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Histogram Shape Based Gaussian Histogram Specification for Contrast Enhancement

Selvaraj Jayasankari*, Sandanam Domnic

Department of Computer Applications, National Institute of Technology, Tiruchirappalli, Tamil Nadu 620015, India

Corresponding Author Email: 405912056@nitt.edu

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ABSTRACT

Contrast enhancement a critical component in image processing is a vital integral part of computer vision in all fields of engineering including surveillance, medical, agricultural, aerospace, electrical, mechanical, etc. Although the existing contrast enhancement methods achieved satisfactory enhancement, they can produce annoying side effects due to variation of intensity levels. In this article, a new model for contrast enhancement that makes use of the given image's histogram shape to capture the variation in the intensity distribution to avoid annoying side effects is anticipated. In the proposed Histogram shape based Gaussian Histogram Specification technique, the desired histogram is obtained by dynamically controlling the parameters, mean and standard deviation. Using the images taken from standard and NASA database along with quality metrics such as contrast, entropy and gradient, the proposed Gaussian Histogram Specification technique performed better than that of the existing contrast enhancement techniques.

1. INTRODUCTION

Image enhancement is a basic key practice that increases the image quality by modifying certain characteristics of the image such as contrast, brightness, etc. to transform the image more suitable than the original for the intended application [1, 2]. Contrast Enhancement (CE) techniques by histogram processing are classified into two categories, namely, Histogram Equalization (HE) and Histogram Specification (HS). In HE, the contrast of an image is enhanced by spreading the intensity levels of the image into a wider intensity range, which results in a uniform histogram [3]. During the HE process, the original mean of the image is shifted in order to spread the intensity level, which adversely leads to intensity saturation and sometimes even results in over-enhanced images with amplified noise [4]. To overcome these drawbacks, Kim [5] proposed a technique with Bisection and Brightness preservation (BBHE), in which the original histogram is bisected using the original mean of the input image before equalization. Further, to eradicate the problem of intensity saturation, which was not fully solved by former technique, Wang et al. [6] developed a Dual Sub-Image HE (DSIHE) technique, in which the total number of pixels were equally divided into two sub-histograms.

Alternatively, Chen and Ramli [7] used a calculated minimum mean brightness error as separating point for HE in their technique MMBEBHE. Another algorithm recursive mean separate HE (RMSHE), was also developed by Chen and Ramli [8], which divides the histogram recursively using the means before HE. Alternatively, medians are used for segmentation in recursive sub image HE (RSIHE) technique developed by Sim et al. [9]. Both the recursive type HE techniques: RMSHE and RSIHE concluded with insignificant enhancement with increased number of recursive. Hybridization of the concepts of bisecting and clipping the histograms was implemented by Ooi et al. [10] in their technique called Bi-HE Plateau Limit (BHEPL), and found that it is effective in avoiding over amplification during HE. A two-stage adaptive CE algorithm (ACEBSF) that uses modified Sigmoid Function was proposed by Lal and Chandra [11], and its efficiency was proven in enhancing different natural gray scale images.

Contrast enhancement using uniform histogram [5-10] is not always the best approach, whereas HS or matching alters the histogram of the given image into a specified form, in which certain grey-levels in the image can be highlighted for efficient contrast enhancement. Zhang [12] proposed a new grey-level mapping law for direct HS, which is a general version of the HE technique that improved the accuracy of HS. Chi-Chia et al. [13] developed a Dynamic HS (DHS) algorithm that enhanced the contrast retaining the original histogram distribution features. During enhancement, to preserve the information content of images, Coltuc et al. [14] proposed an approach of exact HS using strict ordering. Wan and Shi [15] attained exact HS simultaneously with better image enhancement through a wavelet-based HS technique. Avanaki [16] achieved maximization of structural similarity index using a gradient ascent based exact global HS technique. Sen and Pal [17] developed an automatic exact HS that increases the image information positively after modifying the histogram. Nikolova et al. [18] developed a variational approach for exact HS to obtain much better ordering by quantization and minimization of noise. Jung [19] proposed a two-dimensional HS method using pixel-value mapping by cumulative distribution function, that resulted in well-approximated target histogram.

However, the above mentioned HS approaches are facing the problems of seeking the desired histogram and undesirable checkerboard effects on the enhanced images. Recently, Xiao et al. [20] developed Brightness and Contrast Controllable HS (BCCHS) algorithm by utilizing the contextual information of the histogram to control features of enhanced image. But the utilization of information of neighboring pixels in this technique increased the computational complexity.

From the literature survey, it is observed that although the existing CE techniques satisfactorily enhanced the images, adversely they produced annoying side effects due to variation of gray levels. To overcome this contrary effect, the proposed model called Histogram shape based Gaussian Histogram Specification (HGHS) technique uses the input image's histogram shape to formulate the model, which can avoid annoying side effects that may arise in the enhanced image. In the proposed technique, the given image is classified based on its histogram shape using skewness of statistical distribution of gray levels in the image. With respect to the nature of the skewness (symmetry, left and right skewed) of histogram shape, various desired Gaussian histograms or shapes are generated using Gaussian parameters: mean (μ_g) and standard deviation (σ_g). The values for these parameters are decided based on the input image's skewness type. This operation enables to generate various Gaussian desired histograms.

Then, for every generated specified histogram, enhanced image is produced by using transformation function, which maps the input image to specified histogram to produce enhanced image. After this, finally an objective function which combines the quality metrics: contrast and entropy is applied on the produced various interim images to find the best Gaussian specified histogram. In addition, the proposed technique is effectively implemented and evaluated on the various images taken from standard databases and NASA database. The overall flow diagram of the proposed Histogram shape based Gaussian HS (HGHS) technique is given in Figure 1.

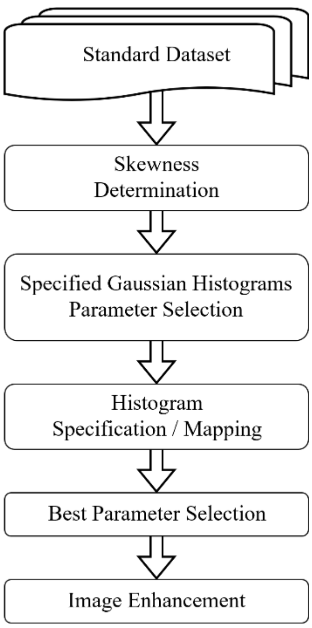


Figure 1. Flow diagram of HGHS technique

Altogether, the issues of the existing HE [5-10] and HS [12-19] techniques such as over enhancement, brightness saturation, annoying artifacts, computation complexity and nonsuitability to enhance images with differently skewed histograms are solved by the proposed HGHS technique. In addition, the difficulty faced by the proposed HGHS technique in the selection of best parameters of specified histograms is overcome by using a unique objective function to identify the optimum parameters to attain better contrast enhancement.

2. PROPOSED MODEL FOR CONTRAST ENHANCEMENT

The sequence of the proposed HGHS technique shown as a flow diagram in Figure 1, is deliberated mathematically as follows:

Consider a digital input image $X = \{x(i,j) | 1 \le i \le M, 1 \le j \le N\}$ with range of intensity level from 0 to$(L-1)$. Where, $x(i,j)$ is the grayscale value in coordinate (i,j), M and N are dimensions of the image, and L is the largest grayscale value. The main objective of HGHS is to obtain an enriched image Y$= \{y(i,j) | 1 \le i \le M, 1 \le j \le N\}$ having improved image quality compared with the input image 'X'.

Initially, skewness (S) of the input image is calculated using Eq. (1), which is used to determine the histogram shape of the image.

$$S = \frac{E(x(i,j)-\mu_{in})^3}{\sigma_{in}{}^3} \tag{1}$$

where, μ_{in} and σ_{in} are the mean and standard deviation of X, and E is the expectation operator. The value of mean (μ_{in}) of input image can be calculated using Eq. (2).

$$\mu_{in} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} x(i,j)}{n} \tag{2}$$

where, n denotes the amount of pixels in X.

The value of standard deviation (σ_{in}) of input image can be determined using Eq. (3).

$$\sigma_{in} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-\mu_{in})^2}{n}} \tag{3}$$

Based on the skewness (S) value obtained from Eq. (1), the image is classified as follows:

$$S = \begin{cases} 0, \ Symmetry \\ < 0, \ Left\ skewed \\ > 0, \ Right\ skewed \end{cases} \tag{4}$$

Further, the probability distribution $P(X)$ of the input image is obtained using the following formula.

$$P(x_k) = \frac{n_k}{MN} \tag{5}$$

where, x_k is the k^{th} intensity value from 0 to L-1 and n_k is the amount of pixel in the image of dimension M rows and N columns with intensity x_k.

Using the probability distribution $P(x_k)$, the cumulative probability distribution $C(x_k)$ of the input image is determined using Eq. (6).

$$C(x_k) = \sum_{j=0}^{k} P(x_j) \tag{6}$$

The probability distribution $P(Z_q)$ of the specified Gaussian distribution or Gaussian specified histogram is determined using Eq. (7).

$$P(Z_q) = \frac{1}{\sigma_g\sqrt{2\pi}}\left(e^{\frac{-(Z_q-\mu_g)^2}{2\sigma_g{}^2}}\right) \tag{7}$$

where, Z_q is the q^{th} intensity value from 0 to L-1, μ_g is the mean and σ_g is the standard deviation of the specified Gaussian distribution and these values are determined using Eq. (8) to Eq. (11).

$$\text{If } (S = 0);\ \mu_g \in \left\{\frac{L-1}{2}, \mu_{in}\right\} \tag{8}$$

$$\text{If } (S < 0);\ \mu_g \in \left\{\frac{L-1}{2}, \frac{3(L-1)}{4},\ \mu_{in}\right\} \tag{9}$$

$$\text{If } (S > 0);\ \mu_g \in \left\{\frac{L-1}{4}, \frac{L-1}{2},\ \mu_{in}\right\} \tag{10}$$

$$\text{and } \sigma_g \in \left\{0, 1, 2, \ldots, \frac{L-1}{2}\right\} \tag{11}$$

The best values of μ_g and σ_g parameters for specified Gaussian distribution are determined based on the perspective of an objective function λ as described in section 3.3.

Further, the cumulative distribution of the specified Gaussian distribution $G(Z_q)$ is obtained using Eq. (12).

$$G(Z_q) = \sum_{j=0}^{q} P(Z_j) \tag{12}$$

HS tries to find the transformation function $Z = F(X)$ to transform the gray intensity X in the given image to Z, to obtain a transformed image with histogram alike to the specified histogram. Generally, in HS, to retain the essential data of the input image, a monotonically increasing function Z is derived as below:

$$G(Z) = C(X) \tag{13}$$

where, $G(Z)$ is the cumulative distribution of specified image and $C(X)$ is the cumulative distribution of the given image.

$$Z = G^{-1}[C(X)] \tag{14}$$

Using the above transformation function Eq. (14), each gray intensity value in the given image is to be transformed to Z, so that the desired output image with histogram similar to the specified histogram can be obtained by HS.

2.1 Assessment criteria

In this paper, the performance metrics, contrast, DIE and gradient given in Eq. (15) – Eq. (18) are used to assess and compare the performance of the proposed work with the existing works.

2.1.1 Contrast

The contrast of the images which mimics the measure of dynamic range of gray levels is determined using the following expression as given by [21].

$$Contrast\ (Y) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} y^2(i,j) - \left|\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} y(i,j)\right|^2 \tag{15}$$

where, M and N denotes image dimension, $y(i,j)$ is the intensity level of the pixel at coordinate(i,j).

To convert the contrast into decibel (dB) unit, $Contrast$ is then taken logarithm as in Eq. (16)

$$Contrast^{\#}(Y) = 10log_{10}Contrast(Y) \tag{16}$$

In general, a greater $Contrast$ is preferred as it indicates a higher dynamic range of gray intensity levels.

2.1.2 Entropy

Entropy, the quantity of richness in data of the images before and after enhancements is determined using the following expression as given by [22].

$$Entropy(Y) = -\sum_{k=0}^{255} P(Y_k) log_2\big(P(Y_k)\big) \tag{17}$$

where, $P(Y_k)$ is the probability of kth gray value of image Y.

In general, closer the entropy value of an enriched and given images, the data information of the given image is said to be well-preserved. It is always preferred to enhance the image without increasing or decreasing the entropy values because increase in the entropy value decreases the ability to compress the enhanced images whereas, decrease in the entropy results in loss of features in the enhanced images. Hence in this analysis of entropy, the increase and decrease in entropy are considered as degradation of image and the closeness of the entropy of the enriched and given images is considered as the objective to obtain optimum parameters.

2.1.3 Gradient

Gradient the measure of sharpness of the image is determined using Eq. (18) as given by [23].

$$Gradient(Y) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{\nabla_i^2(i,j) + \nabla_j^2(i,j)} \tag{18}$$

where, M and N denotes image dimensions, $y_e(i,j)$ is the enhanced pixel intensity at coordinate (i,j) , $\nabla_i(i,j) = y_e(i,j) - y_e(i+1,j)$ and $\nabla_j(i,j) = y_e(i,j) - y_e(i,j+1)$ are the horizontal and vertical gradients.

Higher the value of gradient denotes an anticipated sharp image.

2.2 Parameter optimization

As the principal goal of image enhancement is improving contrast with preservation of image details, a new perspective to evaluate the performance with balanced contrast enrichment and information preservation is deliberated in the proposed work alike to the one suggested by Jiang et al. [23]. To achieve the same, the best parameter values for specified inverted Gaussian distribution mean (μ_g) and standard deviation(σ_g) are determined using the below objective function (λ) to produce better enhanced images.

$$\lambda = Entropy(Y) \times \left(1 - \frac{\delta}{Contrast_{in}}\right) \tag{19}$$

where, $\delta = |Contrast_{en} - Contrast_{in}|$, $Contrast_{en}$ and $Contrast_{in}$ are the contrasts of enhanced and input images respectively. For an insufficient variation in contrast, the original value of image entropy is restored. Whereas, for any excess contrast variation, consequently the entropy is reduced. Hence, maximization of the objective function (λ) is considered as the termination criteria for the search of optimum parameters. For better understanding, the various steps involved in Histogram shape based Gaussian Histogram Specification (HGHS) technique is given in Algorithm-1.

Algorithm-1: Histogram shape based Gaussian Histogram Specification (HGHS)

Input: Given/Input Image X
Output: Output/Enhanced Image Ye

Initialize maximum objective function $\lambda_{max} = 0$, interim image Yi, enhanced image Ye, Specified Gaussian distribution mean μ_g and standard deviation σ_g, maximum grayscale value L
Compute mean (μ_{in}) & standard deviation (σ_{in}) of the given image
Calculate skewness (S) of the given image using Eq. (1)
if (S = 0); $\mu_g \in \left\{\frac{L-1}{2}, \mu_{in}\right\}$
else if (S < 0); $\mu_g \in \left\{\frac{L-1}{2}, \frac{3(L-1)}{4}, \mu_{in}\right\}$
else if (S > 0); $\mu_g \in \left\{\frac{L-1}{4}, \frac{L-1}{2}, \mu_{in}\right\}$
$\sigma_g \in \left\{0, 1, 2, \dots, \frac{L-1}{2}\right\}$
for each value of μ_g do
for each value of σ_g do
Perform Histogram Specification using Eq. (12) to Eq. (14) to obtain interim output image Yi
Compute contrast & entropy for interim image Yi using Eq. (15) to Eq. (17)
Calculate objective function λ for the interim image using Eq. (19)
if ($\lambda_{\max} < \lambda$) then
set $\lambda_{\max} = \lambda$
Ye = Yi
end if
next value of σ_g
next value of μ_g
return objective function λ and enhanced image Ye

3. EXPERIMENTAL ANALYSIS

To implement and validate the suggested HGHS technique, 422 images from various standard databases such as Berkeley [24], CSIQ [25], Kodak [26], LIVE [27], Toyama [28], and USC-SIPI [29] were chosen. Figure 2 shows the histograms of three different images that are classified based on their respective skewness.

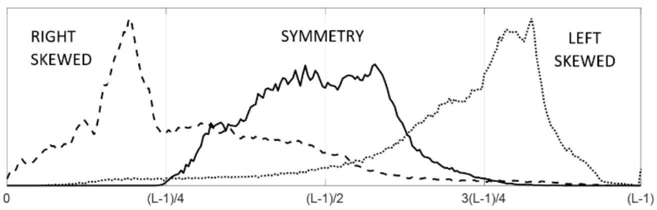


Figure 2. Histograms of images classified based on skewness

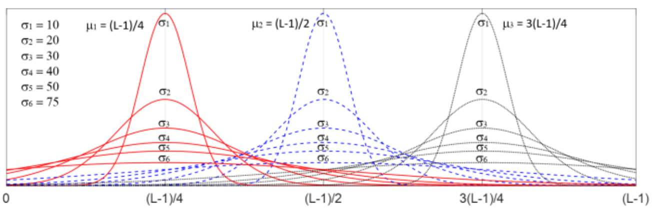


Figure 3. Specified Gaussian histograms with different means and standard deviations

It is observed from the histograms that means of right skewed, symmetry, and left skewed images are adjacent to$(L-1)/4$, $(L-1)/2$, and $3(L-1)/4$ respectively. Based on this fact, the means are selected only as per Eq. (8) to Eq. (10) given in section 2. It is also found that the values of μ_g and σ_g of specified Gaussian distribution are other than the values given in Eq. (8) to Eq. (11), the quality of the enriched images are saturated. The shapes of the specified histograms for different μ_g and σ_g values are shown in Figure 3. It is observed that the increase in the standard deviation of the specified histogram stretches the range of distribution of grey level, which obviously results in contrast enhancement. Whereas, for the means $(L-1)/4$ and $3(L-1)/4$, the increase in the standard deviation results in skewness in the right and left respectively, and intensity saturations occurs on the other side, due to which the effectiveness of contrast enhancement is reduced. Hence, there arises a need for determining the suitable standard deviation (σ_g) for every mean (μ_g) up to which the contrast enhancement is effective. For qualitative and quantitative assessment of the performance of the HGHS technique, its results are compared with that of existing state-of-the-art contrast enhancement techniques, namely, ACEBSF [11], BBHE [5], BHEPL [10], DSIHE [6], MMBEBHE [7], RMSHE [8], RSIHE [9].

3.1 Quantitative assessment

To analyze the quantitative performance of various CE techniques, the values of quality measures such as entropy, contrast and gradient obtained using Eq. (15)-Eq. (18) for the proposed HGHS technique and other existing techniques for 422 standard benchmark images are plotted with respect to image index and are shown in Figure 4 to Figure 6 respectively. For comparison of the performance, the average values of quality measures are also provided in Table 1. For better understanding, the image index for all the input images are individually assigned in the increasing order of their respective contrast, entropy and gradient values. Then the values of input images and enhanced images corresponding to the same image index are compared.

The entropy values obtained for various techniques are shown in Figure 4, and the values obtained by HGHS technique are found to be lower and very close to that of the input images when compared with that of other existing techniques, which is an evidence for preservation of details. Though the entropy values obtained by all the techniques are seem to be close to the entropy of the input images, the average entropy value obtained by the HGHS technique is 98.15% of the entropy values of the input images, which is found to be better than that of other existing techniques. In addition, from Figures 4(f-g) it is observed that the entorpy values obtained by BHEPL and ACEBSF techniques are very poor compared to that of other techniques.

The contrast after enhancement of the images with different skewness are not always improved by the existing contrast enhancement techniques as observed is Figure 5. This evidentially proves that no single algorithm is best suited for images with varying skewness. Whereas, the contrast values of all the images enriched using HGHS technique are found to be improved irrespective of the skewness of the input images as observed in Figure 5. In addition, from Figures 5(h) it is observed that the HGHS technique alone has enhanced the images by increasing the contrast for low contrast images and decreased the contrast for high contrast images which shown that the HGHS technique is best suitable for enhancement of images with varying contrast. It is also observed from the Table 1 that the average contrast value obtained by HGHS technique is 105.51% of the contrast values of the input images which is also higher than that of other techniques compared.

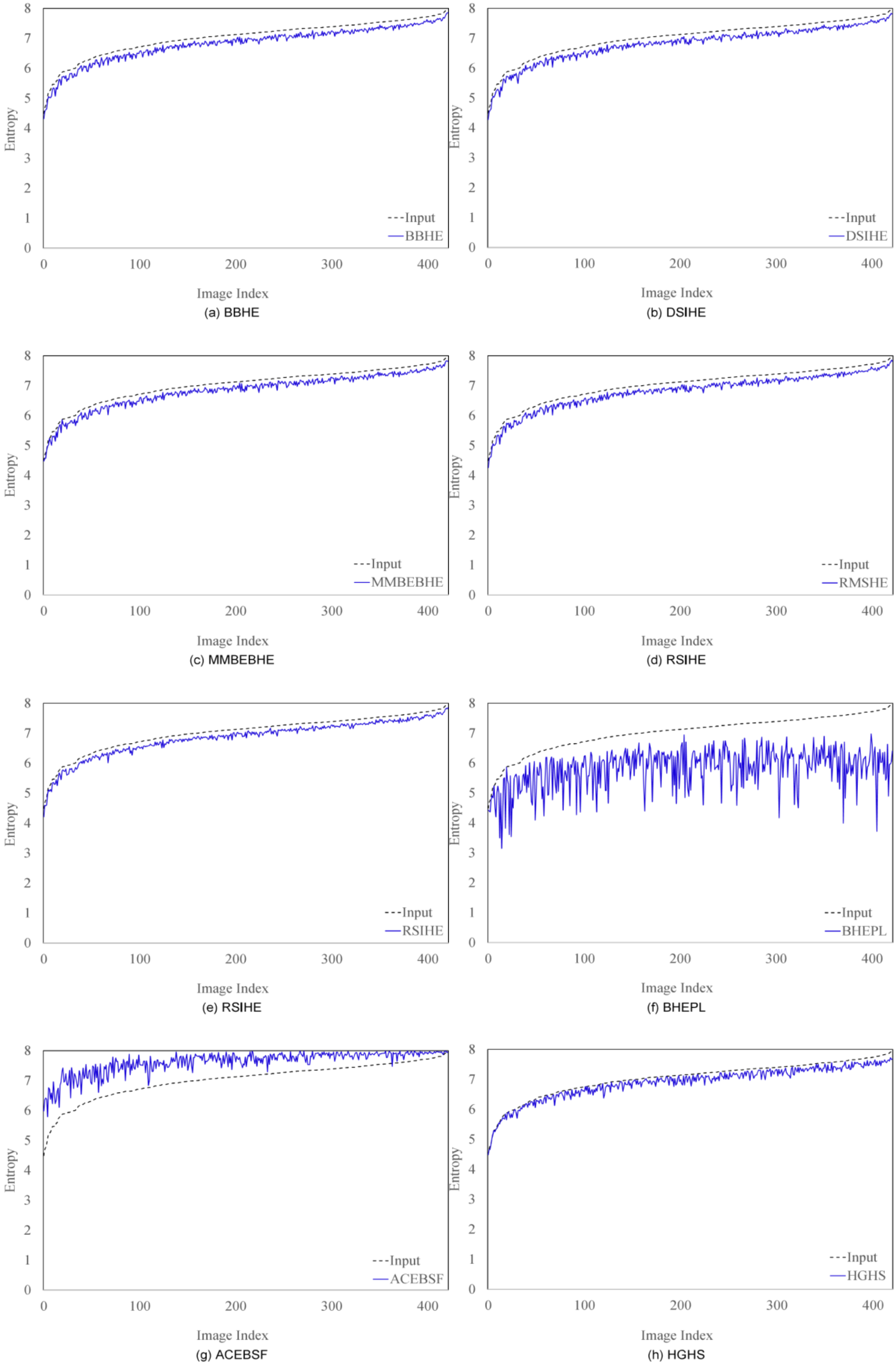


Figure 4. Entropy of standard images enhancement by various techniques

Table 1. Quantitative assessment of various techniques using three metrics

Metric	Original	BBHE	DSIHE	MMBEBHE	RMSHE	RSIHE	BHEPL	ACEBSF	HGHS
Entropy	7.0253	6.8157	6.8094	6.8251	6.8101	6.7438	5.8077	7.6220	6.8915
Contrast	39.9897	40.8985	41.2284	40.3244	40.8957	40.4807	40.9834	41.3311	42.1917
Gradient	4.5304	5.5224	5.6225	5.5591	5.5212	5.1853	5.5329	6.7035	5.6383

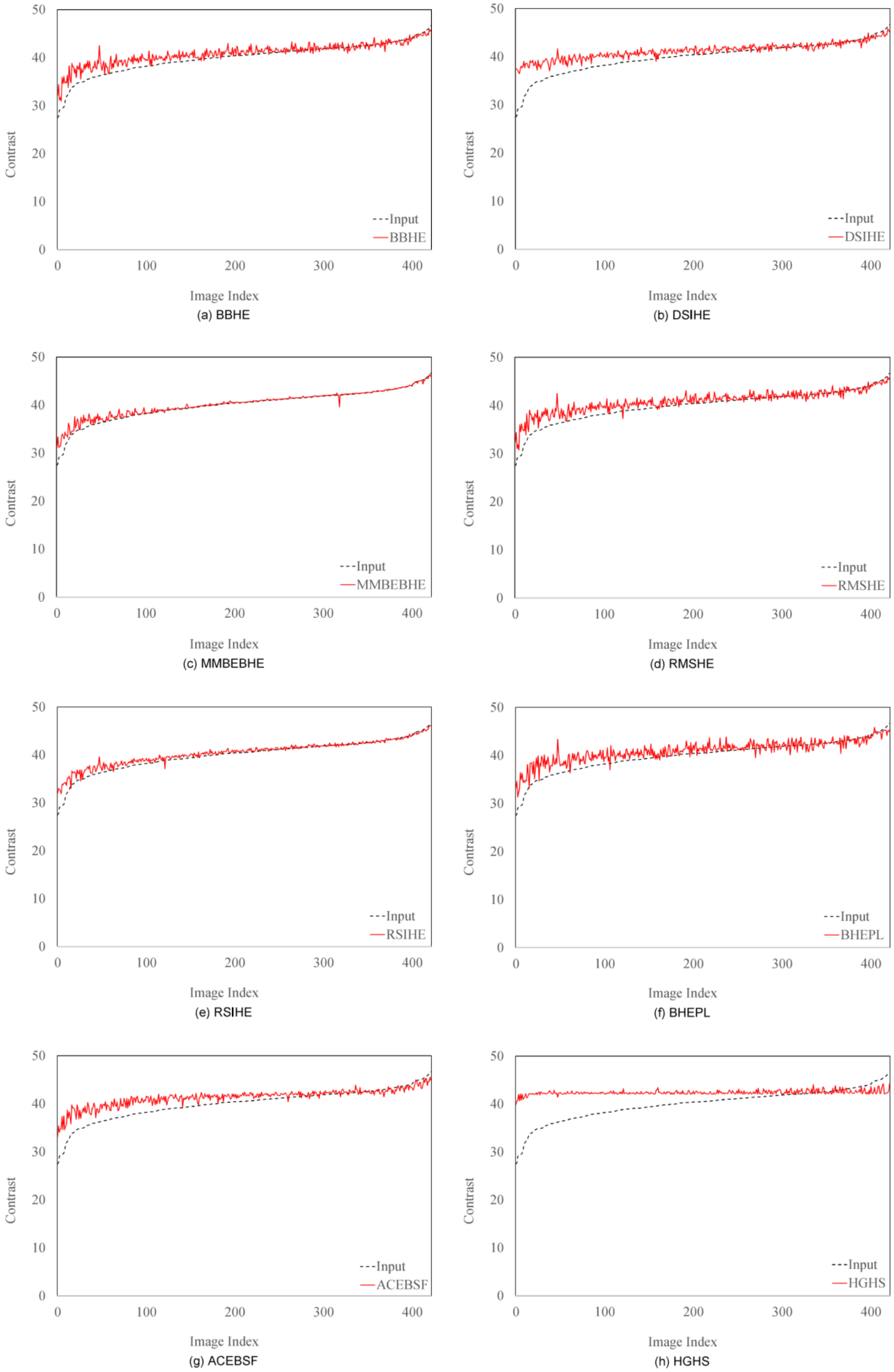


Figure 5. Contrast of standard images enhancement by various techniques

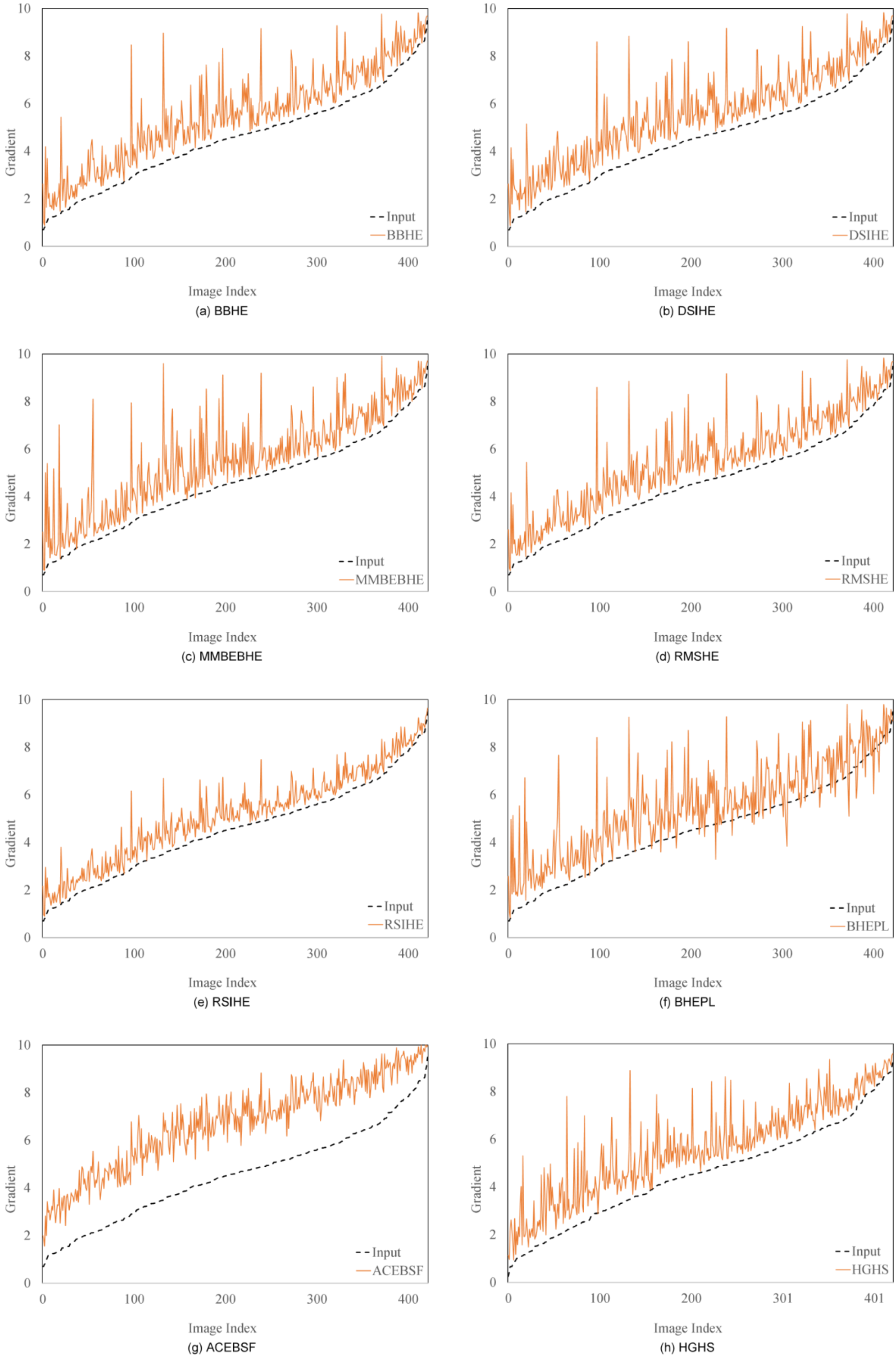
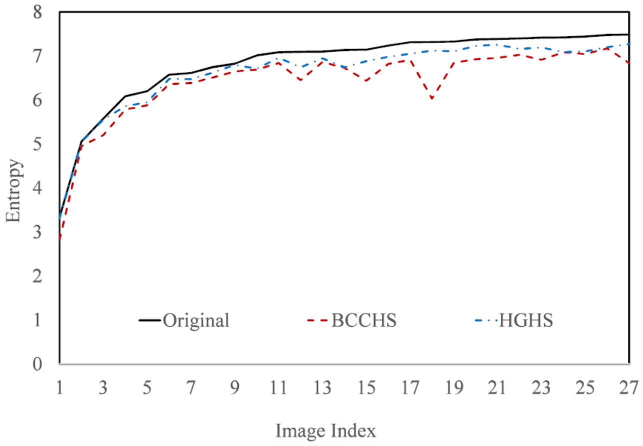


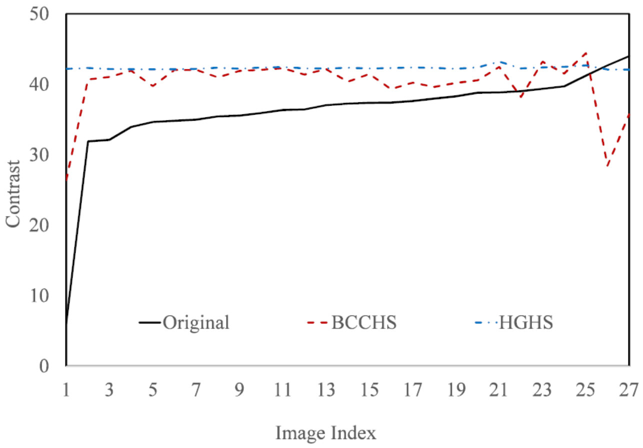
Figure 6. Gradient of standard images enhancement by various techniques

Table 2. Average entropy, contrast and gradient of NASA images [30] enhanced by BCCHS and HGHS techniques

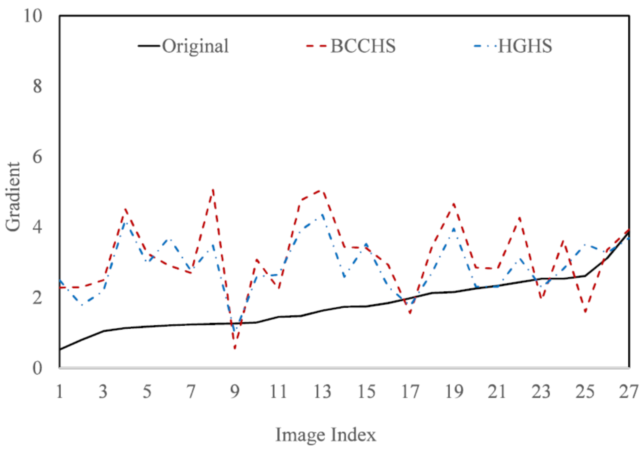
Original			BCCHS			HGHS		
Entropy	**Contrast**	**Gradient**	**Entropy**	**Contrast**	**Gradient**	**Entropy**	**Contrast**	**Gradient**
6.8209	36.1023	1.8058	6.4119	40.0124	3.1477	6.6238	42.3157	2.8960



(a) Entropy



(b) Contrast



(c) Gradient

Figure 7. (a) Entropy (b) Contrast and (c) Gradient of NASA database [30] images enhanced by BCCHS and proposed HGHS technique

The measure of sharpness represented by gradient values obtained for the images enhanced by various techniques are shown in Figure 6. The gradient values obtained for the proposed HGHS technique is higher than that of the original input images and also better than that of the other existing techniques compared. It is also noted that the average gradient value obtained by the proposed HGHS technique is 124.46% of the gradient values of the input images which is higher than that of all the other techniques compared.

The quality measures such as entropy, contrast and gradient values obtained for original NASA database images and images enhanced by another recent technique BCCHS and the proposed HGHS techniques are plotted with respect to image index and shown in Figures 7(a)-(c) and the corresponding average quality metrics are also provided in Table 2. It is observed from Figure 7(a) that the entropy values obtained by using proposed HGHS technique are found to be lower and very close to that of the input images when compared with that of BCCHS technique. From Table 2 it is noted that the average entropy value obtained by the proposed HGHS technique is 97.11% of the entropy values of the input images which is better than that of BCCHS technique.

The contrast values obtained by using proposed HGHS technique are found to be higher than that of input images when compared with that of BCCHS technique, which is observed in Figure 7(b). It is also witnessed that the average contrast value obtained by the HGHS technique is 117.21% of the contrast values of the input images which is better than that of BCCHS technique. From Figure 7(c) and Table 2 it is noted that the average percentage improvement in gradient values obtained by the proposed HGHS technique with respect to the original image is quite lower than that of BCCHS technique. Even though the invisible details in the original images are made better visible in the images enhanced only by the HGHS technique due to high contrast and better entropy values. Based on the observations from the Tables 1-2 and Figures 4-7, it is very clear that HGHS technique provides results better than that of the existing techniques with respect to the quality metrics entropy, contrast and gradient.

3.2 Qualitative assessment

To analyze the qualitative performance of various CE techniques, three input images with different skewness are considered. The subjective viewer perception is used to assess the levels of contrast improvement, preservation of details and improvement of sharpness in the enhanced images. The symmetrically skewed input pollen grain image, its enriched images along with their histograms are given in Figure 8. Though the images enhanced using MMBEBHE and BHEPL are visually good for user perception, the details are lost due to over enhancement in the encircled regions. For the remaining existing methods, the images are poorly enhanced due to brightness degradation. Whereas, in the encircled region of the images the proposed HGHS technique effectively improved the contrast without information lose.

The left skewed input plane image, its enriched images along with their histograms are given in Figure 9. It is noticed that in the images enhanced using the existing methods, annoying artifacts appears in the encircled regions due to brightness degradation. In addition, the texture on the runway in not visible due to over enhancement, which is better visible without artifacts in the image enriched by the proposed HGHS technique. The right skewed input seashore image, its enriched images along with their histograms are given in Figure 10. From the images enhanced by existing techniques it is observed that the details in front of the beach are not clear due to intensity saturation. Whereas, the proposed HGHS technique enhanced the image with better visibility of details all over the image.

Qualitative performance comparison of the proposed HGHS technique with the recent BCCHS technique [20] is also carried out on images from NASA database [30] and the enhanced images are also shown in Figure 11 and Figure 12. From the images shown in Figure 11(2,16,17,19) it is observed that the images enhanced by BCCHS technique using brightness parameter (PB) and contrast parameter (PC) ended up with brightness degradation and annoying artifacts. Whereas the same images enhanced using the proposed HGHS technique are found to be better enhanced without such defects. In addition as shown in Figure 12 (18,19,21,26) the proposed HGHS technique results in clear visibility of objects with improved brightness, enriched sharpness along with preservation of details.

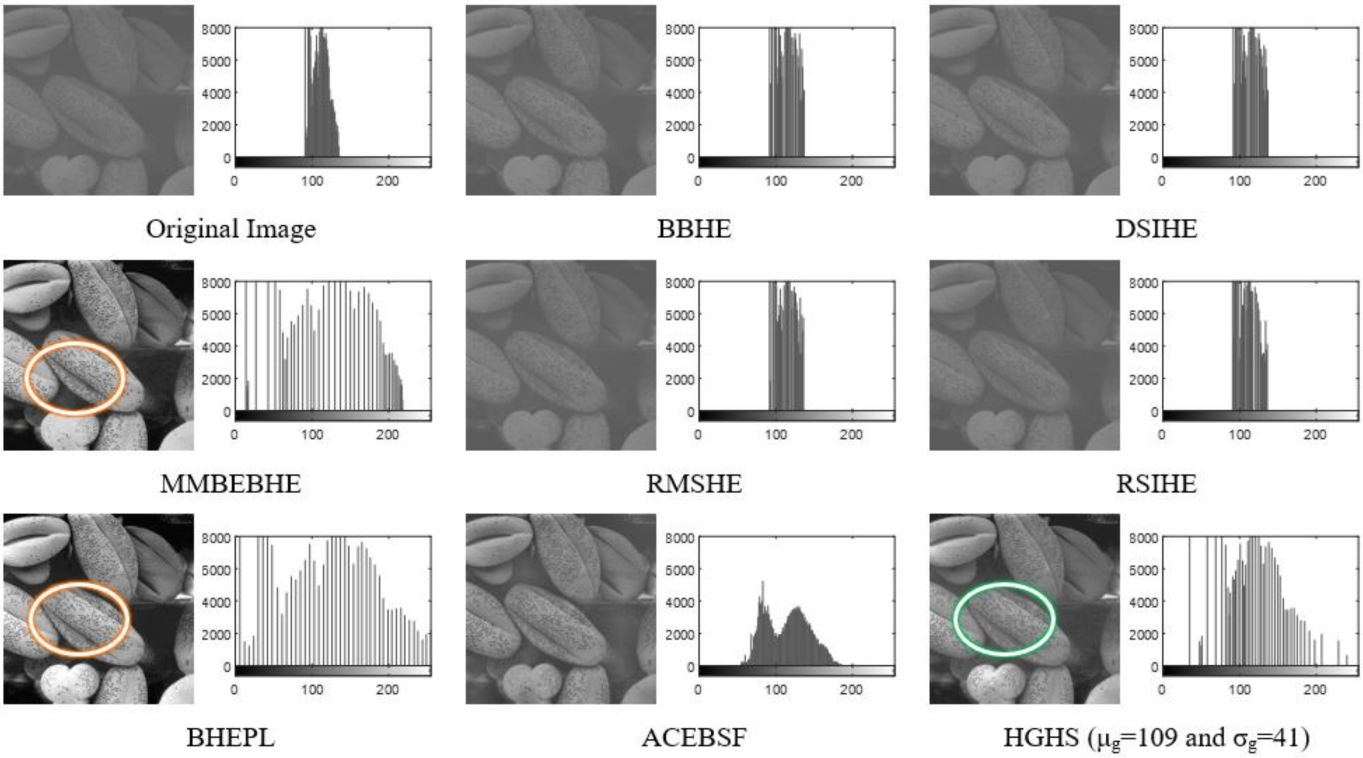


Figure 8. Enhanced images with histograms obtained by different techniques for symmetrically skewed Pollen grain image

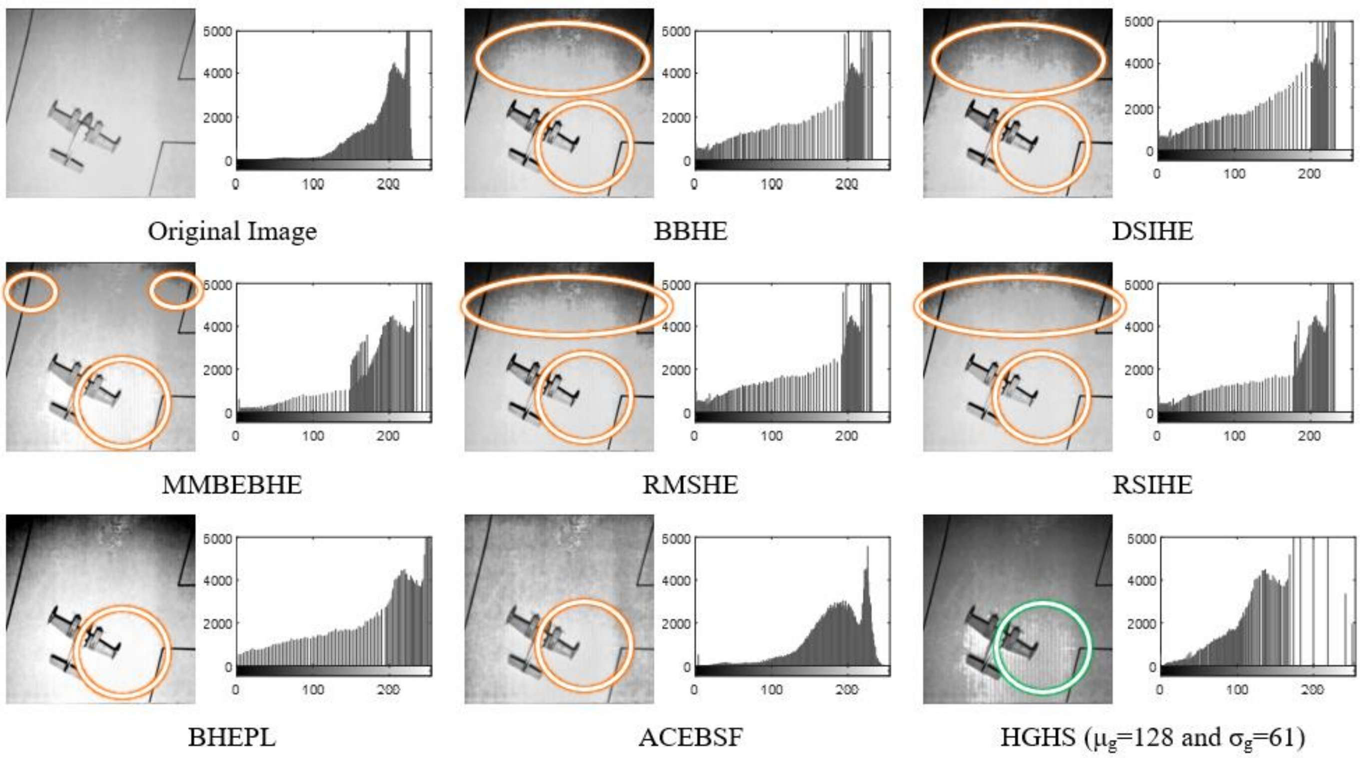


Figure 9. Enhanced images with histograms obtained by different techniques for left skewed Plane image

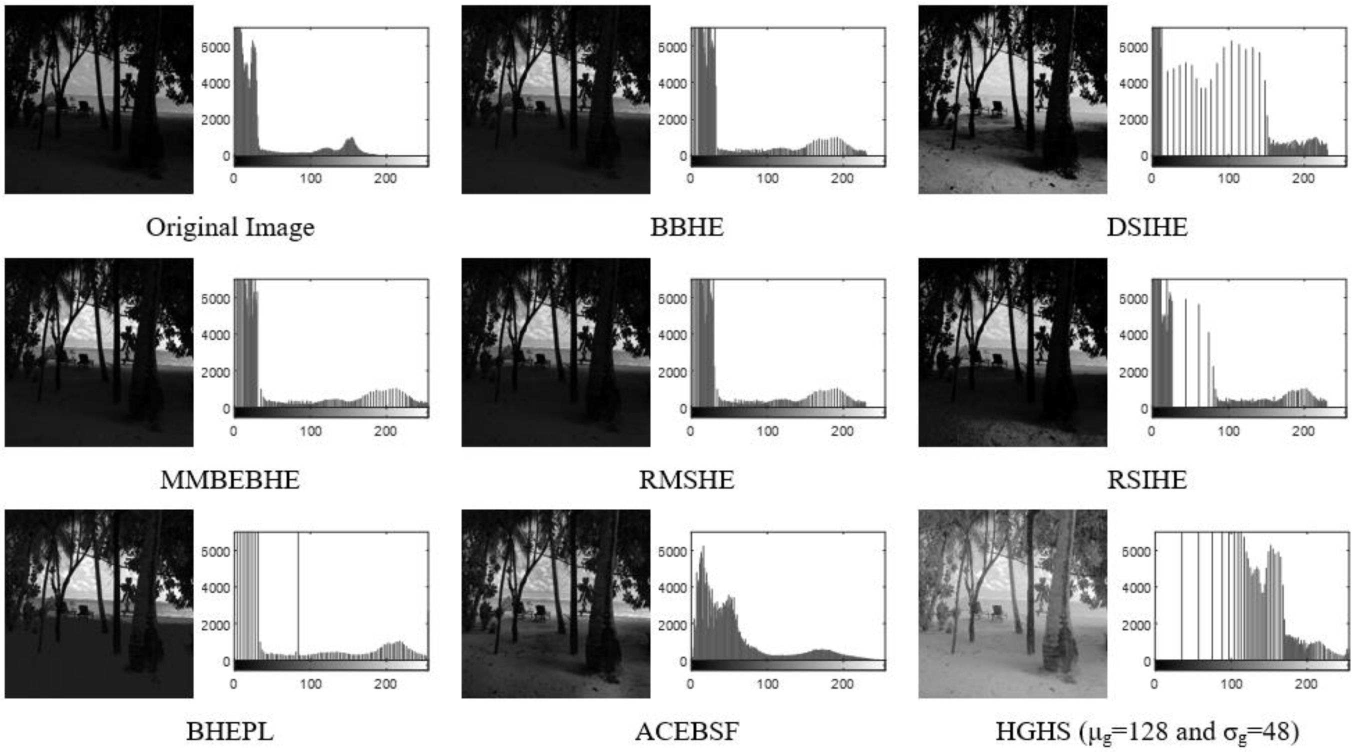


Figure 10. Enhanced images with histograms obtained by different techniques for right skewed Seashore image

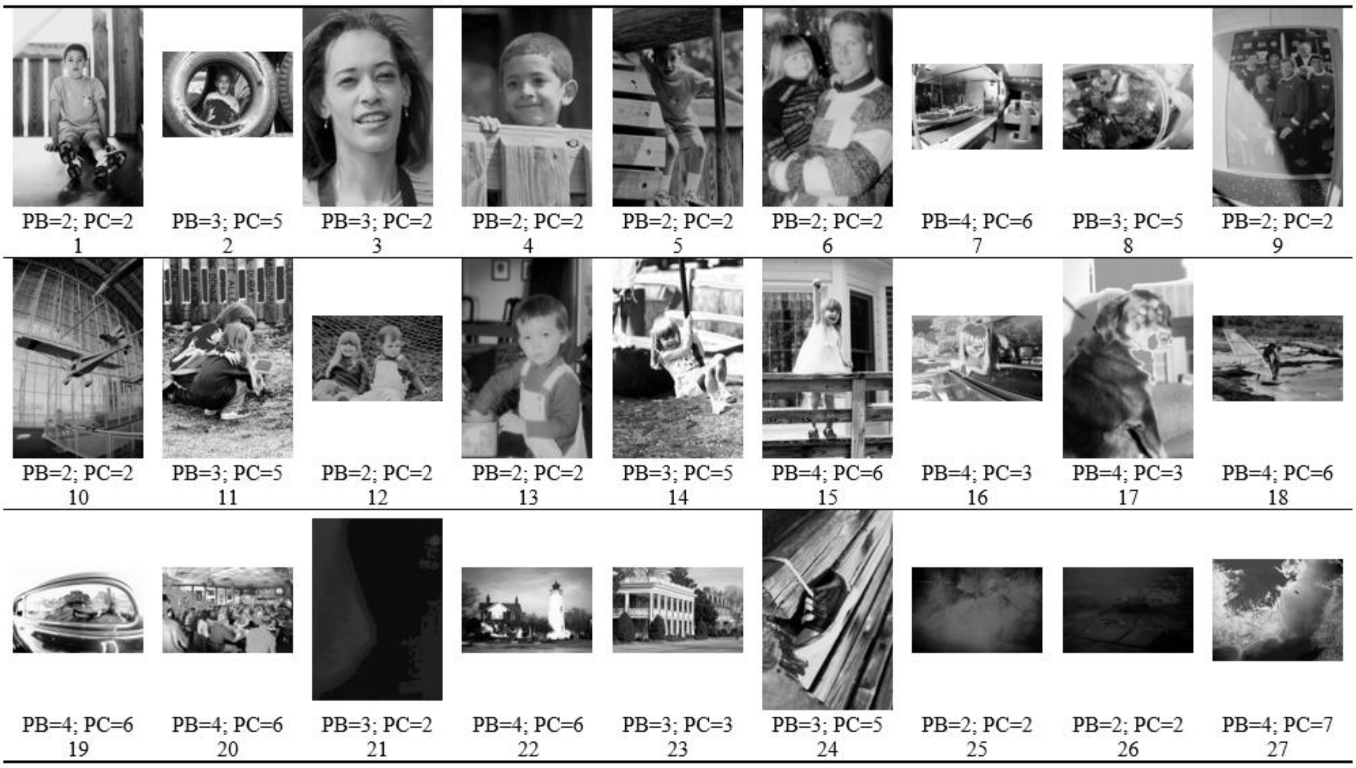


Figure 11. NASA database [30] images enhanced by BCCHS technique [20]

3.3 Computational complexity

To study the computational time taken the proposed HGHS and various existing CE techniques compared a computational complexity analysis is performed by executing the algorithms commonly in a standard system with Core i5 - 2.30 GHz - 2.40 GHz processer and 8 GB RAM in MS Windows 10 OS. The algorithms are executed in MATLAB 2017a environment with the parameters recommended by the respective authors. For computational complexity comparison, the average computational time taken for processing an image of dimension 512×512 pixels by the proposed HGHS and various existing CE techniques are determined and provided in Table 3. From the results obtained the computational time taken by the proposed HGHS technique is found to be lower than that of the existing CE techniques.

Table 3. Average computation time of various techniques in seconds per iteration for a 512 x 512 image

BBHE	DSIHE	MMBEBHE	RMSHE	RSIHE	BHEPL	ACEBSF	HGHS
0.132901	0.133015	0.136986	0.042404	0.026475	0.020933	0.059740	0.020439

Figure 12. NASA database [30] images enhanced by HGHS technique

4. CONCLUSIONS

In this article, a new histogram shape based Gaussian histogram specification CE technique is proposed. The parameters of the proposed CE technique are determined based on the given image's histogram shape to avoid the annoying side effects for increasing the visual quality of the enriched image. The performance of HGHS method is assessed on different images taken from standard databases and NASA database using standard image quality metrics like contrast, entropy and gradient. Finally, the experimental results indicate that the proposed HGHS technique is superior than the existing techniques in performance and hence it is best suitable for contrast enhancement of images with differently skewed histograms. Although the difficult task of selecting the best parameters of specified histograms is done by using a unique objective function in the proposed work, modern deep learning and optimization techniques can be used to further increase the efficiency of the proposed HGHS technique as a future research work.

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