirements for the award of Master of Technology Degree in Information Systems during session 2014-2016 at Delhi Technological University.

The major project is bonafide piece of work carried out and completed under my supervision and guidance. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

Image enhancement is one of the most interesting domain of image processing. One of the techniques of image enhancement is contrast enhancement. Contrast enhancement in image processing is a very important technique. One of the most vastly used techniques for contrast enhancement is histogram equalization. It enhances the contrast of the input image by mapping the intensity levels based on the input probability distribution function of the image. HE finds application in many fields like medical image processing. HE, in general flats the histogram of the image and thus enhances the contrast of the input image. HE the results in the stretching of dynamic range.

Although HE has low computational cost and has high performance, it is rarely used in electronic appliances as its straight use changes the original brightness of the image and hence result in distorted image. Histogram equalized image may also result in annoying artifacts and noise. Hence many techniques for contrast enhancement were developed in order to overcome the defects of HE. These include Bi-histogram brightness preserving histogram (BBHE), Dualistic sub image brightness preserving histogram(DSIH), Minimum mean brightness error bi-histogram equalization(MMBEBHE), Recursive Mean Separate Histogram Equalization(RMSHE),Entropy maximization histogram modification technique(EMHM)etc. The proposed algorithm show better results as compared to other algorithm.

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CHAPTER – 1

INTRODUCTION TO IMAGE ENHANCEMENT

The modification of an image so that it can be used for certain applications is called Image Enhancement. The main aim of image enhancement is to alter a given image such that the resulting image is more appropriate for a specific application. Here specific means that the techniques used are very much related to the problem. For example, that a method that is used for x-ray image enhancement might not be the best method for enhancing pictures of satellites. Image enhancement is one of the most interesting domain of image processing. There are many factors that evaluate the quality of image. Many image enhancement techniques are widely used in many image processing applications to improve the quality of the image. Contrast is one of the important factors in any subjective evaluation of image quality. Contrast is defined as the difference in color or the luminance which makes an object in an image visible. In the real world, contrast can be determined by calculating the difference in the color and brightness of the object and other objects within the same domain. Alternatively, contrast can be difference in visual properties that makes an objects discernable from other objects in the image and the background of the image. Many algorithms for contrast enhancement have been developed in the past and applied to solve the problems in image processing.

Contrast is a very important factor in any subjective analysis of image quality. The pixel under consideration would be distinguishable if there is difference between luminance of pixel and the neighborhood of the pixel. In other words, difference in luminance is directly proportional to the contrast. This means that to increase the contrast of the image the difference in luminance between each pixel and its luminance should be increased. Contrast enhancement techniques can be divided into-

1) Spatial domain methods,
2) Frequency domain methods.

Spatial domain methods, operate directly on pixels while in frequency domain, the Fourier transform of the image is sent through a suitable filter, and then to obtain the output image inverse transform is applied .Frequency domain methods require higher computational costs, memory and the appropriate selection of parameters in comparison with the spatial domain methods. Methods for improving the contrast of an image are among the most vastly used enhancement processes. The two most useful methods of contrast enhancement are described below-

2.1.1 LINEAR CONTRAST STRETCH

Linear contrast stretch is the simplest contrast enhancement technique. a grey level value in the low level in the histogram of input image is given to extreme black value and the value at the high end is assigned to extreme white. The improved contrast ratio calculated enhances different features in the image. For colored images, the individual bands are stretched before finally being combined in color. This technique improves the contrast of most of the values in the image but the value at the extremes suffers a loss of contrast.

2.1.2 NON-LINEAR CONTRAST STRETCH-

This method is made in different ways. A uniform distribution stretch (or histogram equalization) is the one in which the grey level are redistributed to produce a uniform density of pixels. This does not preserves the brightness of the image and hence results in deteriorated image. Another non-linear contrast stretch method is Gaussian stretch. It enhances the contrast of the image. In this stretch the input histogram is fit to a normal distribution curve ranging between 0 to 255. One of the most widely accepted techniques in spatial domain is Histogram Equalization for enhancing the image by enhancing the contrast of the image.

Histogram Equalization (or uniform distribution stretch) is a most common and effective method for contrast enhancement with low computational cost. In this the original histogram of the image is redistributed such as population density of pixels are distributed uniformly. The resulting image has loss of contrast in the light and dark ranges which is similar to that we get in the linear contrast stretch but not that severe. Histogram equalization is widely used for contrast enhancement in lot of real life applications due to its low computational costs and effectiveness. Examples are medical image processing, radar signal processing and satellite image. Disadvantage of the histogram equalization-

1. After the histogram equalization the brightness of an image gets changed hence deteriorating the visual quality of the image quality.
2. It aggregates pixels having low probability into one and stretches the high probability gray values of the image. The mapping takes place without considering local characteristics of the neighborhood of the pixel.
3. HE introduces unnatural, annoying artefacts, noise and saturation in the image.
4. The mean brightness of the resultant image comes to the middle gray level as the histogram equalizes uniformly which is not a desirable property.
5. HE produces washed out, over enhanced images.

Hence, HE is rarely used in electronic appliances such as TV as preserving the original input brightness is a necessity to remove visual deterioration. Hence many new techniques were proposed for contrast enhancement.

CHAPTER – 2

LITERATURE REVIEW

2.1. A FEW GENERAL CONTRAST ENHANCEMENT METHODS

2.1.1. HISTOGRAM EQUALISATION

In this method the concept of spreading pixel values in the given image to the entire histogram more uniformly [1]. Such that the unseen scene details are more visible to the observer. This method uses the histogram of the input image and brings it to its ideal uniform form. Histogram is constructed by calculating the pixel frequencies for the entire dynamic range of the input image. Pixel frequency represents the number of times a gray level seen in the input image. This frequency can be called as the probability density function (pdf). It is calculated as follows:

$$PDF(k) = \frac{p_k}{p} \tag{1}$$

where $0 \leq \mathrm{k} \leq 2^m - 1$

In this formula, p_k represents the frequency of the pixel level k with image depth m, and p is the total number of pixels in the input image. Pixel values in the input image are random variables. Thus, the probability of the pixel value k in the given image is less than or equal to the sum of probability density function up to pixel level k. This operation is called as cumulative distribution function (cdf) and it is calculated as follows:

$$CDF(k) = \sum_{l=0}^{k} PDF(l) \tag{2}$$

where $0 \leq \mathrm{k} \leq 2^m - 1$.

Finally, the transformation of the pixel value from input to output is calculated as follows:

$$k' = (2^n - 1) \times CDF(k) \tag{3}$$

where $0 \leq \mathrm{k} \leq 2^m - 1$

Where k' denotes the value corresponding to the pixel value k in the enhanced image with depth n.

The histogram equalization method has less computational complexity. However, this method converts the pixel values with higher-frequency counts to the very large gray level intervals. This means that small details disappear between the objects with high frequencies (background, large objects, etc.) at the output image. The HE over enhances or over stretches the image as a result of the dynamic range expansion, HE flattens a histogram as well. HE may also introduce a vast change in brightness of an input image, hence the direct application of HE in electronics appliances is example.

2.1.2 HISTOGRAM MATCHING (HISTOGRAM SPECIFICATION) METHOD

This method produces an output image for applications, which needs a specific histogram distribution scheme. The histogram of an input image is converted to the desired output with matching of the histograms [1]. The method purpose is obtained by two-stage transformation. There are two values k and z, which correspond to the intensity values of the input and enhanced images respectively. The first step of the algorithm is to calculate the transformation function for input image. PDF denotes the probability density function of the input image; CDF denotes the cumulative distribution function of the input image, and T denotes the transformation function.

$$PDF(k) = \frac{p_k}{p} \tag{4}$$

$where\ 0 \leq \mathrm{k} \leq 2^m - 1.$

$$CDF(k) = \sum_{l=0}^{k} PDF(l) \tag{5}$$

$$(k) = (2^m - 1) \times CDF(k)_l \tag{6}$$

The second step of the algorithm is to calculate the transformation function for the output image. PDF_0 Denotes the probability density function of the output image; CDF_0 denotes the cumulative distribution function of the output image, and G denotes the transformation function for the desired output image.

$$PDF(z)_0 = \frac{p_k}{p} \tag{7}$$

Where $0 \leq z \leq 2^n - 1$

$$CDF_0(z) = \sum_{l=0}^{z} PDF_0(l) \tag{8}$$

$$\mathrm{T}(z) = (2^n - 1) \times CDF_0(z) \tag{9}$$

The final step of the algorithm is to obtain the output image with inverse transformation. It is obtained as follows:

$$z = G^{-1}(T(k)) \tag{10}$$

The primary aim of this method is to obtain uniform gray level distribution between the upper and lower limits. However, it gives similar results to the histogram equalization, because there is no control over higher histogram frequencies. Therefore, over enhancement is introduced at the final image.

2.1.3 PLATEAU HISTOGRAM EQUALIZATION METHOD

This method is the modified version of the histogram equalization. Histogram equalization method covers the entire dynamic range of the output histogram. Therefore, it provides a fine contrast enhancement. However, histogram equalization method assigns a large gray level interval to the objects with high frequencies (background, large objects, etc.). This method introduces a plateau threshold value to the histogram equalization algorithm in order to suppress over enhancement in the final image. If the frequency of an object background is limited to a threshold value, then the gray level range of the object background will be less than the expected values. This process provides better enhancement of the targets in the final image. An appropriate threshold value T is used to limit the frequencies of the objects in the input histogram. Any frequency which is greater than the threshold value T is made equal to T. If it is smaller than T, then it is left unchanged. It is implemented in the probability density function as follows:

$$PDF_T(k) = \begin{cases} PDF(k), PDF(k) \leq T \\ T, PDF(k) > T \end{cases} \tag{11}$$

Where $0 \leq k < 2^m$-1,

where k denotes the pixel value in the input image; PDF(k) denotes the occurrence value of pixel level k in the original histogram, and $PDF_T(k)$ denotes the probability density function after thresholding operation. The cumulative distribution function is calculated as follows:

$$CDF(k) = \sum_{i=0}^{k} PDF_T(l), \tag{12}$$

2.1.3.1 Selection of the Threshold Value

The threshold value of the plateau histogram equalization affects the output performance of the algorithm. It is very clear that this algorithm turns into the histogram projection if T equals to 1, and it turns to histogram equalization if T equals to the maximum frequency value in the histogram. It is very likely that this maximum value corresponds to the background of the image because the background generally has the higher frequency in the original histogram. An appropriate threshold value prevents the excessive gray level stretching for background area. Therefore, objects in the original image will be enhanced greatly while suppressing the object background. Apart from a manual threshold selection, an adaptive method for the calculation of the threshold value T is proposed in [7]. The processes of this algorithm are as follows:

- Histogram is calculated from the input image.
- Median filter is applied to the histogram for the window size 3. This operation smooths the rapid frequency change in the histogram.
- Nonzero histogram values are obtained from the smoothed histogram.
- Local minimum values are calculated
- The median value of the local minimum vector is selected as the threshold value.

2.1.3.2 Tail-less Plateau Histogram Equalization Method

This method is the modified version of the plateau histogram equalization. It forces the frequency values at the beginning and end of the histogram to zero, thus forces the cumulative distribution function to saturation [8]. Therefore, resulting histogram gives a better dynamic range for the remaining input values and further enhances the image compared to the plateau histogram equalization method. The performance of this operation depends on the clipping percentage. This percentage, tmax, takes a value between 0 and 0.5. PDF_{-T}(k) denotes the frequency value in the histogram after the plateau threshold value is applied, and CDF_T(k) denotes the cumulative distribution value corresponding to the PDF_T(k).

This PDF is calculated as follows:

$$PDF(k) = \begin{cases} PDF_T(\mathrm{k}), CDF_T(\mathrm{k}) \in [tmax, 1 - tmax] \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases}, 0 \leq k \leq 2m - 1 \tag{15}$$

2.2.4 ADAPTIVELY MODIFIED HISTOGRAM EQUALIZATION METHOD

A method is proposed in [9] to control enhancement rate and preserve the shape of the histogram. This method is named as Adaptively Modified Histogram Equalization. PDF denotes the probability density function of the input image. The length of the PDF function depends on the depth of an input image. Minimum, maximum and mean frequency values of the PDF function are found as follows:

$$PDF_{MAX}\text{=max } (PDF) \tag{16}$$

$$PDF_{MAX}\text{=min } (PDF) \tag{17}$$

$$PDF_{MEAN}\text{=}(PDF_{MAX} + PDF_{MIN})/2 \tag{18}$$

The mean PDF value is used to divide an image into two sub images. After this, new PDF function is calculated by modifying the upper and lower sub images with their gradient information. The probability density function of the input image is modified as follows:

$$PDF_{AHME}(k) = \begin{cases} PDF_{MEAN} + \alpha \times \frac{(PDF(k) - PDF_{MEAN})^2}{(PDF_{MAX} - PDF_{MEAN})}, PDF(k) > PDF_{MEAN} \\ PDF_{MEAN} + \alpha \times \frac{(PDF_{MEAN} - PDF(k))^2}{(PDF_{MEAN} - PDF_{MIN})}), otherwise \end{cases} \tag{19}$$

The variable α determines the enhancement rate, and it is calculated adaptively. Mean frequency count also corresponds to the mean pixel intensity value. Therefore, these sub images contain intensity values, which are smaller and given by-

$$\alpha = \frac{k_m - k_{ml}}{k_{mu} - k_{ml}} \tag{20}$$

$$\alpha = \frac{k_{mu} - k_m}{k_{mu} - k_{ml}} \tag{21}$$

The constants k_{mu} and k_{ml} denote the mean values of the first and second sub images respectively. The variable has a value for each half of image. The modified pdf function is set to zero when the equation is negative. The cumulative distribution function (cdf) and final mapping are obtained as follows:

$$CDF_{AHME}(k) = \sum PDF_{AHME}(l), \tag{22}$$

$$k' = \frac{CDF_{AHME}(k)}{CDF_{AHME}(k)(2^m - 1)} \times (2^n - 1), \tag{23}$$

The constants m and n represents the depth of input and output images respectively. AMHE method divides an input image to two sub images based on the mean histogram frequency value and enhances them separately. It can enhance contrast by preventing the significant change in gray level. This method has better output performance compared to HE. However, it has a higher computational load.

2.2. SOME MORE METHODS INTRODUCED IN LITERATURE

2.2.1. BRIGHTNESS PRESERVING BI-HISTOGRAM EQUALIZATION (BBHE)

To overcome the drawback introduced by the HE method described, brightness preserving Bi-HE (BBHE) [2] technique was introduced. In this method, decomposition of the original image into two parts is done, by using the image mean intensity pixel, and then application of the HE method on each of the sub-images is done independently. The resultant image is obtained by union of the two equalized sub -images. The main purpose of BBHE method is to preservation of the mean brightness of an input image and enhancing the contrast of the input image.

In BBHE the input image is separated into two sub images according to the mean of the image. First sub-image, has pixels which have intensity value less than or equal to the mean of the input image and the second sub image has pixel values that have intensity value more than the mean. Such that first sub image is equalized over the range of values less than the mean and the second sub image is equalized over the range of pixel values from the mean based on their histograms. Thus, the output histogram is obtained by the merging of the two histogram bounded around the mean and hence preserving the mean brightness of the image. Let m be the mean of the image **X**. According to the mean of input image the image is divided into two sub-images $\boldsymbol{X_L}$ and $\boldsymbol{X_U}$ where

$$X_L = \{X(i,j) | X(i,j) \leq X_m, \forall\, X(i,j) \in X\} \quad (26)$$

$$X_U = \{X(i,j) | X(i,j) > X_m, \forall\, X(i,j) \in X\} \quad (27)$$

The cumulative density functions (CDF) for **{$\mathbf{X_L}$** and **{X}u** are given as-

$$C_{L(x)} = \sum_{j=0}^{k} p_L(X_j) \quad (28)$$

$$C_{L(x)} = \sum_{j=m+1}^{k} p_U(X_j) \quad (29)$$

The transformation functions of the images are given below-

$$f_L(x) = X_0 + (X_m - X_0)c_L(x) \tag{30}$$

$$f_U(x) = X_{m+1} + (X_{L-1} - X_{m+1})c_U(x) \tag{31}$$

That is, the resultant image of the BBHE, **Y,** is given as

$$\text{Y}=\{Y(i,j)\} = f_L(X_L) \cup f_U((X_U) \tag{32}$$

2.2.2. DUALISTIC SUB IMAGE HISTOGRAM EQUALIZATION (DSIHE)

In Dualistic sub-image histogram equalization (DSIHE) method the input histogram is separated into two sub images [3] same as in BBHE. Both BBHE and DSIHE algorithms are similar other than the fact that DSIHE decomposes the histogram based on intensity level equal to the median instead of the mean as used in BBHE, i.e. instead of separating the image in two parts based on its mean gray level, the DSIHE technique decomposes the image such that maximization of the Shannon's entropy of the resultant image is obtained.

2.2.3. MINIMUM MEAN BRIGHTNESS ERROR BI-HISTOGRAM EQUALIZATION (MMBEBHE)

The basic principle of the BBHE and DSIHE methods of separating an image and then applying the histogram equalization method to equalize the output sub-images independently same as in the technique proposed in MMBEBHE [4]. The main difference between the BBHE and DSIHE methods and the MMBEBHE is that in MMBEBEHE a threshold level is obtained that decomposes the image into two sub-parts, keeping in mind that the minimum brightness difference between the image and the resultant image is obtained.

Then the two sub images obtained after the decomposition of the image according to the threshold are equalized using the classical HE process, hence the output image obtained.

MMBEBHE technique comprises of three steps:

1. Calculation of the Absolute Mean Brightness Error (AMBE) for each of the threshold level.
2. The threshold level, XT such that it yields minimum brightness error (MBE) is obtained.

3. Separating the input image histogram so as to equalize each sub part independently.

There are some images that need higher degree of brightness preservation such as to avoid annoying artifacts. These images are not handled well by BBHE and DSIH In this technique the histogram division is done according to the threshold intensity level which has minimum Absolute Mean Brightness Error (AMBE). It is defined as the absolute difference between the means of input and the output image:

$$AMBE = | E(\mathbf{X}) - E(\mathbf{Y}) | \qquad (34)$$

Lesser the AMBE implies more better brightness preserved image is obtaned.

Algorithm for MMBEBHE:

1. For each and every threshold intensity level AMBE is calculated.
2. The threshold level *XT* that yields minimum MBE is found out.
3. Separate the input histogram into two based on the *XT* found in step 2 and equalized them independently as in BBHE.

Step 1 requires a lot of computation complexity which is the major disadvantage of MMBEBHE

2.2.4. RECURSIVE MEAN SEPARATE HISTOGRAM EQUALIZATION (RMSHE):

In Recursive mean-separate histogram equalization (RMSHE) technique [5], decomposition of the image is done many number of times not as in BBHE. Decomposition of the image is done recursively, up to a parameter r, creating 2r sub-images. Then Histogram Equalization method is applied to each of the sub images obtained. Taking r = 0 (i.e. no sub-image) and taking r =1, the RMSHE method is the HE and BBHE methods, respectively. The value of r is directly proportional to the increase in preservation of output image.

2.2.5. BRIGHTNESS PRESERVING DYNAMIC HISTOGRAM EQUALIZATION (BPDHE)

In BPDHE technique [6], the division of the original image into multiple sub images according to the corresponding local maxima is done, and then to each of the images dynamic histogram equalization is applied and finally, the sub images are merged. The division of the histogram is done based on the local maxima obtained. The ouput image has mean intensity almost equal to HE mean intensity of the input image, hence maintains the mean brightness of the image. Firstly the image is smoothened with one dimensional filter and then it is partitioned according to the local maxima. Then it distributes new dynamic range to each of the partitions obtained. Input image histogram does not normally occupy all dynamic ranges level. BPDHE technique consists of five steps:

1. The histogram of the input image is smoothened with Gaussian filter.
2. The location of local maximums are detected from the smoothened histogram obtained is step 1.
3. Each partition is mapped into a new range.
4. Equalization of each partition is done independently.
5. Image brightness is normalized.

2.2.6. ENTROPY MAXIMISATION HISTOGRAM MODIFICATION SCHEME FOR IMAGE ENHANCEMENT

Global Histogram Equalization methods are very common and competitive as they have easy calculations as compared to others. The GHE techniques enhance images without distorting the image using a single valued transformation function. Study of techniques shows that all GHE methods are divided into two steps, that is, the pixel populations' mergence (PPM) step and the grey-levels distribution (GLD) step. The two steps are as follows-

The two steps are as follows-

1. PPM: A merged histogram is obtained by merging the pixel population of gray scales.
2. GLD: The new pixel populations in the merged histogram are redistributed according to transformation function.

The Pixel population mergence step is only related to pixel population and GLD only relates to the intensity level of pixels of the image. The entropy of an image can only be influenced by pixel populations, maximization of the entropy in the PPM step is done and then the histogram obtained after mergence is redistributed according to a log based transformation function to obtain the enhanced image in the GLD step as proposed in a novel entropy maximization histogram modification (EMHM) technique [6], which consists of PPM and GLD steps as described above. In the PPM step, the entropy of output image is maximized by using a mergence rule as proposed in the paper, i.e, entropy maximization rule (EMR). In the GLD step, the distribution of the new grey scales to the merged grey scales by applying a log-based distribution function (LDF) such as to avoid over enhancement of the image. The EMHM also makes the enhancement level of the input image controllable. Hence, the PPM operation in EMHM reduces the redundancy of original image and increases the entropy and controls the number of grey scale with non-zero pixel populations (GNPP) of output image. The control of GNPP is advantageous in image compression.

CHAPTER – 3

PROPOSED ALGORITHM

3.1. APPROACH USED

In the proposed algorithm, to overcome the problems faced by applying the HE directly to the input image. Firstly the image is decomposed in two parts sub image by the mean, such that the first image is composed of intensities in between the lowest intensity and mean and the second image is composed of intensities in between mean and the highest gray level. Then the two steps as defined below are applied to each of the two image. The resultant of the two images after applying the two steps are merged to obtain the final image. Inspired by the entropy maximization histogram modification method the proposed algorithm also consists of two intermediate steps the Pixel Population Mergence step and the Gray Level Distribution step as is used in all global histogram equalization techniques (GHE).

PROPOSED ALGORITHM-

Step 1: Divide the image in two parts according to the mean of the input image.

Step 2: Apply steps 3 and 4 to both the images separately to obtain two output histograms

Step 3: PPM -

To maximize entropy of the output image ppm step is used

The algorithm is given below:

(a) The intensity m with minimum number of pixels in the input histogram is obtained.

(b) The number of pixel populations in m is added to the adjacent pixel value which has more comparable values, the value of pixel population of m is assigned to zero.

(c) Repeat above (a) and (b) for Tm times,

where Tm is the given mergence times.

$$T_m = k * L_o \tag{38}$$

$$m = -\frac{mean(h(l))}{standard\ deviation(h(l))} \tag{39}$$

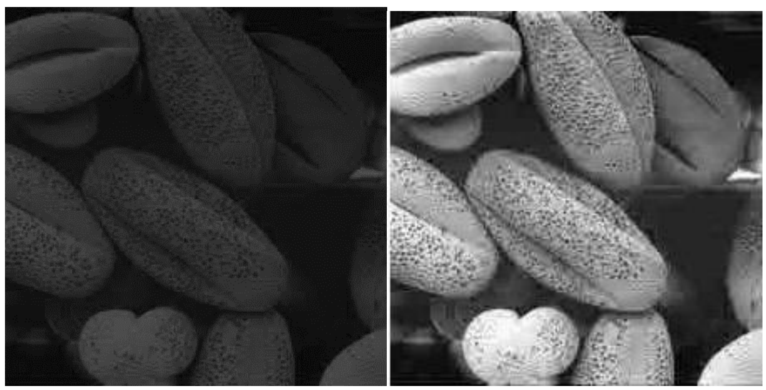
Step 4: GLD:

The histogram obtained after the 3rd step is transformed according to the transformation function. The gray levels of the histogram obtained from step 2 are redistributed in the output histogram transformation function T (l).

$$T(l) = \sum_{j=0}^{l} 1 + \left[\frac{\left[sigmoid(h_{out}(j)/\bar{h}) \times e^{1/m} + 1) \right]}{\sum_{j=1}^{L} sigmoid(h_{out}(j)/\bar{h}) \times e^{1/m} + 1} \right] \times (N - L - 1) \qquad (40)$$

Step 5:

The two output histograms are merged into one resultant histogram of the output.



(a) (b)

Figure 1: Test image beans along with output of proposed approach (a) Original image (b) proposed enahnced image

3.3. FLOWCHART OF PROPOSED METHOD

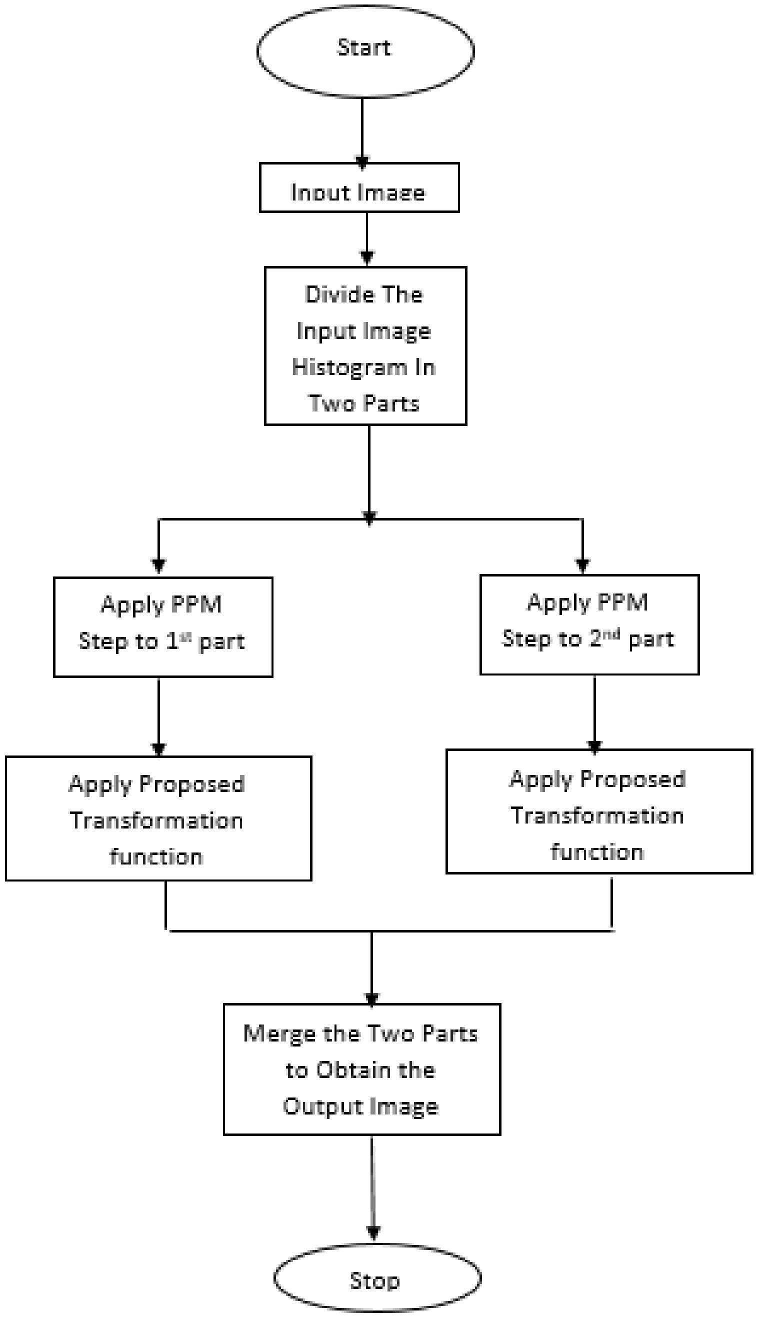


Figure 2- Flowchart of proposed approach

CHAPTER-4

EXPERIMENTAL RESULTS

The Intel® Core™ i7-2630QM CPU @ 2.00 GHz and MATLAB is used to implement the proposed approach. More than 100 images of different sizes and formats have been used as test images to evaluate the performance of the proposed approach and some of these images are presented here. The performance of the proposed approach is evaluated using the objective measures such as Discrete Entropy (DE) and Peak Signal to Noise Ratio(PSNR). The proposed approach is evaluated using different test images shown in Figure 2. The proposed approach has been used on 12 different images of different sizes to obtain enhanced image. All the images used are gray images. The results are then compared to the many contrast enhancement methods – Histogram Equalization [4], Brightness Preserving Bi-Histogram Equalization [5], Dualistic Sub Image Histogram Equalization [3], Minimum Mean Brightness error Bi-Histogram Equalization [2] and Entropy Maximization Histogram Modification technique [1].. Figure 3, Figure 4, Figure 5, and Figure 6 shows the result of application of the 4 mentioned images enhancement techniques and the application of the proposed approach. The result of application of the proposed technique on 8 different images is given in Figure 7, Figure 8, Figure 9, and Figure 10. The visual and quantitative results show that the proposed approach provides better results as opposed to results of others techniques.

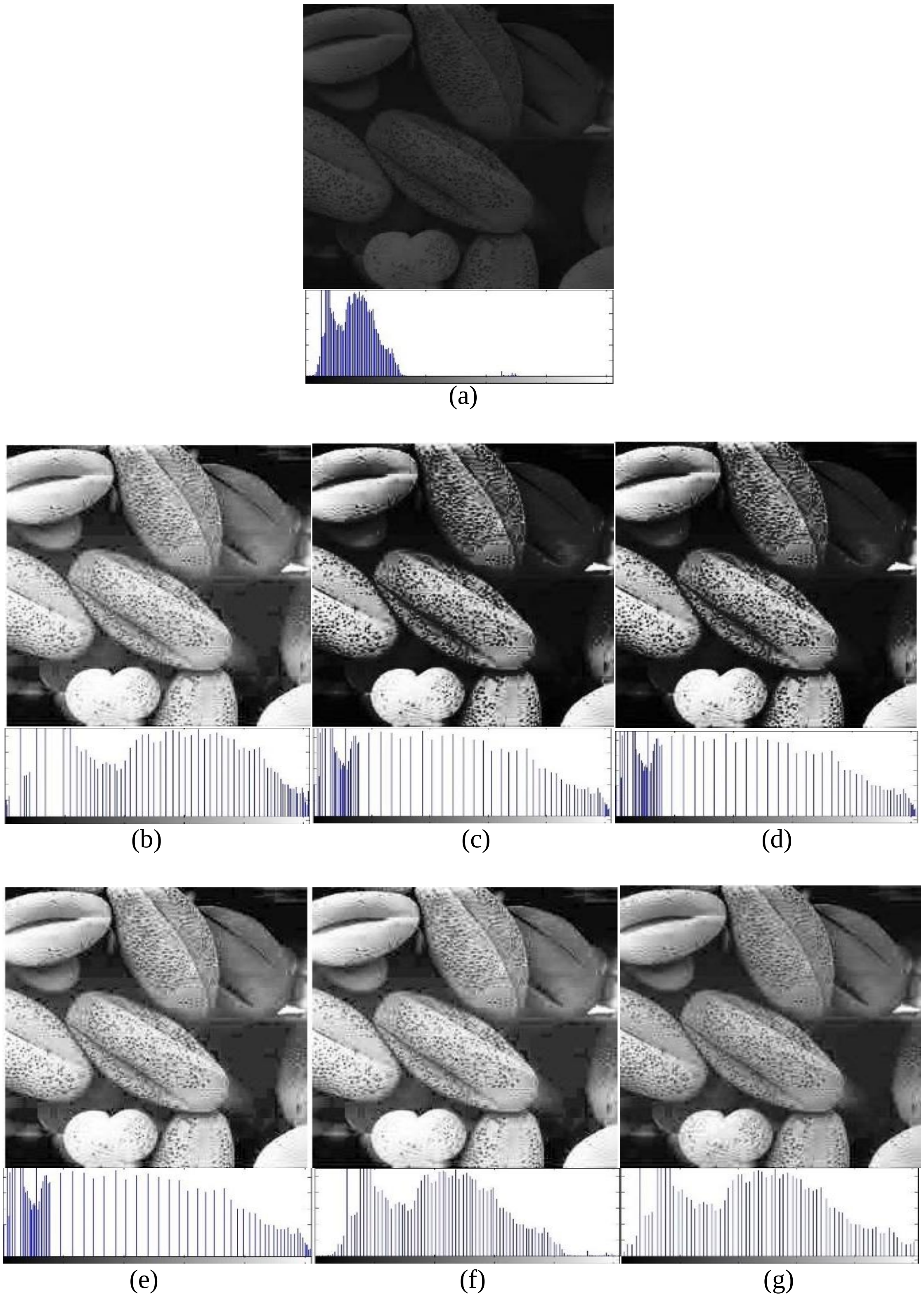
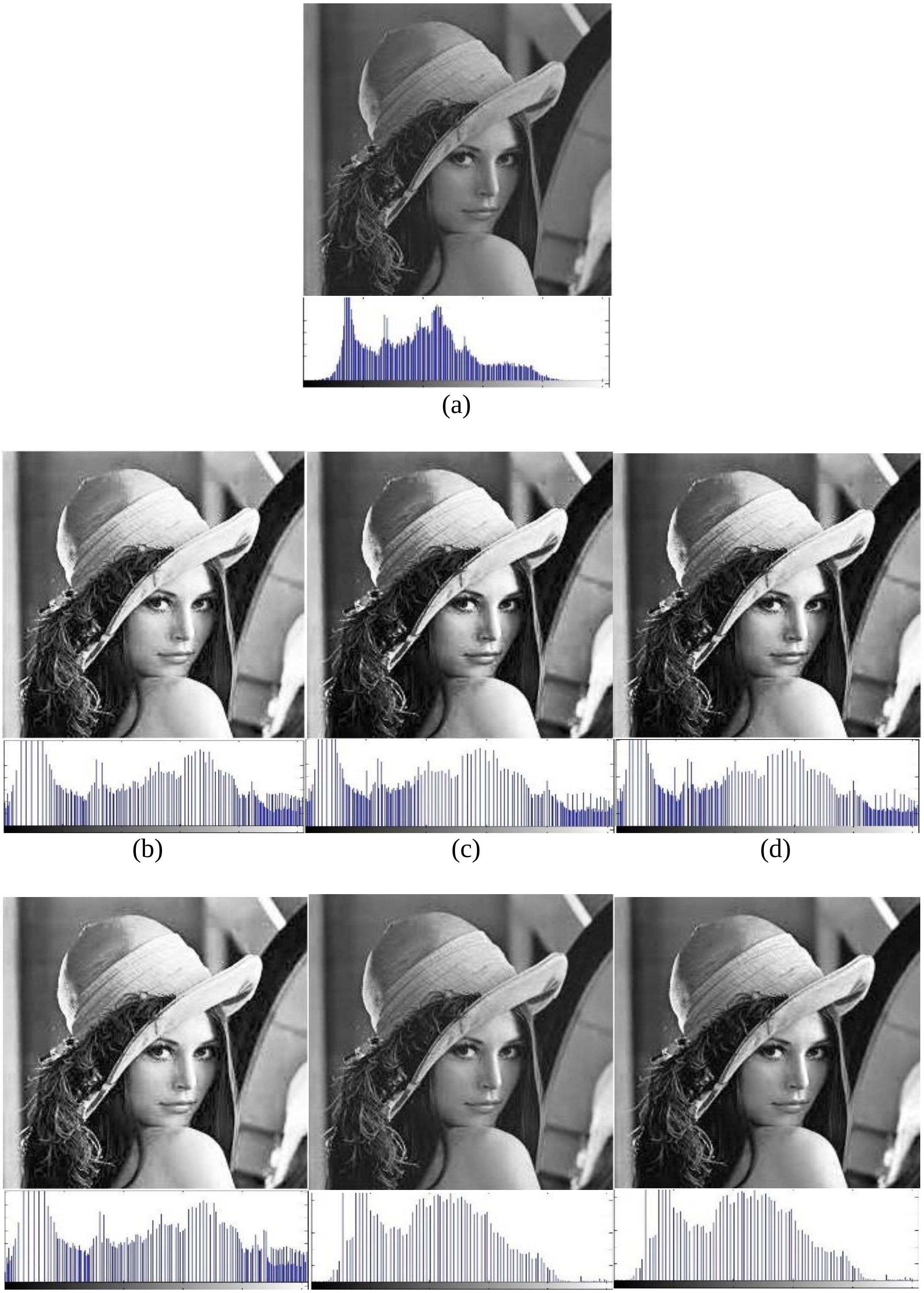


Figure 3: Test image beans along with output of different algorithms and output of the proposed approach (a) Original image (b)HE (c) BBHE (d) DSIH (e) MMBEBHE (f) EMHM (g) proposed approach enhanced image



(a)

(b) (c) (d)

(e) (f) (g)

Figure 4: Test image lena along with output of different algorithms and output of the proposed approach (a) Original image (b)HE (c) BBHE (d) DSIH (e) MMBEBHE (f) EMHM (g) proposed approach enhanced image

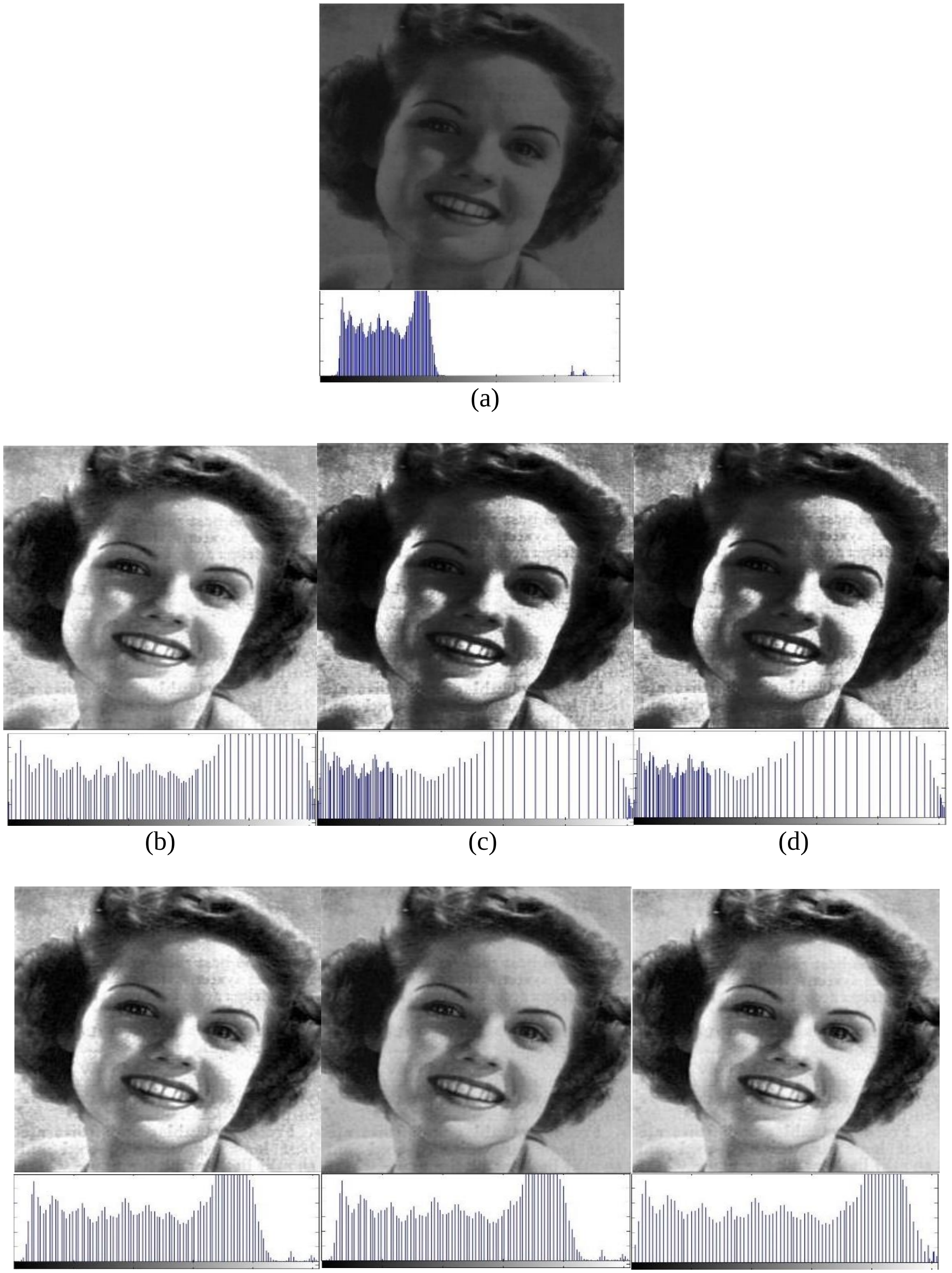


Figure 5: Test image women along with output of different algorithms and output of the proposed approach (a) Original image (b)HE (c) BBHE (d) DSIH (e) MMBEBHE (f) EMHM (g) proposed approach enhanced image

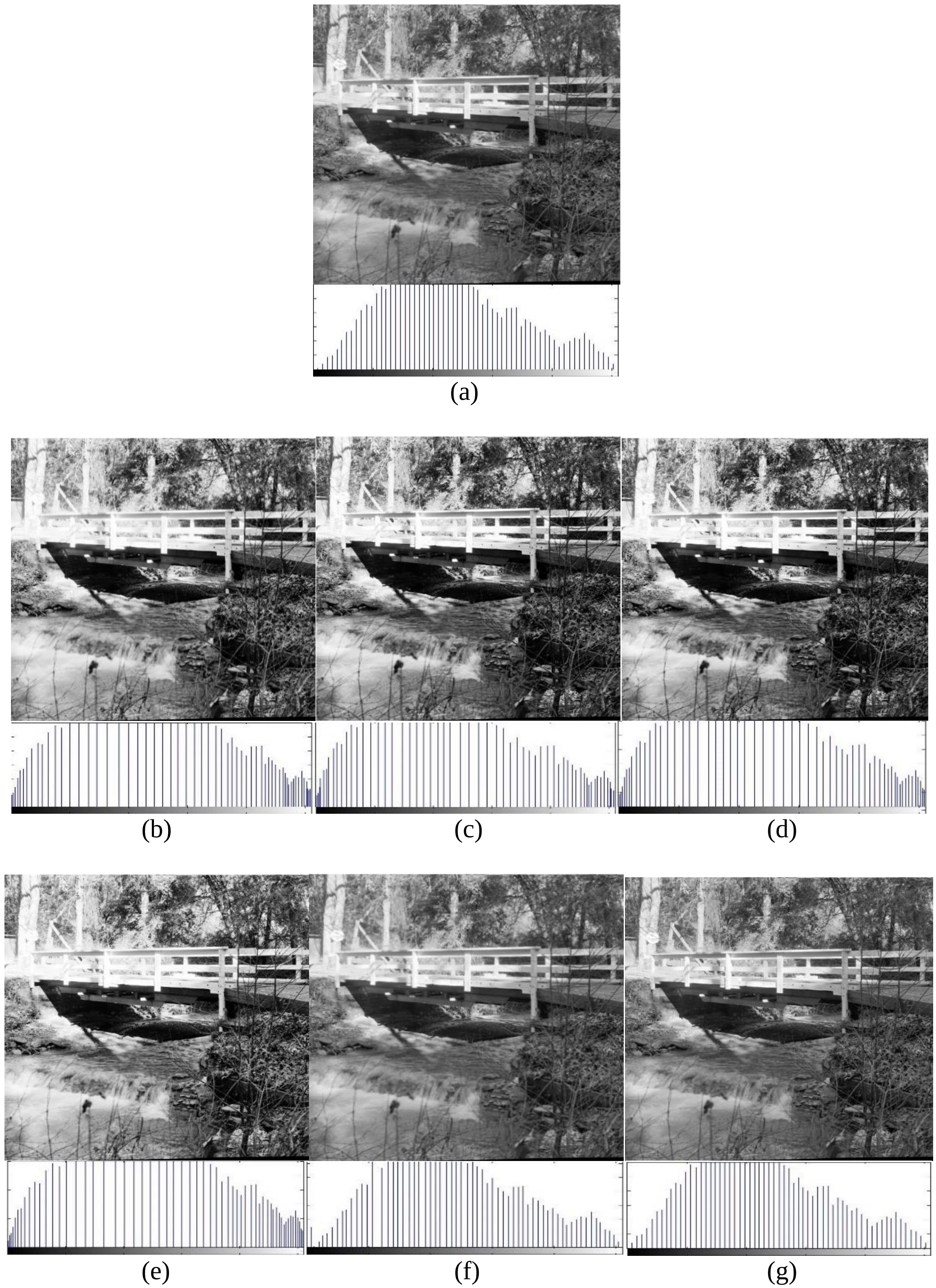


Figure 6: Test image bridge along with output of different algorithms and output of the proposed approach (a) Original image (b)HE (c) BBHE (d) DSIH (e) MMBEBHE (f) EMHM (g) proposed approach enhanced image.

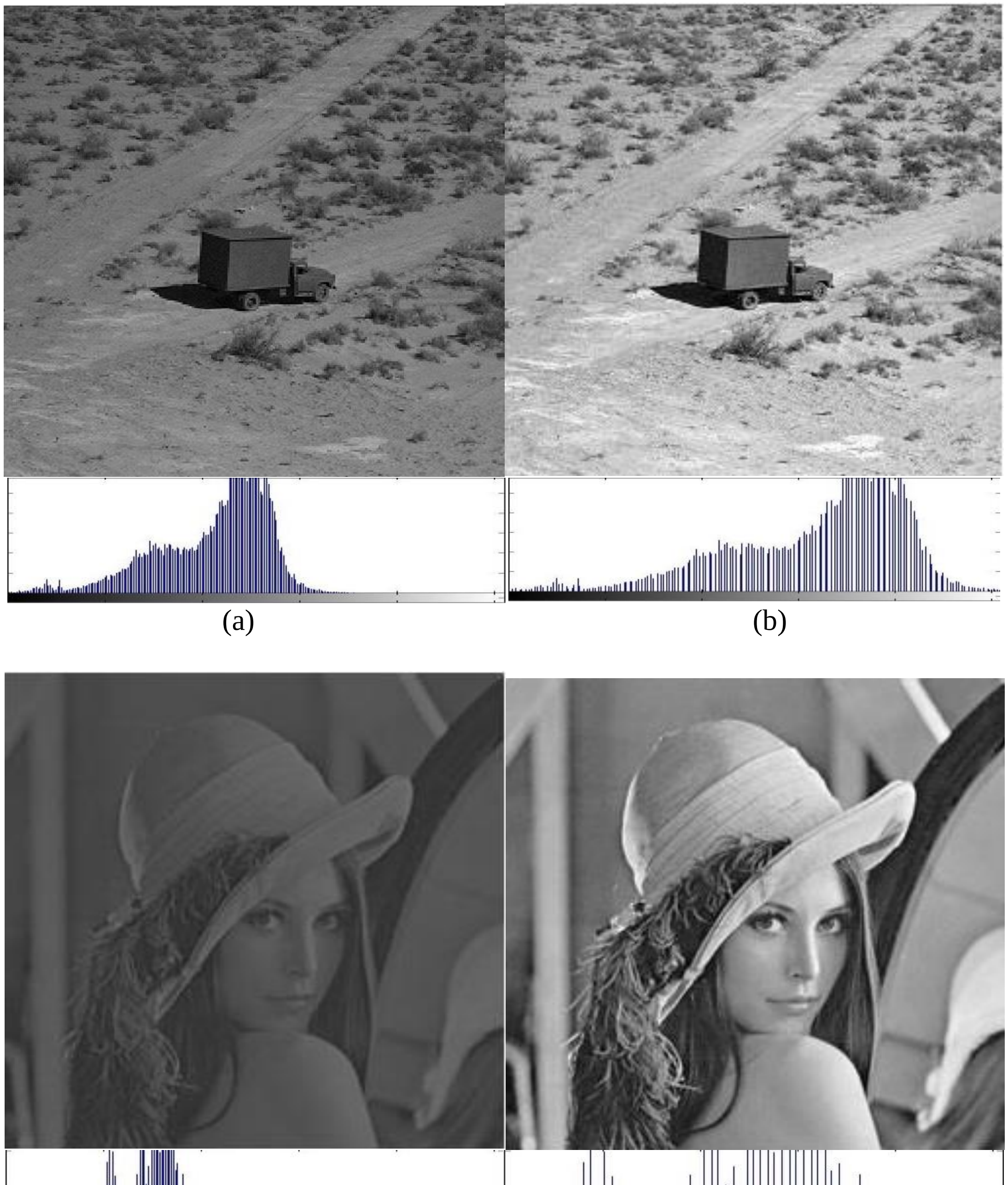
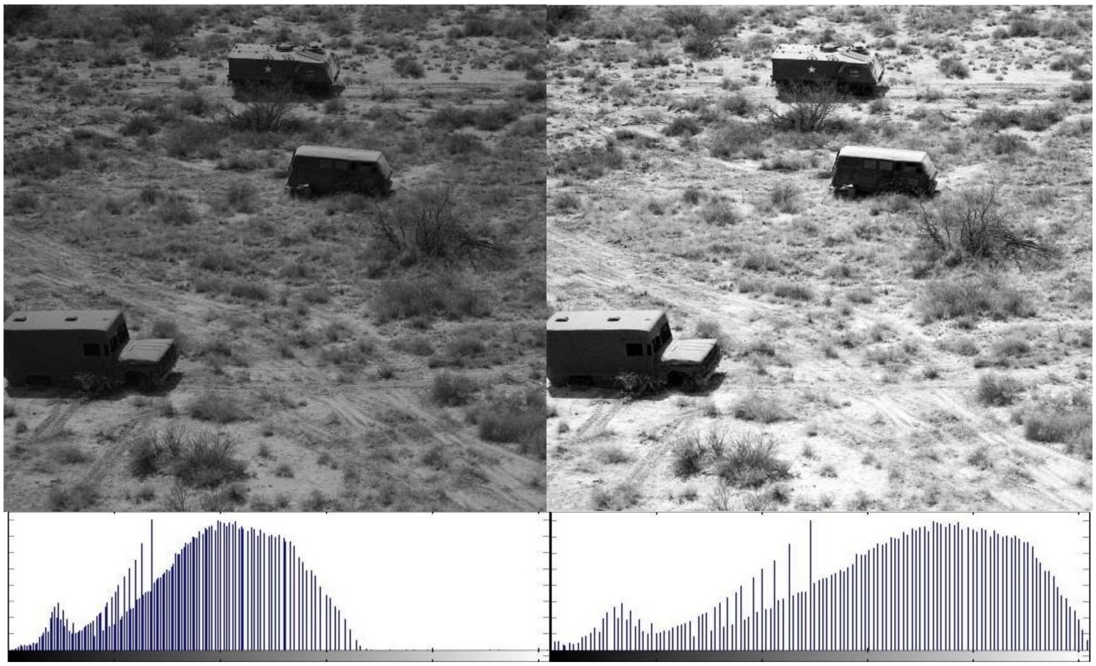
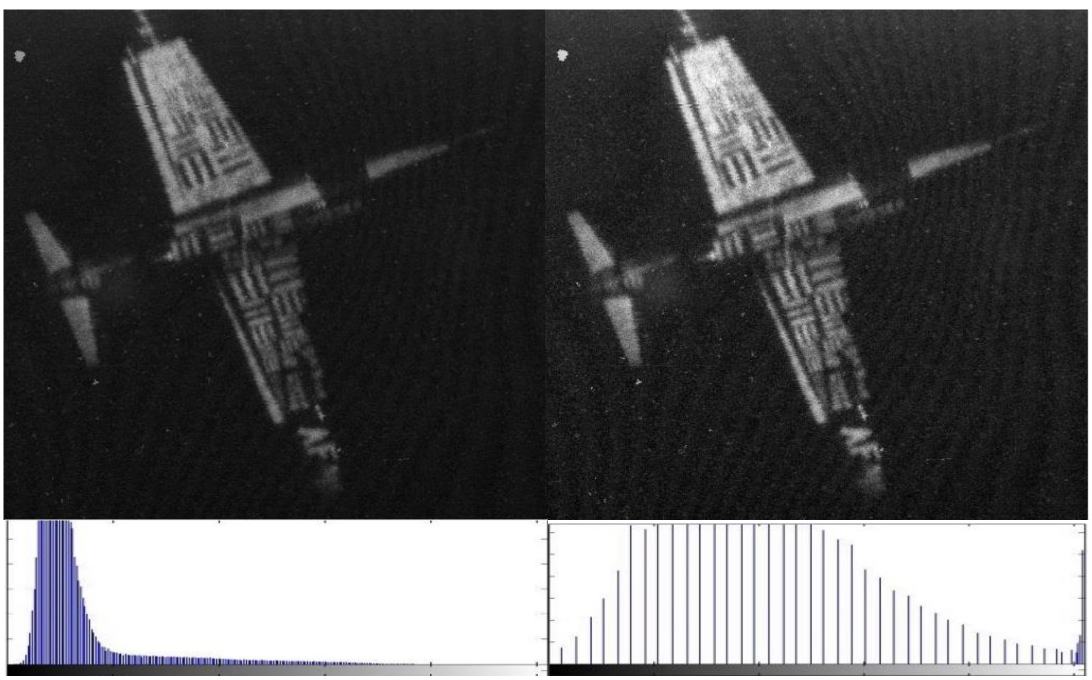


Figure 7: Test image truck and lena_low along with output of the proposed approach (a) Original image truck (b) proposed approach enahnced image of truck (c) original image lena_low (d) proposed approach enhanced image of low_lena

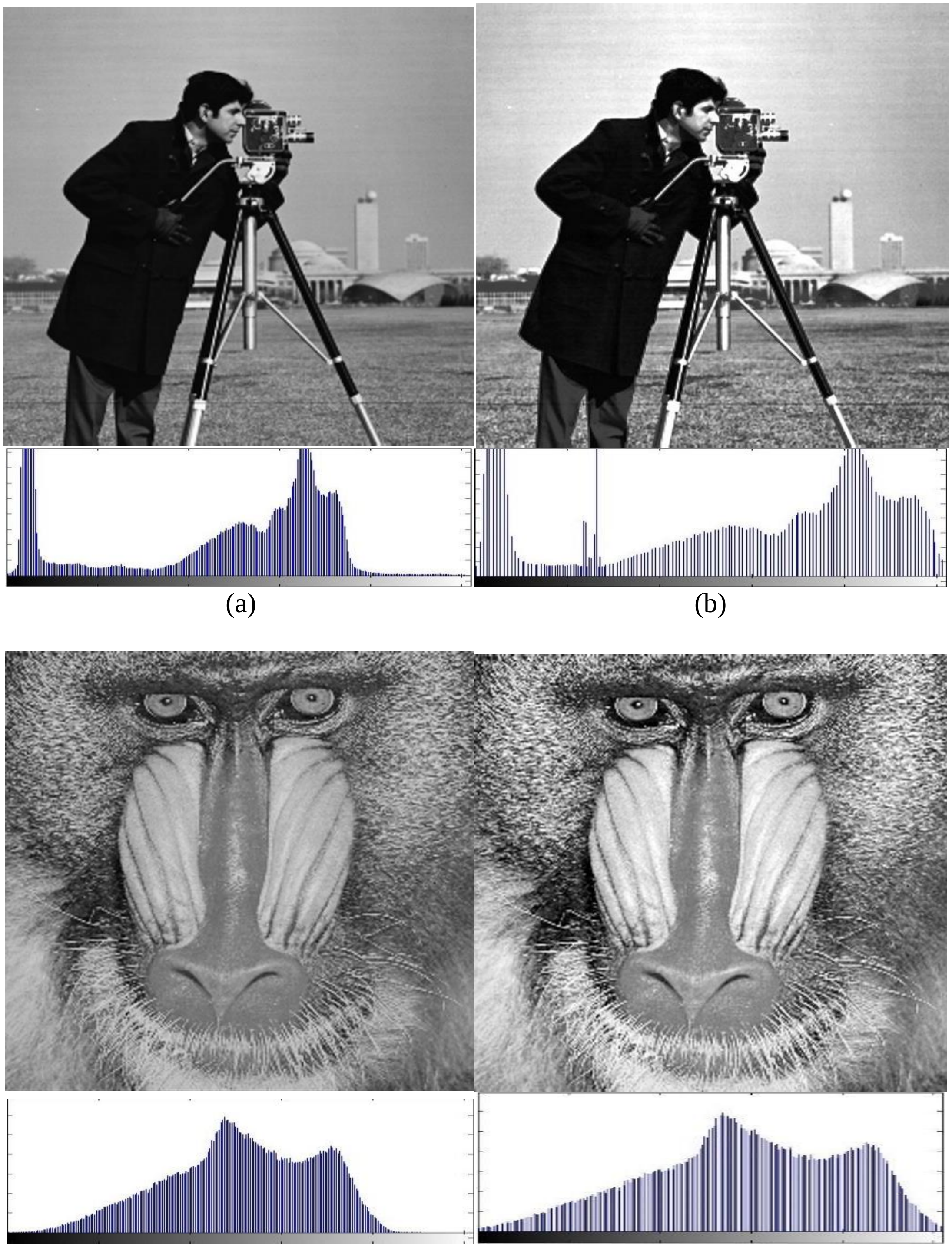


(a) (b)



(c) (d)

Figure 8: Test image desert and aircraft along with output of the proposed approach (a) Original image desert (b) proposed approach enahnced image of desert (c) original image aircraft (d) proposed approach enhanced image of aircraft



(a) (b)

(c) (d)

Figure 9: Test image cameramen and mandril along with output of the proposed approach (a) Original image cameramen (b) proposed approach enahnced image of cameramen (c) original image mandril (d) proposed approach enhanced image of mandril

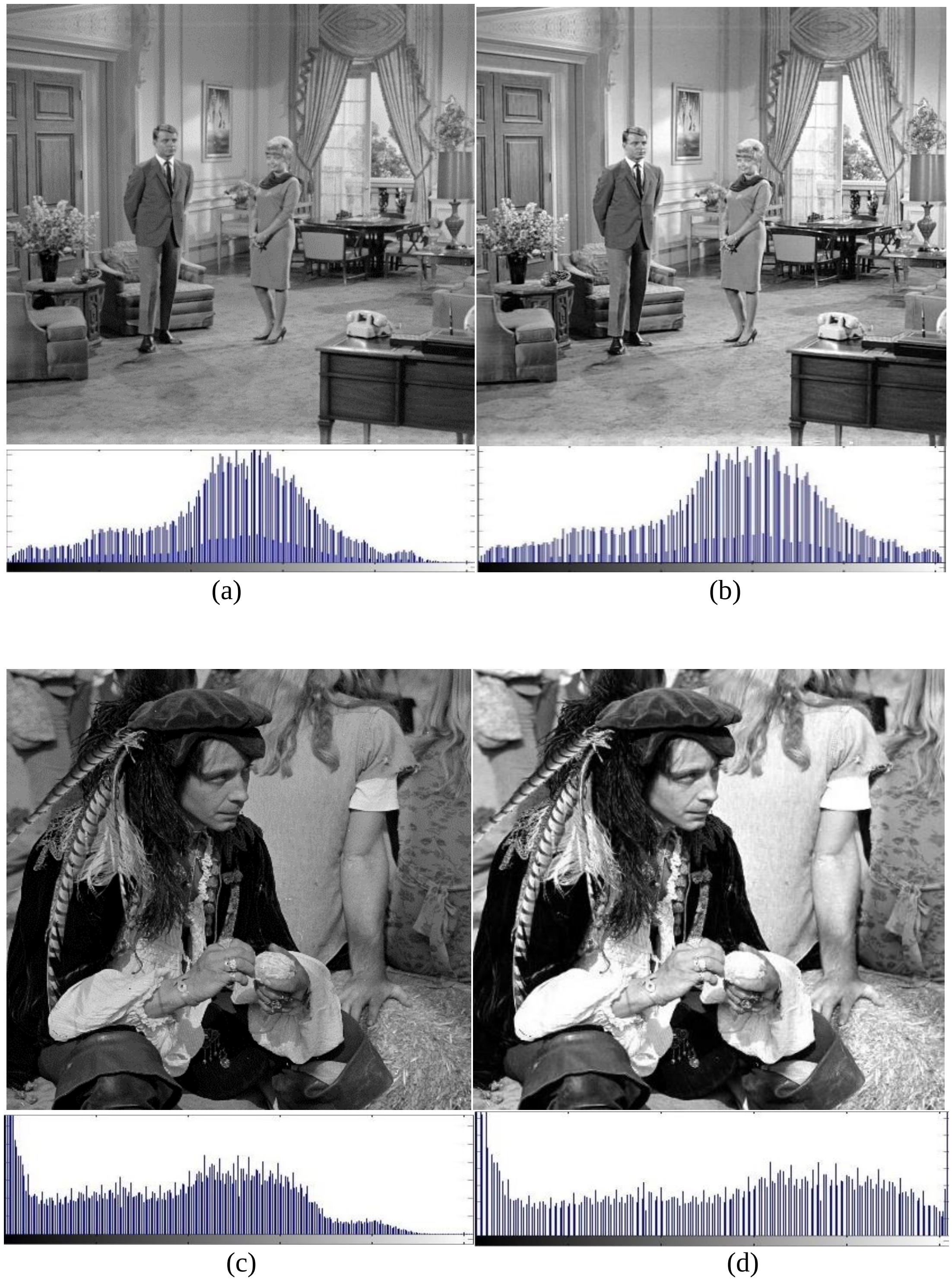


Figure 10: Test image living room and pirate along with output of the proposed approach (a) Original image living room (b) proposed approach enahnced image of living room (c) original image pirate (d) proposed approach enhanced image of pirate.

4.2. PERFORMANCE MEASURES

4.2.1. DISCRETE ENTROPY

Entropy is the spread of states which a system adopts. Low entropy shows that the system occupies a small number of such states and higher entropy means that system occupies a large number of states. For an image these states correspond to the number of gray levels. Thus a perfect histogram equalized image will have high entropy. For an image I entropy is given by-

$$E = -\sum_{k=0}^{L-1} p_k \, log_2(p_k) \tag{41}$$

Where L is the number of gray levels and p_k is the probability of occurrence of gray level with intensity. Discrete entropy compares the entropy of output image with respect to the input image. For input and output image it is defined as-

$$DE(X) = -\sum_{k=0}^{L-1} p_{Y_k} \, log_2(p_{Y_K}) \tag{42}$$

Where p_{Y_k} is the probability of occurrence of intensity level X_k. Normalized entropy $DE_N(X, Y)$ is given by –

$$DE_N(X, Y) = \frac{1}{1+\frac{log_2 256 - DE(Y)}{log_2 256 - DE(X)}} \tag{43}$$

Where X in the input image and Y is the output image. Increase in contrast results in uniform distribution of the histogram and this means that the entropy of the image should increase.

Table 1

DISCRETE ENTROPY VALUES

Image	**HE**	**BBHE**	**DSIH**	**MMBBHE**	**EMHM**	**Proposed**
Lena	0.4182	0.4525	0.4503	0.4173	0.4672	0.4834
Beans	0.1825	0.2512	0.2542	0.1818	0.2575	0.3478
Girl 1	0.2879	0.3504	0.3536	0.2873	0.3118	0.3869
Truck	0.4330	0.4258	0.3892	0.4516	0.4527	0.4531
Bridge	0.4554	0.4848	0.4800	0.4530	0.4928	0.4990
Scene	0.3876	0.4279	0.4297	0.3866	0.3448	0.4381
Aircraft	0.1682	0.3428	0.2527	0.1680	0.3900	0.4443
Girl 2	0.2869	0.3954	0.3599	0.2864	0.4300	0.4664
Woman	0.3846	0.4520	0.4366	0.3818	0.4797	0.4975
LivingRoom	0.4731	0.4679	0.4770	0.4719	0.4850	0.4926

As we can see in the above table, the proposed method has the highest value of DE even better than the EMHM. Higher value of DE shows that the output image has highest entropy possible.

4.2.2. PEAK SIGNAL TO NOISE RATIO (PSNR)-

PSNR expresses the ratio to signal (power to power of the distorting signal). PSNR is computed by first calculating Mean Squared Error (MSE) between original image X and output image Y as –

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[X(i,j)-Y(i,j)]^2}{MXN} \tag{44}$$

PSNR is decibels is given as –

$$PSNR = 20log\left(\frac{\max(Y(i,j))}{\sqrt{MSE}}\right) \tag{45}$$

PSNR is inversely proportional to MSE which measures the squared difference between the pixel intensity between the pixel intensity values of output image w.r.t the original image. Thus smaller the MSE (higher would be PSNR) closer is the output image to the original image.

Table 2
PSNR VALUES

Image	**HE**	**BBHE**	**DSIH**	**MMBBHE**	**EMHM**	**Proposed**
Lena	16.7171	19.5887	19.3933	16.6428	25.7766	29.0746
Beans	7.5648	10.4336	10.4336	7.5293	11.4108	16.3111
Girl 1	9.6134	11.8748	11.9944	9.5934	11.4987	15.2961
Truck	13.4599	13.3181	13.8349	13.4692	13.9740	19.5854
Bridge	19.3042	21.7274	21.2022	19.0685	37.6565	39.7077
Scene	13.0110	14.4266	14.5138	12.9901	11.5520	17.9392
Aircraft	6.9381	15.6117	10.9213	6.9258	22.7183	24.9716
Girl 2	10.0191	16.6065	14.3324	9.9959	22.9444	27.2686
Woman	13.3838	17.4325	16.3210	13.1493	30.9606	38.9831
LivingRoom	17.4836	17.3889	17.5370	17.4879	30.6861	32.3298

As seen in the above table the PSNR values for the propose method are the highest, which means that the output is much closer to the original image and is less distorted as compared to other methods.

CHAPTER 5

CONCLUSION

In the work presented, image enhancement is done such that the brightness of the image is preserved and we can get the maximum entropy. Step by step methodology for image contrast enhancement is presented. In the proposed method the image is divide in two parts and the two steps of Global Histogram Equalization (GHE) is applied which is modified to get maximum entropy. Comparison with other methods shows that the presented work has better performance as compared to BBHE , DSIH, MMBBHE, HE , EMHM .comparison is done using the two parameters discrete entropy and peak sound to noise ratio. Higher values of PSNR show that the resultant image is much closer to the original image. Higher discrete entropy shows that the image entropy is maximized. Hence the presented work shows better results and overcomes the drawbacks of Histogram Equalization. Combines the advantages of the two methods BBHE and EMHM.

CHAPTER 6

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