A project report on

BRIGHTNESS PRESERVING CONTRAST ENHANCEMENT USING ADAPTIVE GAMMA CORRECTION

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

Master of Technology

In

Information Systems

Submitted by:

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CERTIFICATE

This is to certify that Ms. Anchal Goswami (2K14/ISY/02) has carried out the major project titled "***Brightness preserving Image Contrast Enhancement using Adaptive Gamma Correction***" as a partial requirement for the award of Master of Technology degree in Information Systems by Delhi Technological University.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2016. The matter contained in this report has not been submitted elsewhere for the award of any other degree.

(Project Guide)

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M.Tech (Information Systems)

ABSTRACT

Nowadays image processing has become a prerequisite in most of the major applications such as surveillance, remote sensing, navigation, medical science, human identification, radiography, forensics etc. Different image processing techniques deployed in different applications help to find particular features and analyze the image for specific purposes. There is a wide domain of such techniques used specifically. One of the major areas of image processing is contrast enhancement in which intensities of image are distributed over the entire range of intensities in proportional to original image so as to achieve maximum contrast. There are various methods proposed and analyzed in this field such as histogram equalization, BBHE, MMBEBHE, RSIHE etc. The proposed approach achieves contrast enhancement thereby restoring maximum brightness and content of an image. Results show a visually better image and are compared with other algorithms using image evaluation parameters.

LIST OF FIGURES AND TABLES

Chapter 1

INTRODUCTION TO CONTRAST ENHANCEMENT

Image enhancement improves interpretability or perception of images for human vision and provides better input for automated image processing techniques. The main objective of image enhancement is to change image attributes to make itsuitable for a specific application or observer. The selection and modification of attributes varies with applications which introduces a great deal of subjectivity into the selection of image enhancement technique. There are a lot of techniques which enhance images based on certain parameters producing specific changes. Edge detection and segmentation are the methods to detect edges, corners and objects in an image. Gamma correction changes the brightness of an image based on a fixed parameter gamma. Contrast enhancement is one of the image processing areas which improves the visibility of an image by enhancing the difference in brightness of objects and their backgrounds. It is performed typically as a contrast stretch i.e. intensities are distributed over the entire range of intensities. Thus it improves the brightness differences across the dynamic range of the image. It is better than tonal enhancements as tonal enhancements improve the brightness differences in different gray level regions (dark, mid, bright) at the expense of the brightness in the other regions. A probability density function spanning full range of gray-level values produces a high contrast image; therefore, a low contrast image can be converted into a high-contrast image by stretching the intensity values so that the histogram spans the full gray values range.

The contrast stretch is referred to as histogram equalization. Histogram equalization is for contrast adjustment using histogram of the image. It maps the gray levels on the basis of the probability of distribution. It flattens the histogram to occupy the entire range of gray level values and thus results in improving contrast of the image. It increases the global contrast of images, specifically when the content of the image is presented by close values of contrast. In this way, intensities are better distributed on the dynamic range of histogram. This converts low contrast areas to high contrast. This process spreads out the high frequent intensity values efficiently to stretch the histogram. For a given image X, the probability density function $p(X_k)$ is defined as

$$p(X_k) = n^k/n \tag{1}$$

for k = 0, 1, …, L – 1, where n_k represents the number of times that the intensity level X_k appears in the input image X and L is the total number of intensity samples in the image. It is to be noted that $p(X_k)$ is probability density function of the input image which represents the number of pixels that have a specific intensity X_k. The plot of n_k vs. X_k is known histogram of X. Based on the probability density function, the cumulative density function is defined as

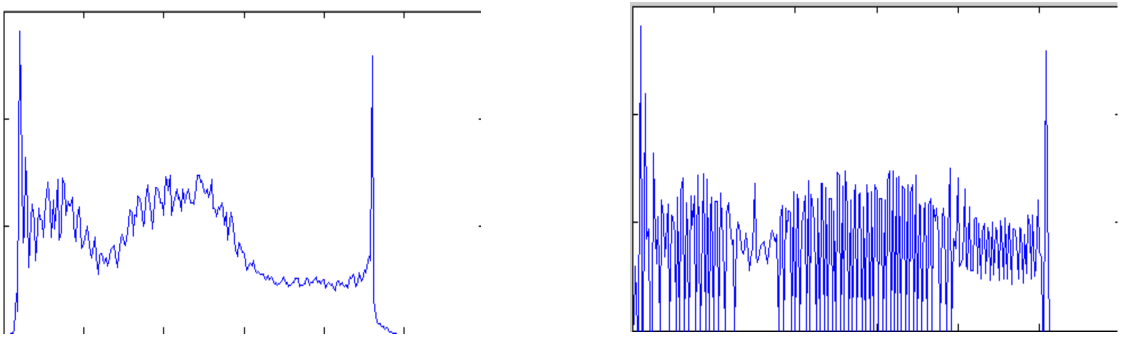
$$c(\mathrm{x}) = \sum_{j=0}^{k} p(Xj) \tag{2}$$

where X_k is the intensity level, for k = 0, 1, …, L – 1. Note that $c(X_{L-1}) = 1$ by definition. HE is a method that maps the input image histogram so as to occupy the entire dynamic range, i.e. (X_0, X_{L-1}). For this purpose, it uses cumulative density function as the transform function. Define a transform function f(x) based on the CDF as

$$f(x)=X_o + (X_{L-1} - X_o)\, c(x) \tag{3}$$

Then the output image of the Histogram Equalization, Y = {Y(u,v)}, can be expressed as

$$\begin{aligned} Y &= f(X) \\ &= \{f(X(u,v)) \mid \forall\, X(u,v) \in X\} \end{aligned} \tag{4}$$



(a) (b)

Fig.1. Contrast Enhancement using histogram equalization (a) Histogram of unprocessed image, (b) Histogram of histogram-equalized image

The performance of the HE to enhance the contrast of the image is the effect of expansion in the entire dynamic range. Besides, HE also flattens a histogram. As per information theory, the entropy of source will be the maximum when the message has the property of uniform distribution. Furthermore, HE tends to combine gray levels of relatively low probability density, and results in decrease of entropy although such action tends to increase the contrast of an image.

Chapter 2

LITERATURE SURVEY

2.1 Brightness preserving Algorithms:

2.1.1 Bi-histogram equalization (BBHE):

This method was proposed to correct the problems of histogram equalization method. BBHE first separates the histogram of input image into two, dividing using its mean. Thus, one has a range from minimum gray level to mean gray level and the other ranges from mean to the maximum gray level. Next, it equalizes the two histograms independently. It has been analyzed both mathematically and experimentally that this technique is capable to preserve the original brightness to a certain extent, better than histogram equalization. Let X_m denotes the mean of the image X and $X_m \in \{X_0, X_1, \ldots, X_{L-1}\}$. Based on the mean, the input image is divided into two sub-images X_L and X_U as

$$X = X_L \cup X_U \tag{5}$$

where $X_L = \{X(u,v) \mid X(u,v) \leq X_m \ \forall X(u,v) \in X\}$

$X_U = \{X(u,v) \mid X(u,v) \geq X_m \ \forall X(u,v) \in X\}$

Thus, the sub-image X_L is composed of $\{X_0, X_1, \ldots, X_m\}$ and the other image X_U is composed of $\{X_{m+1}, X_{m+2}, \ldots, X_{L-1}\}$.The respective probability density functions of the sub-images X_L and X_U as

$$p_L(Xk) = n^k{}_L / n_L$$

$$p_U(Xk) = n^k{}_U / n_U$$

where k = m+1, m+2, …, L-1, in which n^k_L and n^k_U represent the respective numbers of X_k in X_L and X_U, and n_L and n_U are the total number of samples in X_L and X_U, respectively.

Similarly, $c_L(x)$ and $c_U(x)$ are respective cumulative density functions for X_L and X_U. Note that $c_L(X_m) = 1$ and $c_U(X_{L-1}) = 1$ by definition. Similar to the case of HE where a cumulative density function is used as a transform function, following transform functions are used to calculate equalized sub images:

$$f_L(x)= X_o+(X_m-X_o)\, c_L(x) \tag{8}$$

$$f_U(x)= X_{m+1}+(X_{L+1}-X_{m+1})\, c_U(x) \tag{9}$$

Based on these transform functions, sub images are equalized independently and the composition of the resulting equalized sub-images constitute the output of BBHE. That is, the output image of BBHE, Y, is finally expressed as

$$\begin{aligned} Y &=\{Y(u,v)\} \\ &= f_L(x_L) \cup f_U(x_U) \end{aligned} \tag{10}$$

where $f_L(x_L) =\{ f_L(x(u,v) \mid \forall X(u,v) \in X_L\}$

$f_U(x_U) =\{ f_U(x(u,v) \mid \forall X(u,v) \in X_U\}$

It should be noted that $0 \le c_L(x), c_U(x) \le 1$, it is easy to see that $f_L(X_L)$ equalizes the sub-image X_L over the range (X_0, X_m) whereas $f_U(X_U)$equalizes the sub-image X_U over the range (X_{m+1}, X_{L-1}). As a consequence, the input image X is equalized over the entire dynamic range (X_0, X_{L-1}) with the constraint that the sample less than the input mean are mapped to (X_0, X_m) and the samples greater than the mean are mapped to (X_{m+1}, X_{L-1}). The preservation of mean intensity of input image indicates the brightness preserving capability of an algorithm. The output mean of the BBHE is a function of the input mean brightness X_m. This fact clearly indicates that the

BBHE preserves the brightness compared to the case of typical HE where output mean is always the middle gray level.

2.1.2. *Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE)*

This method claimed to outperform BBHE in terms of brightness as well as entropy preservation. Both BBHE and DSIHE are similar for the difference that DSIHE divides the histogram on the basis of gray level with cumulative probability density equal to 0.5 instead of the mean gray level as in BBHE. The justification behind this is that this modification yields maximum entropy for the output image. Though, still there are cases which are not handled well by both the BBHE and DSIHE. After the sub-blocks of the image overlap due to segmentation, the Threshold Histogram Equalization method should be deployed several times to stretch the local contrast per block.

2.1.3. *Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)*

This algorithm proposed better brightness preservation. It is an extension of BBHE. The main strategy lies in separating the histogram using a threshold level that yields minimum Absolute Mean Brightness Error (AMBE). This calculation is highly complicated and requires lot of computation to obtain a minimum threshold where there is minimum absolute mean brightness error since it is required to divide and apply whole procedure to histogram at every gray level and then comparing output mean brightness. Therefore, it has also implemented an efficient, recursive and integer-based solution to approximate the output mean as function of threshold level.

Algorithm works as follows:

1. Calculate AMBE for each of the threshold level i.e. each gray level.
2. Find a threshold level, X_T that yields minimum MBE,
3. Divide the input histogram into two on the basis of X_T found in step 2 and equalize the histograms independently.

To calculate Mean Brightness Error (MBE), first calculate the input mean E(X) with similar assumption that $X_0 = 0$, as in the calculation of output mean E(Y). It follows that:

$$E(X) \quad = \sum_{i=0}^{L-1} iP(Xi) \tag{11}$$

Then it follows that these two terms shall cancel off each other in the calculation of MBE as shown below:

$$MBE= (E(Y) + X_o) – (E(X) + X_o)) = E(Y) – E(X) \tag{12}$$

$$MBE_T=MBE_{T-1} + [1-LP(X_T)]/2 \tag{13}$$

The above calculation of MBE involves P(X) which are floating point numbers. Since the application requires only finding the threshold level with minimum AMBE, the scaled MBE would be sufficient Scaled MBE involves only integer numbers. Finally, a recursive algorithm for scaled MBE is proposed to find threshold intensity. The number of gray levels are often of base 2. In such cases, the multiplication with L could be replaced with basic shift operation. Suppose $L = 2^l$, it follows that:

$$SMBE_T = SMBE_{T-1} + [N-(F(X_T)<<l)] \tag{14}$$

In order to find the absolute value of SMBE, a comparator is required. Check each SMBE and if it is negative, negate the value as shown below:

IF (SMBE<0) THEN

ASMBE = - SMBE

ELSE

ASMBE = SMBE

It allows high level of brightness preservation in Bi-Histogram Equalization avoiding unpleasant artifacts and unnatural enhancement because of excessive equalization while enhancing an image as much as possible.

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2.1.4. *Recursive Mean-Separate Histogram Equalization(RMSHE)*

The RMSHE performance is claimed to be better in some applications where HE and BBHE fail. In BBHE, separation is done once on the basis of mean, thus there is brightness preservation in most of the situations. It is explained that if mean-separations are done recursively, brightness can be preserved with a high extent. The recursive level for RMSHE is changed according to number of divisions required to divide histogram.

- It is equal to 0 in typical HE, since there is no mean-separation. Equalization is done over the entire range of gray level values.
- Recursive level is equal to 1 in BBHE, and equalizations are executed on two sub-images.
- When it is equal to 2, the input image is separated into four sub-images by separating it recursively on the basis of mean of corresponding sub-images. It is divided on the basis of mean and then further divided into two respective sub-images. The final output image is combination of four equalized sub-images.

2.1.5. *Recursive Sub-Image Histogram Equalization (RSIHE)*

This approach separates the histogram on the basis of gray level with cumulative probability density equal to 0.5. When CDF value is equal to 0.5, the total number of pixels in a sub-image, WU, and the total number of pixels in the second sub-image, WL, are equal. This method possesses the same time complexity, but improves DSIHE as there are multi-equalizations in it to reduce the generation of undesired artifacts. The mean brightness of the output image using RSIHE is the average value of the segmentation gray level and the middle gray level of the gray scale. Therefore, the mean brightness of the original image can be preserved so that the image content and energy is preserved.

2.1.6. *Recursively Separated and Weighted Histogram Equalization (RSWHE)*

In addition to histogram separation techniques, the method uses a weighting function to smooth each sub-histogram for image enhancement as well as brightness preservation.

2.2 Adaptive Gamma Correction with Weighted Distribution

AGCWD is a hybrid histogram modification method which combines Traditional Gamma Correction and Traditional Histogram Equalization methods. A normalized gamma function is used to modify each sub-histogram. The process includes multi-equalizations for brightness preservation. Though the modified sub-histograms lose some statistical information, thereby reducing the enhancement effect. In this method, cumulative density function is directly used and a normalized gamma function is applied to modify the transformation curve according to the input image without losing the available histogram of input image. Consequently, the gamma parameter with low value creates a more significant adjustment in the histogram.

This observation led to deploy a compensated cdf as an adaptive parameter, which modifies the gray values with a progressive increment of the original trend. The adaptive gamma correction (AGC) is formulated as follows:

$$T(l) = l_{max}(l/l_{max})^{\gamma} = l_{max}(l/l_{max})^{1-cdf(l)} \tag{15}$$

For an input dimmed image, most of the pixels are distributed densely in the low-gray level region. On the basis of weighted distribution function, the variant phenomenon is smoothed. This reduces the over-enhancement done by gamma correction. This is a first research work which deploys a combination of cdf, weighting distribution, and gamma correction. The AGCWD method enhances a color image and does not generates any artifacts or distorts the color. Following is the flowchart of AGCWD method:

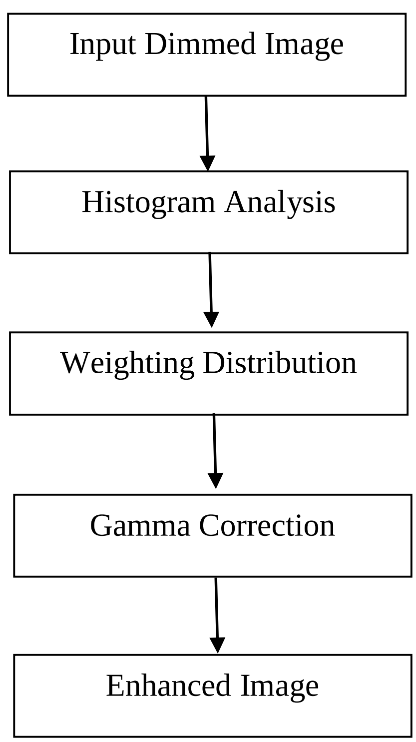


Fig. 2 Flowchart of AGCWD

The AGC method increases the low intensities progressively and avoid the decline of the high gray levels. Moreover, the weighted distribution (WD) function is deployed to modify the statistical histogram and reducing the generation of any adverse effects. The WD function is defined as:

$$pdfw(i) \;=\; pdfmax\left(\frac{pdf(l)-pdfmin}{pdfmax-pdfmin}\right)^{\propto} \qquad (16)$$

where α is the adjusted parameter, pdfmax is the maximum pdf of the input image histogram, and pdfmin is the minimum pdf. On the basis of equation (16), the modified cdf is formulated as

$$\text{cdfw(l)} = \sum_{l=0}^{lmax} pdfw(l) \;/\; \sum pdfw \qquad (17)$$

where the sum of pdfw is calculated as follows:

$$\sum pdfw = \sum_{l=0}^{lmax} pdfw(l) \qquad (18)$$

Finally, the gamma parameter is calculated as follows:

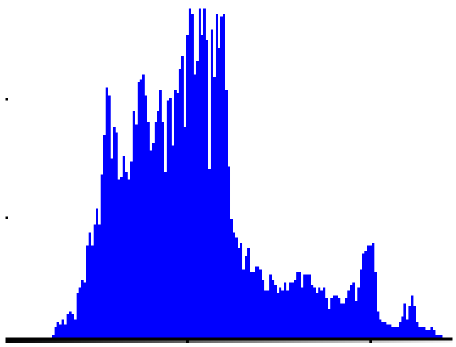
$$\gamma = 1 - cdfw(l) \qquad (19)$$

Therefore, the method can be summarized in few steps. The histogram analysis of input image gives the spatial information of the e image based on probability distribution and statistical information. The weighting distribution is deployed to smoothen the fluctuations and thereby avoiding generation of undesired artifacts. Finally, gamma correction enhances the image contrast using of a smoothing curve.

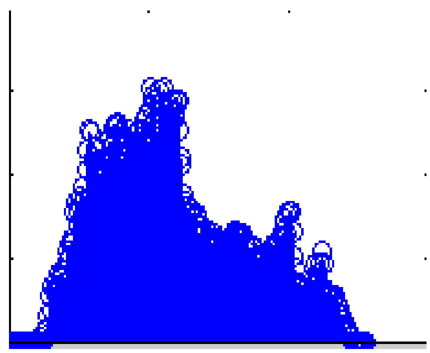
Results of applying AGCWD to monarch image :

(a)

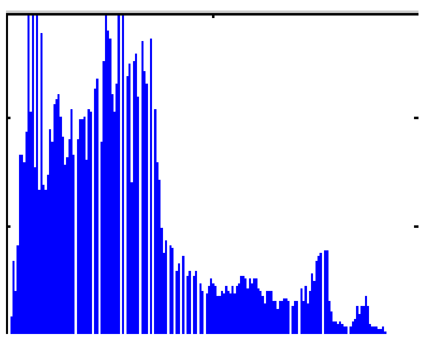
(b)



(c)



(d)



(e)

Fig. 3 AGCWD results (a) Original monarch image , (b) image after applying AGCWD, (c) Histogram of original image ,(d) Weighted PDF ,(e) Histogram of AGCWD image

Chapter 3

GAMMA CORRECTION

Gamma correction is a method to vary the brightness of the image based on a fixed parameter. It is a non-linear variation to individual pixel intensity values. It defines a relation between the intensity value of a pixel and its actual luminance. Each pixel in an image has a level of brightness, called luminance. This ranges from 0 to 1, where 0 implies complete darkness (black), and 1 indicates the brightest value (white). Gamma correction techniques create a combination of general histogram modifying techniques obtained by using a varying adaptive parameter called γ. The simple transformation of gamma correction is derived by

$$T(l) = l_{max}(l/l_{max})^{\gamma} \tag{20}$$

where l_{max} is the maximum intensity in the image. The gray value l of each pixel in the image is transformed to T(l) by performing Eq. (1). As per the formula, the gamma curves with $\gamma > 1$ produce exactly the reverse effect as generated with $\gamma < 1$, as shown in Fig. 1(a). It is to be noted that gamma correction inclines towards the identity curve when $\gamma = 1$ and produces the identical image.

However, when contrast of an image is directly modified using gamma correction, different images exhibit the same modifications in intensity as a fixed parameter is used. To achieve contrast enhancement using gamma correction, the gamma parameter is varied according to the input image intensity levels and there is a different value for each pixel. For example, one approach can be to apply a $\gamma < 1$ for darker pixels and vice versa. Further it is required that the values of gamma should be in consonance with the input gray levels so as to avoid undesired artifacts.

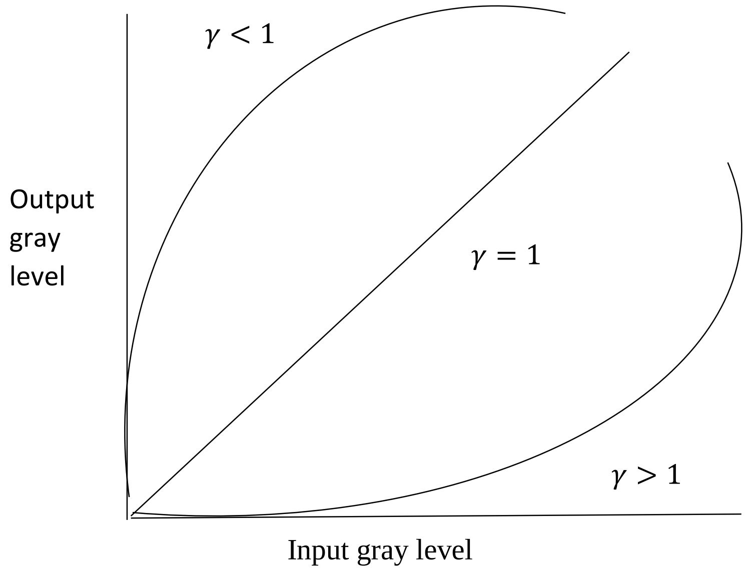


Fig. 4 Gamma curves corresponding to
$\gamma = 1$, $\gamma < 1$ and $\gamma > 1$

Results of applying AGCWD to tulips image :

The following results show that when gamma is equal to 1 , image produced is identical to o riginal image. On the other hand, when gamma is less than 1 , it produces brighter image and when it is more than 1 , darker image is produced.

(a) (b) (c)

Fig. 5 Tulips mage after applying gamma correction (a) Original image ($\gamma = 1$) , (b) image with ($\gamma = 0.8$) , (c) image with ($\gamma = 1.5$)

Chapter 4

PROPOSED APPROACH

4.1 Proposed Algorithm

The proposed approach is intended to enhance contrast of the image preserving its brightness and information content to the maximum level. This approach is an improvement over the previous contrast enhancement techniques as it focuses on retaining maximum information content along with brightness of the image, not completely focusing on stretching contrast. The strategy used to enhance contrast of the image is to first preprocess the histogram by the following procedure. The intensities with high value of probability density function are adjusted to have comparatively low values and vice versa for low-valued intensities. In other words, histogram is adjusted graphically. Let *pdf(i)* represents the value of probability density function at *i*th intensity level for an image X with L intensity levels i=0,1,2,…..L-1. The formula used to achieve this can be described as:

If pdf(i) ≥ meanpdf, then

$$Ppdf(i) = pdf(i)\left(\frac{pdf(i) - meanpdf}{maxpdf - meanpdf}\right)^{cdf(i)}$$

else

$$Ppdf(i) = maxpdf\left(\frac{meanpdf - pdf(i)}{maxpdf - meanpdf}\right)^{cdf(i)} \tag{21}$$

where Ppdf represents preprocessed histogram, maxpdf is the maximum value of probability density function, meanpdf represents mean of the histogram, cdf represents the cumulative density function.

The above described function normalizes the pdf values according to the difference of maximum and mean pdf values. It is to be noted that maximum value of Ppdf is bounded by maximum pdf and calculation takes place according to the relative probabilistic distribution of intensities raised to a degree. This degree of contribution is cumulative distribution of intensities i.e. CDF. This implies that an intensity is transformed to the new intensity with a degree based on its cumulative distribution.

The preprocessed histogram is then used to apply adaptive gamma correction procedure. For this, we create an image by the preprocessed histogram by applying standard procedure. Then spatial adaptive gamma correction procedure is applied. The following procedure is used to calculate spatial gamma values:

- Input image is divided into two sub images on the basis of mean intensity.
- Maximum PDF is calculated separately for the two images i.e. maxpdfL for sub-image with gray level values less than mean intensity and maxpdfU for the other image.

If X(i,j) < mean intensity

$$\gamma(i,j) = 2^{\log(pdf(X(i,j))/\log(maxpdfL)}$$

else

$$\gamma(i,j) = 2^{1-\log(pdf(X(i,j))/\log(maxpdfU)} \quad (22)$$

γ(i,j) represents the array having pixel wise gamma values.

The objective behind the calculation of gamma i.e. γ(i,j) is to increase contrast of the image by increasing intensity of dark pixels by equating gamma value to be less than 1 and decreasing intensity of bright pixels by equating gamma value to be more than 1. In this way, it increases the contrast of image, thereby restoring the image content being adaptive in nature.At the end following formula is used to apply gamma correction:

$$O(i,j) = lmax(l/lmax)^{\gamma(i,j)} \tag{23}$$

where lmax is the maximum gray level value and O(i,j) is the final image obtained.

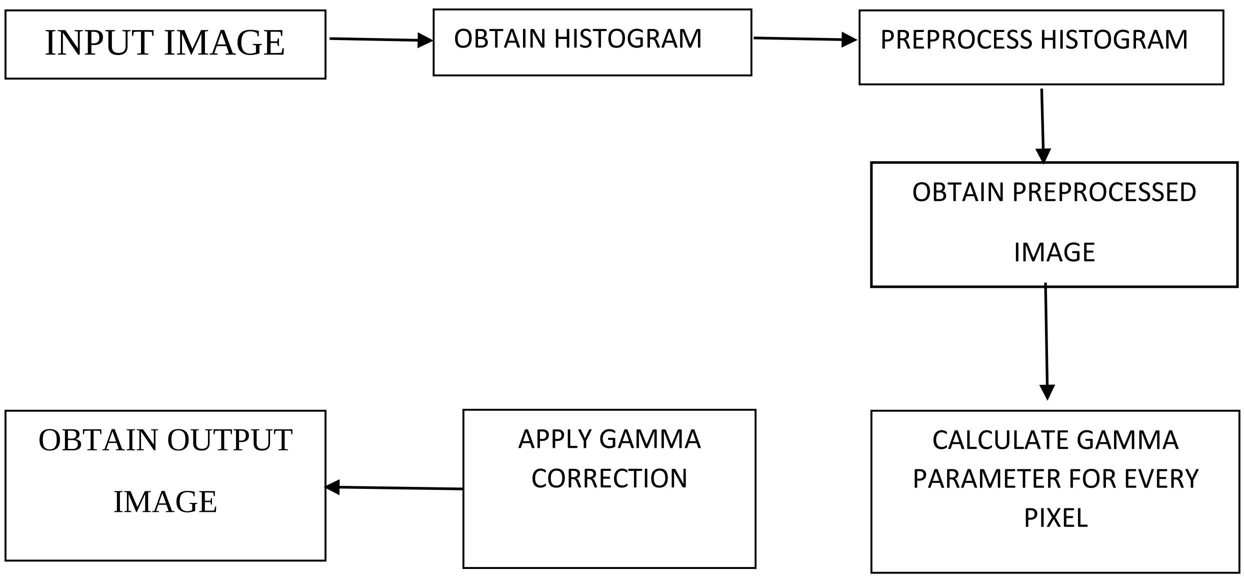


Fig. 6 Block diagram of proposed algorithm

4.2 Pseudocode:

1. Read image img and convert it into gray scale image.
2. Calculate size of the image and initialize required arrays : pdf, cdf, ppdf and gamma_arr. Size of each array will be equal to the number of possible intensity values.
3. Calculate the probability density function pdf and cumulative density function cdf using eq. (1) and eq(2) respectively. Calculate minimum pdf minpdf and maximum pdf maxpdf.
4. Preprocess the histogram using eq.(21). Read intensity of each pixel and apply the formula at intensity level to obtain the processed histogram Ppdf. Obtain image from preprocessed histogram. Calculate cumulative sum of pro cessed histogram as pcdf. Calculate output array:

   Output =round(pcdf*imax)

   where imax is the maximum intensity round function rounds off the value.

   Use this output array to calculate intermediate image FImage as:

   FImage(I,j)= output(img(I,j))
5. Calculate gamma_arr using eq.(22)
6. Calculate final image using eq.(23)

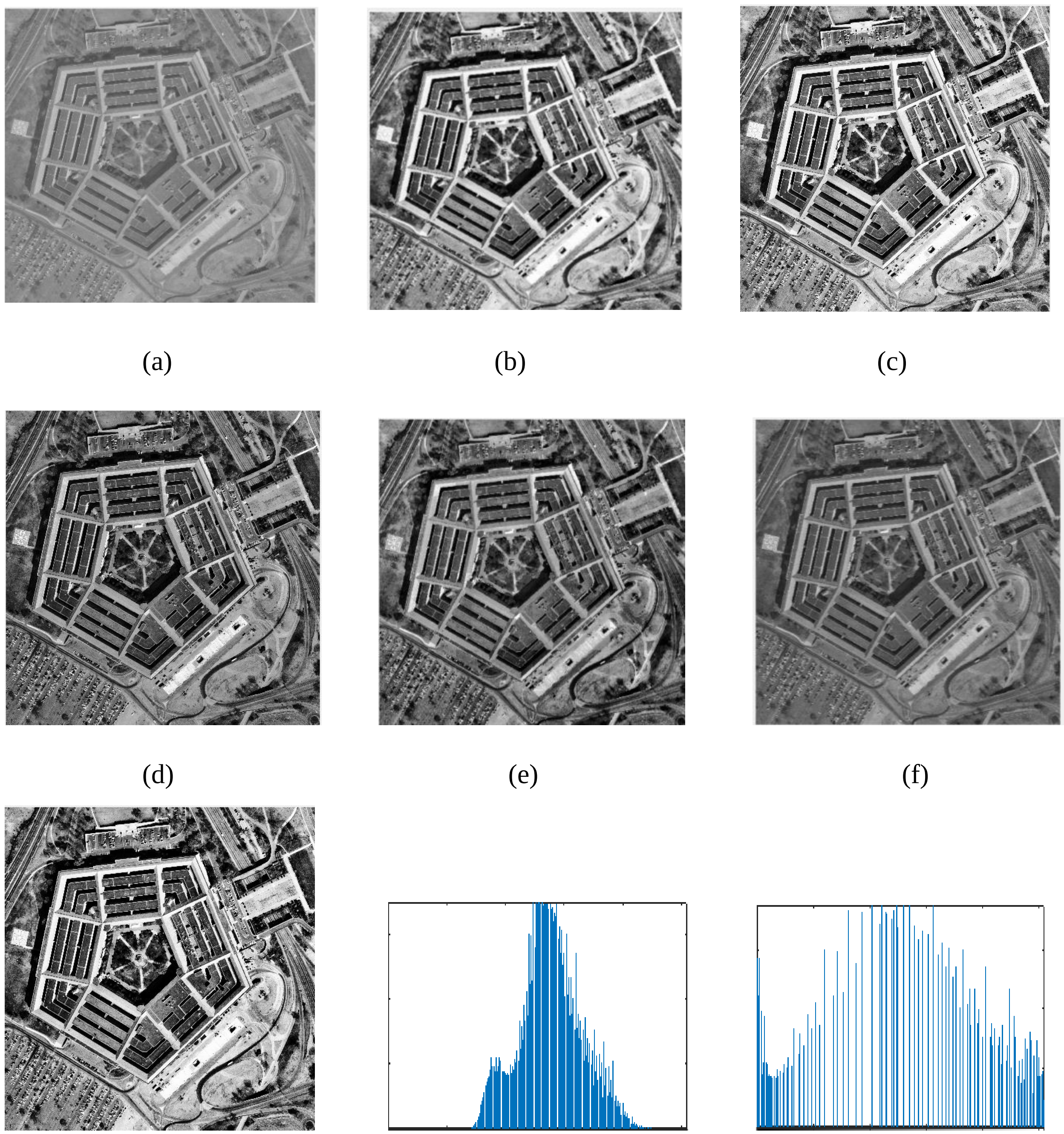
Chapter 5

EXPERIMENTAL RESULTS AND ANALYSIS

5.1 Visual Assessment

MATLAB is used to implement the proposed approach. More than 50 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 Shannon's entropy and mean brightness. The proposed approach is evaluated using different test images. The results are then compared to the most commonly used contrast enhancement techniques– Histogram Equalization, BBHE, MMBEBHE, AGCWD methods and a combination of BBHE and MMBEBHE. The results are shown in Figs 7-11.

To demonstrate the improved characteristics of the images processed by proposed algorithm, the criteria based on mean intensity and entropy is used. Moreover, the improvement can be deduced from values of measures given in Tables 1 and 2.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 7 Radolph image (a) original image, (b) after applying HE technique, (c) BBHEd image (d) MMBEBHEd image, (e) after combining BBHE and MMBEBHE, (f) after applying AGCWD, (g) final image after applying proposed algorithm, (h)Histogram of original image, (i)Histogram of final image.

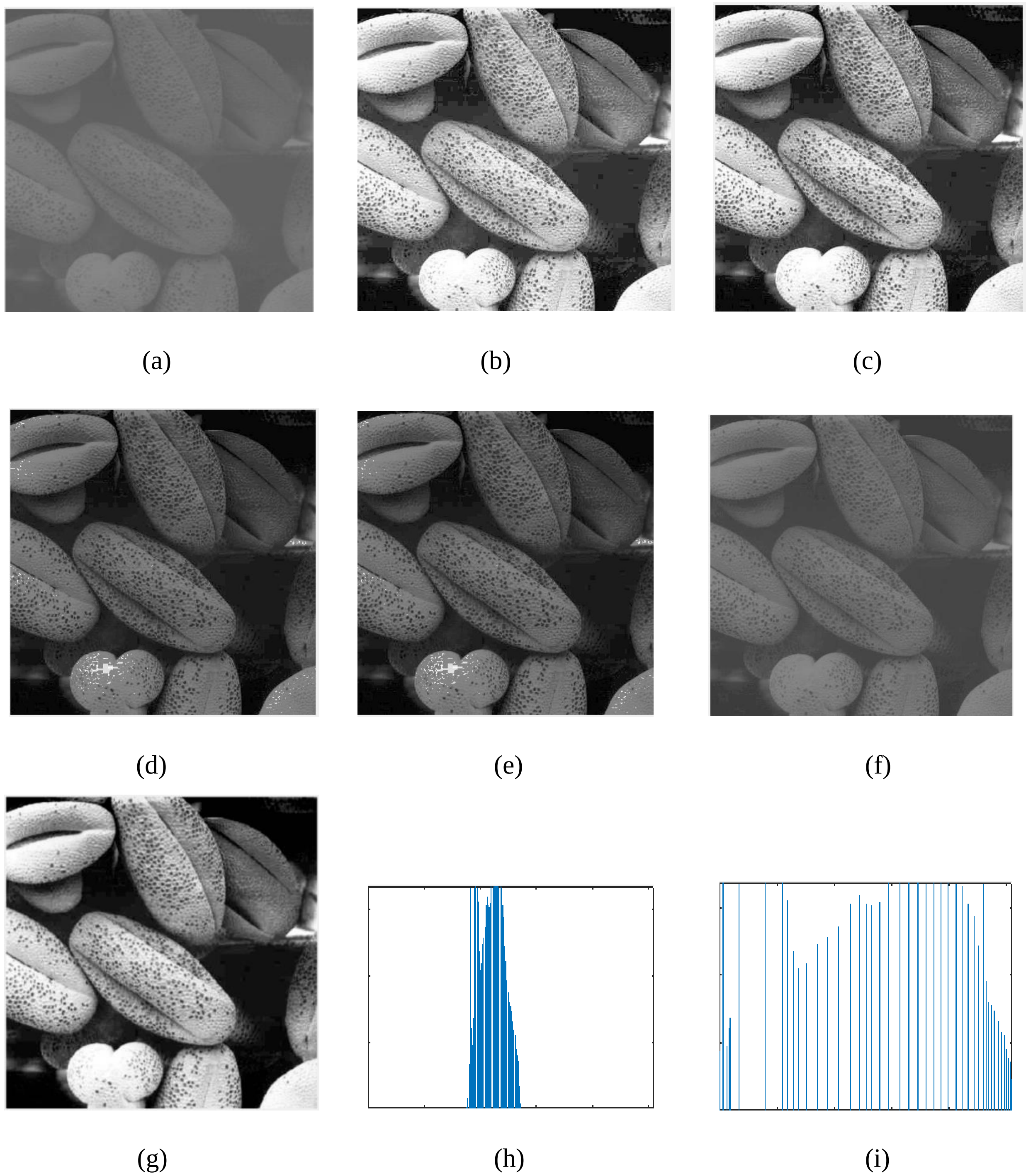
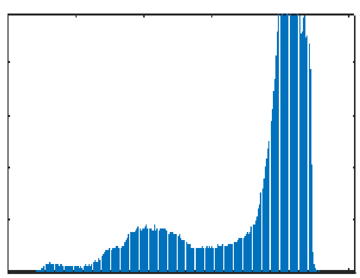
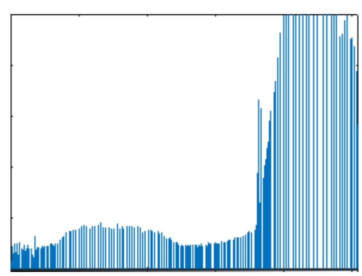


Fig. 8 beans image (a) original image, (b) after applying HE technique, (c) BBHEd image (d) MMBEBHEd image, (e) after combining BBHE and MMBEBHE, (f) after applying AGCWD, (g) final image after applying proposed algorithm, (h)Histogram of original image, (i)Histogram of final image.

(a) (b) (c)

(d) (e) (f





(g) (h) (i)

Fig.9 airplane image (a) original image, (b) after applying HE technique, (c) BBHEd image (d) MMBEBHEd image, (e) after combining BBHE and MMBEBHE, (f) after applying AGCWD, (g) final image after applying proposed algorithm, (h)Histogram of original image, (i)Histogram of final image.

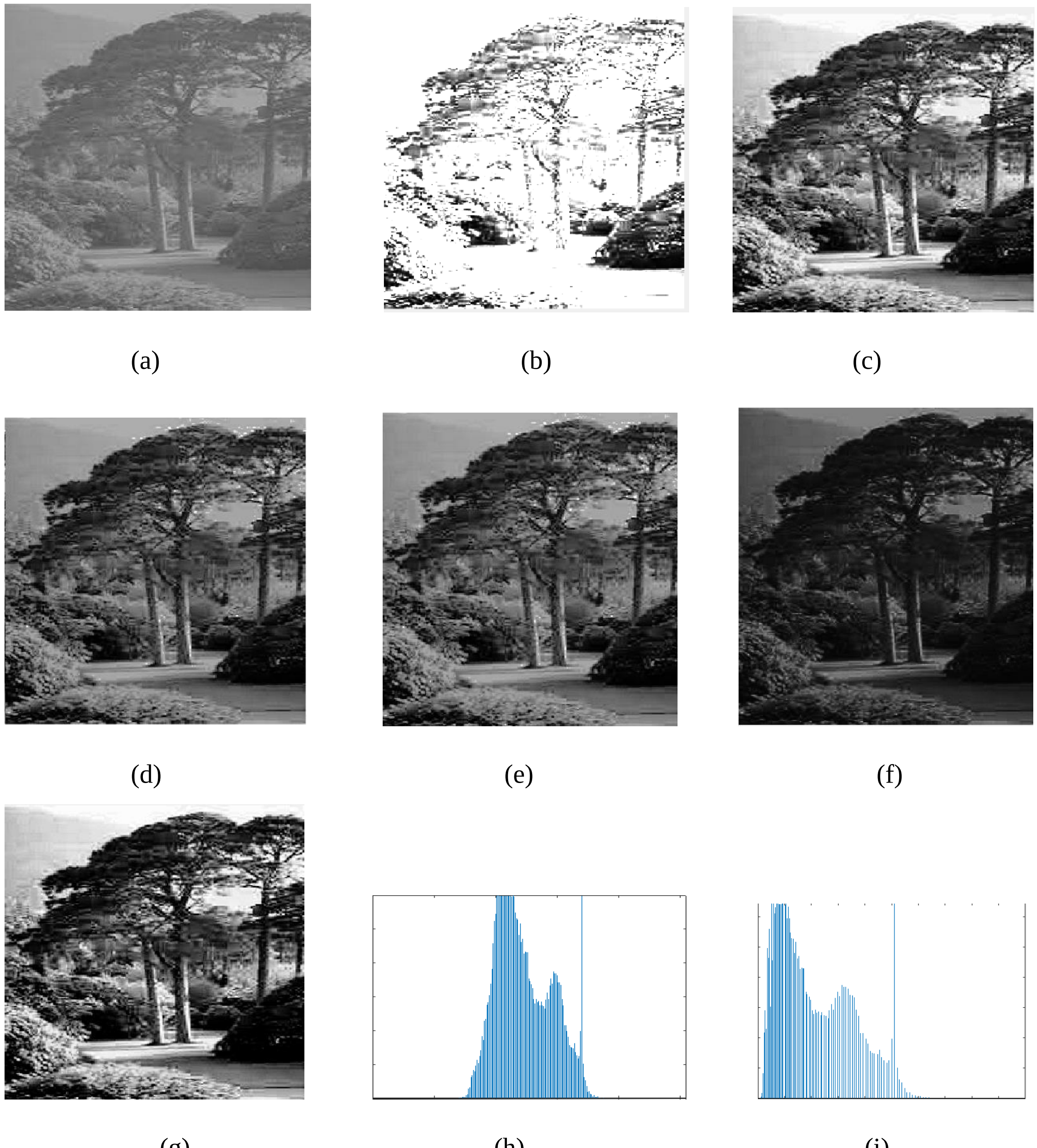
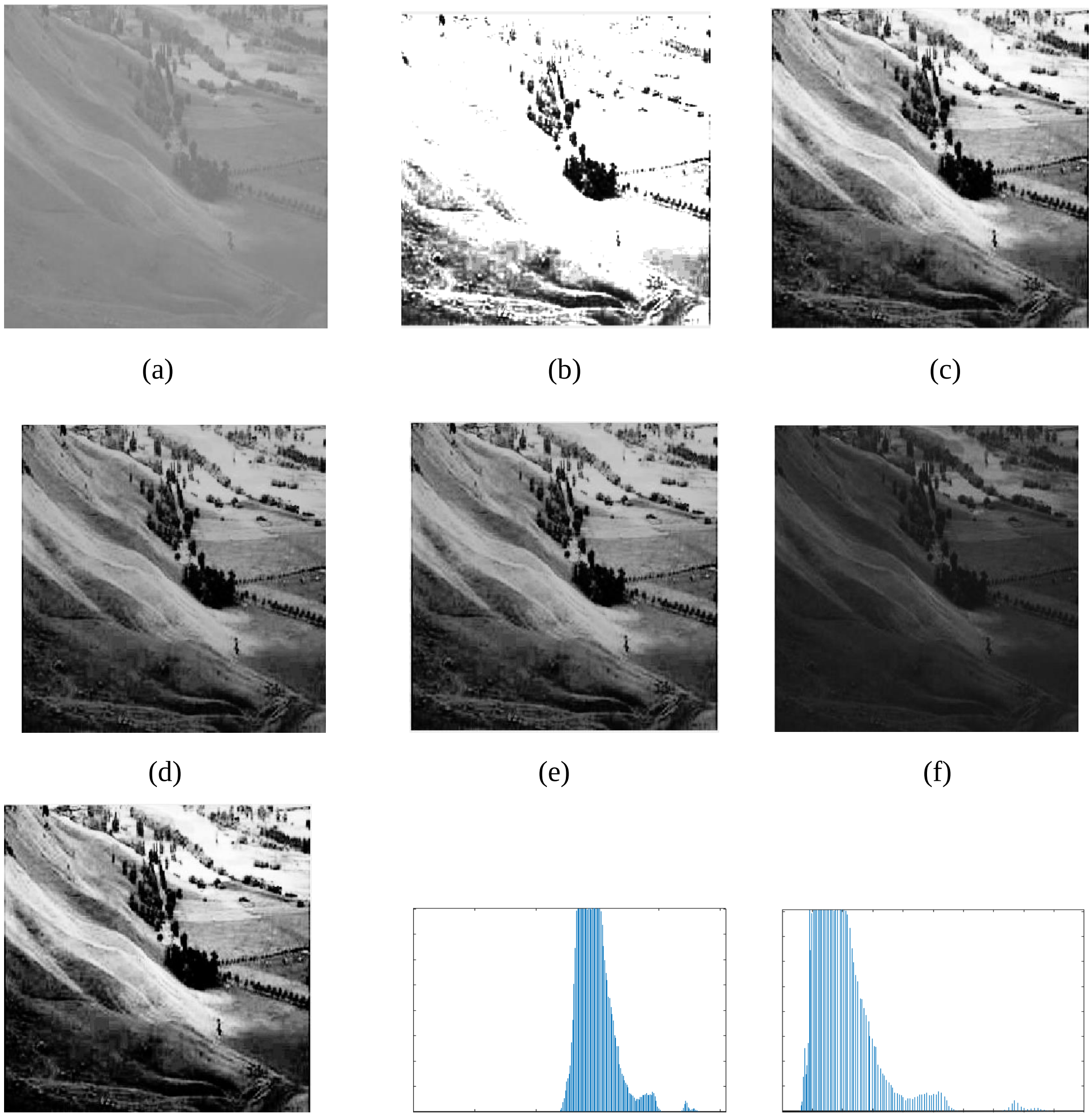


Fig. 10 tree image (a) original image, (b) after applying HE technique, (c) BBHEd image (d) MMBEBHEd image, (e) after combining BBHE and MMBEBHE, (f) after applying AGCWD, (g) final image after applying proposed algorithm, (h)Histogram of original image, (i)Histogram of final image.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 11 hills image (a) original image, (b) after applying HE technique, (c) BBHEd image (d) MMBEBHEd image, (e) after combining BBHE and MMBEBHE, (f) after applying AGCWD, (g) final image after applying proposed algorithm, (h)Histogram of original image, (i)Histogram of final image.

5.2 Mean Brightness

AMBE is the abbreviation of Absolute Mean Brightness Error. It is the absolute difference between the mean of input and output image. It is formally defined by

$$AMBE = E(X) - E(Y) \tag{24}$$

where, X and Y denote the input and output image respectively, and E(·) denotes the expected value, i.e. the statistical mean.

Eq. (24) clearly shows that AMBE is designed to detect one of the distortions i.e. excessive brightness change. In fact, all the automatic methods so far have been designed to preserve brightness. This idea of preserving brightness was originated by the author of BBHE. The fundamental reason HE could produce undesirable distortions was because it did not take the mean brightness of an image into account. In current practice, lower AMBE implies that the original brightness is better preserved and hence, should yield a better quality output.

Table 1

Mean intensity obtained by applying eq. (24)

Image	Original	HE	BBHE	MMBE BHE	Combined BBHE & MMBHE	AGCWD	Proposed Algorithm
Randolph	138.4860	128.9101	129.8280	100.9041	98.9998	121.4532	130.3125
Beans	109.0666	131.2547	104.8337	105.0783	105.3939	93.5244	110.7172
Airplane	179.1789	129.3303	176.7449	114.1039	114.1039	167.056	178.0686
tree	122.9186	214.5137	118.8207	102.8055	103.8055	99.3245	112.4828
hills	148.1055	216.5177	112.3723	103.1414	103.1414	100.7621	118.3112

5.3 *Shannon's Entropy*

The entropy here refers to the Shannon Entropy. It is a measure of the uncertainty associated with a random variable. It quantifies, in the sense of an expected value, the information contained in an information source (the image), usually in units such as bits. Theoretically, the higher the entropy, the more information is available from the information source. HE is designed to maximize the entropy of an image by remapping the gray levels using the gray levels' probability density function such that they are distributed uniformly. It is assumed that by increasing the entropy,

the image could reveal more information. Consequently, an image with higher entropy is regarded to have better quality. For global gray-level transformation, remapping gray levels using their probability density to obtain uniform distribution can only be achieved if the data is in continuous (non-discrete) form. In discrete form, the mapping using probability density function which is always monotonic can never increase the entropy. Furthermore, HE tends to combine gray levels of relatively low probability density, and results in decrease of entropy although such action tends to increase the contrast of an image.

Table 2

Comparison of entropy with various algorithms

Image	Original	HE	BBHE	MMBE BHE	Combined BBHE & MMBEBHE	AGCWD	Proposed Algorithm
Randolph	6.7326	6.5365	6.6251	6.6672	7.4887	6.7269	6.7271
Beans	5.3099	5.1552	5.3040	5.3085	6.2474	5.3099	5.3099
Airplane	6.7021	6.5072	6.6056	6.3814	6.2076	6.6720	6.702
tree	6.3776	6.1918	6.3383	6.3095	6.1377	6.1867	6.2443
hills	5.6830	5.5125	5.6011	5.5959	5.4435	5.5821	5.6332

Chapter 6

CONCLUSION

In the presented work, a better contrast enhancement technique is proposed. The presented algorithm combines histogram stretching and adaptive gamma correction. The histogram of original image is first preprocessed adjusting the probability distribution so as to get a flattened histogram, then spatial gamma correction is applied to increase brightness of the image. The adaptive gamma correction produces gamma values for every pixel thereby preserving image content to a high extent. Also, the preprocessed histogram provides a better input to the gamma correction procedure and hence produces improved results over traditional gamma correction technique. It has been proved that this procedure produces better results as compared to other traditional contrast enhancement techniques such as HE, BBHE, MMBEBHE and AGCWD as the results are compared using quantitative measures: mean brightness and entropy. The visual assessment also shows that proposed algorithm produces better images. The proposed algorithm can also be improved by improving the formulae for histogram stretching and gamma correction so as to make it more adaptive towards the original image.

Chapter 7

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