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High-speed quantile-based histogram equalisation for brightness preservation and contrast enhancement

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Abstract: In this study, the authors introduce a new histogram equalisation-based contrast enhancement method called high-speed quantile-based histogram equalisation (HSQHE) suitable for high contrast digital images. The proposed method is an effective tool to deal with the 'mean-shift' problem, which is a usual problem with the histogram equalisation-based contrast enhancement methods. The main idea of HSQHE is to divide input image histogram into two or more sub-histograms, where segmentation is based on quantile values. Since the histogram segmentation is based on the quantile values, the entire spectrum of grey level will always play an important role in enhancement process. In addition, the proposed method does not require the recursive segmentation of the histogram as in many other methods, and hence the proposed method requires less time for segmentation. The experimental results show that the performance of the proposed HSQHE method is better as compared with other existing methods available in the literature. In addition, this method preserves image brightness more accurately than the prevailing state of art and takes less time as compared with the other methods.

1 Introduction

Large number of digital image contrast enhancement methods are available in order to optimise the visual quality of the image through grey-level or histogram modification. Histogram equalisation is one of the simplest and widely used method for digital image contrast enhancement [1]. In histogram equalisation, we reduce the number of grey levels by combining two or more less frequent neighbouring grey levels (having small probabilities) in one grey level; also we stretch high frequent intensities over high range of grey levels. This process of combining less frequent grey levels and stretching more frequent grey levels leads to a more flat histogram of grey levels of a given image, that is, the probability distribution of grey levels converges to uniform probability distribution. As we know that the entropy of an image will be maximum if the probability distribution of grey level is uniform.

In histogram equalisation we do not have any mechanism to control the enhancement level, because of this sometimes the processed image may have over enhanced regions. In addition, histogram equalisation (HE) could not effectively work, when the input image contains regions that are significantly darker or brighter than other parts of the image [2]. In addition, in theory it is clearly shown that mean brightness of histogram equalise image is always middle grey level; regardless the mean brightness of input image. This problem is known as the 'mean-shift' problem. In [3], Zuiderveld proposed a widely used method known as 'contrast limited adaptive histogram equalisation' (CLAHE). The CLAHE method is able to reduce the over enhancement of contrast in the processed image, but it is not capable in reducing the mean brightness change in the processed image. To solve the 'mean-shift' problem, in [4] Yeong-Taeg proposed 'brightness preserving bi-histogram equalisation' (BBHE), in this method the input image X is divided into two sub-images X_L and X_U based on mean X_M of brightness of input image and then equalise these two sub-histograms separately. Later Wang *et al.* in [5] proposed 'equal area dualistic sub-image histogram equalisation' (DSIHE), through this approach also separates an input image into two sub-sections, the only difference between BBHE and DSIHE is, in later method the separation is based on the median value.

An extension of BBHE has been proposed by Chen and Ramli in [6], known as 'minimum mean brightness error BHE' (MMBEBHE). This method provides maximum brightness preservation. The MMBEBHE proposes to perform the separation based on the threshold level, which would yield minimum absolute mean brightness error (AMBE) [6]. The MMBEBHE is a useful tool to control the brightness difference between input and output images. In [7], Chen and Ramli proposed another interesting method called 'recursive mean-separate histogram equalisation' (RMSHE), here authors suggested recursive division of histograms, based on the local mean. In each recursive step, existing sub-histogram is divided into two sub-histograms. After rth recursion, the number of sub-histograms are 2^r, where number of recursion depends on choice of user. In addition, authors proved mathematically that as r increases, the mean brightness of processed image approaches towards the mean brightness of input image. Sim *et al.* in [8] improved DSIHE into 'recursive sub-image histogram equalisation' based contrast enhancement (RSIHE), by introducing recursive segmentation in the similar manner as Chen and Ramli proposed in [7], this method is similar to RMSHE but it uses median values instead of mean values to divide histogram of input image into sub-histograms.

Kim [9] observed that in all previously developed algorithms, increment in level transformation function is given as

$$\Delta f(X_k) = f(X_k) - f(X_{k-1}) = (X_{L-1} - X_0) P[X_k] \quad (1)$$

From (1) it is clear that the increment is proportional to the probability value $P(X_k)$. Hence, grey levels of high probabilities will be assigned large dynamic range. In other words, grey levels of higher probabilities dominate other grey level of lower probabilities, because of this, image regions with high probabilities are over enhanced and other less probable regions are less enhanced, this leads to losing important visual details present in the image [9]. To solve this problem, Kim proposed 'recursively separated and weighted histogram equalisation' (RSWHE), in this method a power-law function is applied to sub-histograms before applying HE process. Using power-law function, authors assigned a slightly higher weight to the less frequent grey levels and slightly less weight to more frequent grey levels. The main advantage of RSWHE is that this method not only enhances image contrast, but preserves the image brightness as well. In the method, a recursive process is used to divide the given histogram into sub-histogram thus resulting in time complexity. Based on some specific requirements, the RSWHE method is modified by [10–15]. Huang *et al.* [16] propose 'efficient contrast enhancement using adaptive gamma correction with weighting distribution' (AGCWD). This method is an automatic transformation technique that improves the brightness of dimmed images via the gamma correction and probability distribution of luminance pixels [16].

We propose a new HE-based contrast enhancement method named 'high-speed quantile-based histogram equalisation' (HSQHE) which enhances the image contrast as well as preserves the image brightness in comparatively less time.

The organisation of this work is as follows. In Section 2 we completely describe histogram equalisation method, Section 3 covers a brief introduction of various histogram equalisation-based image enhancement methods. In Section 4, we completely describe the proposed method HSQHE. Section 5 provides the simulations on running time analysis, contrast enhancement and brightness preservation with visual examples and numerical results. Finally, conclusions are drawn in Section 6.

2 Histogram equalisation method

Histogram equalisation is a pre-processing technique to enhance contrast in all types of images. Equalisation implies mapping input grey-level distribution (the given histogram) to another distribution (a wider and having a more flat grey-level distribution) so that the intensity values are spread over the whole range. Through this adjustment, the grey-level distribution becomes closer to uniform grey-level distribution.

In histogram equalisation, we consider an image as a two-dimensional (2D) array of grey levels. Let the (i, j) element of this array is $X(i; j)$ be the intensity of (i, j) pixel of the image, where $X(i; j)$ is from the L discrete grey levels denoted by $\{X_0, X_1, \ldots, X_{L-1}\}$. The probability mass function (PMF) of grey level X_k is denoted by $P[X_k]$ and defined as

$$P[X_k] = \frac{n_k}{n}, \quad k = 0, 1, \ldots, L-1 \quad (2)$$

where n_k is the number of pixels having intensity X_k and n be the total number of pixels in image.

The cumulative distribution function (CDF) of X_k is denoted by $C[X_k]$ and defined as

$$C[X_k] = P[X \le x] = \sum_{j=0}^{k} P[X_j] = \sum_{j=0}^{k} \frac{n_k}{n}, \quad k = 0, 1, \ldots, L-1 \quad (3)$$

It is clear that $C[X_{L-1}] = 1$. Now we define a transformation function $f(.)$ for histogram equalisation, which maps an input grey level X_k into an output grey level $f(k)$, given as

$$f(X_k) = X_0 + (X_{L-1} - X_0)C[X_k], \quad k = 0, 1, \ldots, L-1 \quad (4)$$

3 Enhancement methods based on histogram equalisation

In this section, we are providing a brief description for various important HE-based image contrast enhancement methods:

(1) *BBHE:* This method basically divides the input image into two sub-parts namely X_L and X_U based on mean X_M of brightness of input image (where $X = X_L \cup X_U$ and $X_L \cap X_U = i$), then the HE process works independently on both the sub-histograms. This method preserves the brightness of input image to some extent. In this method, it is clearly shown that if histogram of given image $H(X)$ has a symmetric distribution around X_M, then the mean brightness of processed image can be calculated using formula $(X_M + X_G)/2$, where X_G is middle grey level of image and is expressed as $X_G = (X_0 + X_{L-1})/2$.
(2) *Equal area DSIHE:* This method is very similar to BBHE the only difference is that rather than using mean value it uses median value of the brightness of input image to decompose it into two sub-histograms. If a grey level X_D satisfies $C(X_D) = 0.5$, then it is called the median of the image X, based on this value the image is divided into two sub-parts namely X_L and X_U (where $X = X_L \cup X_U$ and $X_L \cap X_U = \phi$). Each of X_L and X_U is then equalised independently as in BBHE.
(3) *RMSHE:* Mean separation is a basic process for preserving certain level of brightness and this is what RMSHE does. In fact, for $r = 0$ and $r = 1$ RMSHE is equivalent to HE and BBHE, respectively, and for $r > 1$ it generates 2^r sub-histograms. To achieve higher brightness preservation, multiple recursive mean separations are needed. It is declared that as the recursion level r increases, the mean brightness of the processed image comes near to the mean brightness X_M of input image.

(4) *RSIHE:* As RMSHE is a generalisation of BBHE similarly RSIHE is a generalisation of DSIHE, it performs median-based segmentation more than once. Its working process is similar to RMSHE, but the only difference is that for histogram segmentation it uses median values instead of mean values.
(5) *RSWHE:* Kim and Chung [9] observed that all previously mentioned algorithms only perform HE process and these algorithms do not modify the histogram of input image, hence they developed RSWHE which first modifies the input image histogram using a power-law function and then perform the HE process recursively in each sub-histogram. We can say that RSWHE is nothing but a modification in RMSHE or RSIHE where the input image histogram is first modified based on a power-law function and then the HE process is applied in each sub-histogram separately.

4 HSQHE method

This section contains the detailed description of the proposed method HSQHE for brightness preservation and contrast enhancement. This method consists of three modules namely histogram segmentation module, histogram weighting module and histogram equalisation module.

We propose the histogram segmentation based on quantile values of grey-level distribution of image. The quantiles are defined as follows.

'Quantiles' are points taken at regular intervals from the CDF. Dividing ordered data (in our case grey level) into q essentially equal sub-section for q-quantiles.

For example, rth, q-quantile for a random variable X is the value x such that

$$C[x] = P[X \leq x] = \frac{r}{q}, \quad \text{where } r = 0,\ 1,\ 2,\ \ldots,\ q \tag{5}$$

4.1 Segmentation by quantiles

The image histogram graphically represents number of pixels against the intensity of the pixel of image and denoted by $H(X)$, defined over $[X_0,\ X_{L-1}]$. Now we divide image histogram $H(X)$ in q equal proportions (sub-histograms) using q-quantiles (here $q \leq L-1$); $H_1 = [a_0,\ a_1]$, $H_2 = [a_1,\ a_2]$, …, $H_q = [a_{q-1},\ a_q]$, such that

$$P[X \in H_k] = P[a_{k-1} = X \leq a_k] = 1/q, \quad k = 1,\ 2,\ \ldots,\ q \tag{6}$$

where $a_0 = X_0$, $a_q = X_{L-1}$ and $a_k \in \{X_0,\ X_1,\ \ldots,\ X_{L-1}\}$, $\forall k = 0,\ 1,\ \ldots,\ q$. The division of histogram using the proposed method can easily be done with the help of CDF and this division requires less time as compared with other methods that use recursive division.

Let p_k be the accumulated probability of sub-histogram H_k, and is defined as

$$p_k = \sum_{h \in [a_{k-1}, a_k]} P[X_j = h], \quad j = 0,\ 1,\ 2,\ \ldots,\ L-1 \tag{7}$$

Then the normalised grey-level PMF for sub-histogram H_k will be

$$P_k[X_i] = \frac{P[X_i]}{p_k} \tag{8}$$

and the corresponding CDF of sub-histogram H_k will be

$$C_k[X_i] = \sum_{h=a_{k-1}}^{X_i} \frac{P[X_j = h]}{p_k} \tag{9}$$

Based on CDF, the transformation function for sub-histogram H_k will be as follows

$$f_k(X_i) = a_{k-1} + (a_k - a_{k-1})C_k[X_i], \quad k = 1,\ \ldots,\ q \tag{10}$$

Suppose Y be the processed image, then

$$Y = \cup_{k=1}^{q} f_k(X_i) \tag{11}$$

It is clear that the final processed image is basically union of all these sub-histograms.

4.2 Histogram weighting module

Let H_k, $k = 0, 1, \ldots, L-1$ be a sub-histogram of image $X(i, j)$. Let $P_{\max} = \max_k P_k[X_i]$ and $P_{\min} = \min_k P_k[X_i]$, for $i = 0,\ 1,\ 2,\ \ldots,\ L-1$; are maximum and minimum probabilities of input image histogram.

Now for each sub-histogram H_k, we replace the original PMF P_k by the modified weighted PMF P_k^w, such that

$$P_k^w[X_i] = P_{\max}\left(\frac{P_k[X_i] - P_{\min}}{P_{\max} - P_{\min}}\right)^{p_k} \tag{12}$$

The above weighting model gives higher weights to the lower probabilities, that is, it gives higher weights to those intensities which are less frequent in the image and gives lesser weights to more frequent intensities. These weights help to minimise the distance between grey-level distribution and the uniform distribution.

The sum of all the values of P_k^w from $k = 0$ to $L-1$ is no longer one, as we have changed the weight. To make P_k^w a PMF, it needs to be normalised as follows

$$P_k^{nw}[X_i] = \frac{P_k^w[X_i]}{\sum_{k=0}^{L-1} P_k^w[X_i]} \tag{13}$$

where $P_k^{nw}[X_i]$ is weighted and normalised histogram in the range $[0,\ L-1]$. This $P_k^{nw}[X_i]$ is now forwarded to next HE module.

4.3 Histogram equalisation module

This module takes weighted and normalised histogram from previous module and then apply HE process in each sub-histogram independently.

4.4 HSQHE–algorithm

See Fig. 1.

4.5 Brightness changed by HSQHE

Let us consider an image as a 2D array of grey levels and the (i, j) element of this array is $X(i; j)$ be the intensity of (i, j) pixel of the image, where $X(i; j)$ is from the L discrete grey levels denoted by $\{X_0,\ X_1,\ \ldots,\ X_{L-1}\}$. The PMF of X_k is denoted by $P[X_k]$ and defined as in (2). Then grey-level probability mass after simple histogram equalisation is as

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Algorithm 1

```
SET GREY_RANGE ← 256
Require: qValue ≥ 1 AND qValue ≤ 255
  CALCULATE HISTOGRAM OF IMAGE IMG[][]
  HIST[] := HISTOGRAM_IMAGE(IMG[][])
  CREATE QUANTILE ARRAY OF SIZE qValue
  qArray[].SIZE() ← qValue
  CALCULATE QUANTILE ARRAY VALUES.
  SET COUNTER := 1
  while COUNTER ≤ qValue do
     SET SUM := 0
     SET CNT := 0
     while CNT ≤ GREY_RANGE do
        SET SUM := SUM + HIST[CNT]
        if SUM ≥ COUNTER/qValue then
           qArray[COUNTER − 1] := CNT
           BREAK
        end if
        SET CNT = CNT + 1
     end while
     SET COUNTER = COUNTER + 1
  end while
  SET qArray[qValue − 1] = GREY_RANGE − 1
  SEGMENT ORIGINAL HISTOGRAM INTO SUB-HISTOGRAM BASED ON QUANTILE AR-
  RAY VALUES.
  NORMALISE EACH SUB-HISTOGRAM.
  APPLY HISTOGRAM WEIGHTING MODULE IN EACH SUB HISTOGRAM.
  NORMALISE WHOLE HISTOGRAM.
  APPLY HISTOGRAM EQUALISATION IN EACH SUB-HISTOGRAM INDEPENDENTLY.
  CALCULATE PROCESSED IMAGE FROM PROCESSED HISTOGRAM.
```

Fig. 1 *The quantile based histogram segmentation algorithm*

follows

$$P[X] = \frac{1}{X_{L-1} - X_0}, \quad \forall X \in \{X_0, X_1, \ldots, X_{L-1}\} \tag{14}$$

The mean brightness $E[Y]$ of the processed image Y, will be

$$E[Y] = \frac{X_{L-1} - X_0}{2} \tag{15}$$

This shows that mean brightness of processed image after histogram equalisation does not depend on the grey-level distribution of original image.

In the proposed HSQHE method, the grey-level distribution is as $\cup_{k=1}^{q}\{p_k | k \in [a_{k-1}, a_k]\}, > k = 1, 2, \ldots, q$ where $a_0 = X_0$ and $a_q = X_{L-1}$, such that (6) is satisfied. Then, we have

$$p_k = \frac{1}{q(a_k - a_{k-1})}, \quad k = 1, 2, \ldots, q \tag{16}$$

and the average brightness of H_k sub-histogram is

$$E[Y|H_k] = \frac{a_k - a_{k-1}}{2q} \tag{17}$$

Hence, the average brightness of processed image is

$$\begin{aligned} E[Y] &= \sum_{k=1}^{q} E[Y | a_{k-1} \le X \le a_k] \\ &= \frac{1}{2q} \sum_{k=1}^{q} (a_k - a_{k-1}) \end{aligned} \tag{18}$$

Fig. 2 shows some intermediate results produced by our method. From Fig. 2, it is clear that after applying histogram weighting module in a given histogram, less frequent grey levels obtain higher weights than more frequent grey levels. Owing to this, no over enhancement

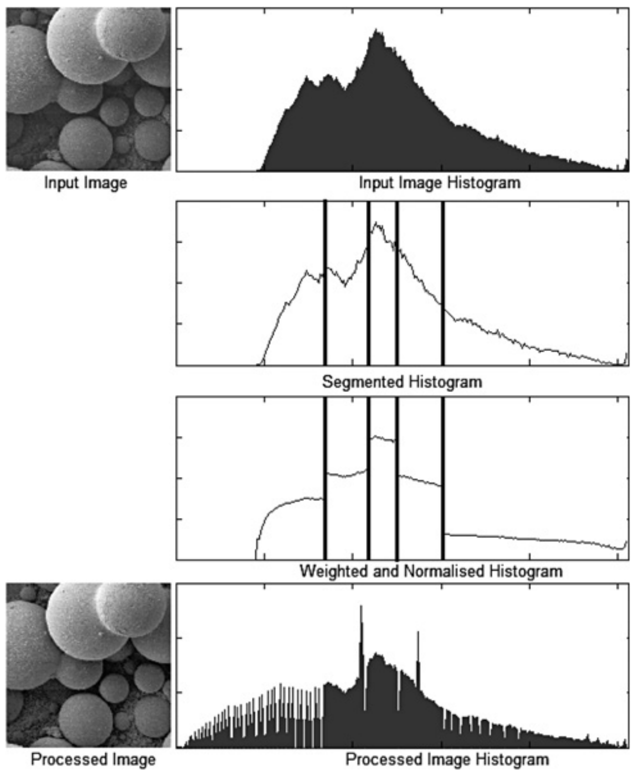

Fig. 2 *Intermediate results produced by HSQHE along with histograms*

Fig. 3 *Enhancement results for elaine and lady images*

a Input image
b Result of HE
c Result of CLAHE
d Result of BBHE
e Result of DSIHE
f Result of RMSHE
g Result of RSIHE
h Result of RSWHE-M
i Result of HSQHE AGCWD
j Result of HSQHE $q = 5$
k Result of HSQHE $q = 6$

takes place for more frequent grey levels by HSQHE and hence no information is lost during the whole process.

Fig. 3 shows enhancement results by various methods including the proposed method on elaine and lady images.

5 Experimental results

In this section, we demonstrate the performance of our proposed method HSQHE in comparison with some other

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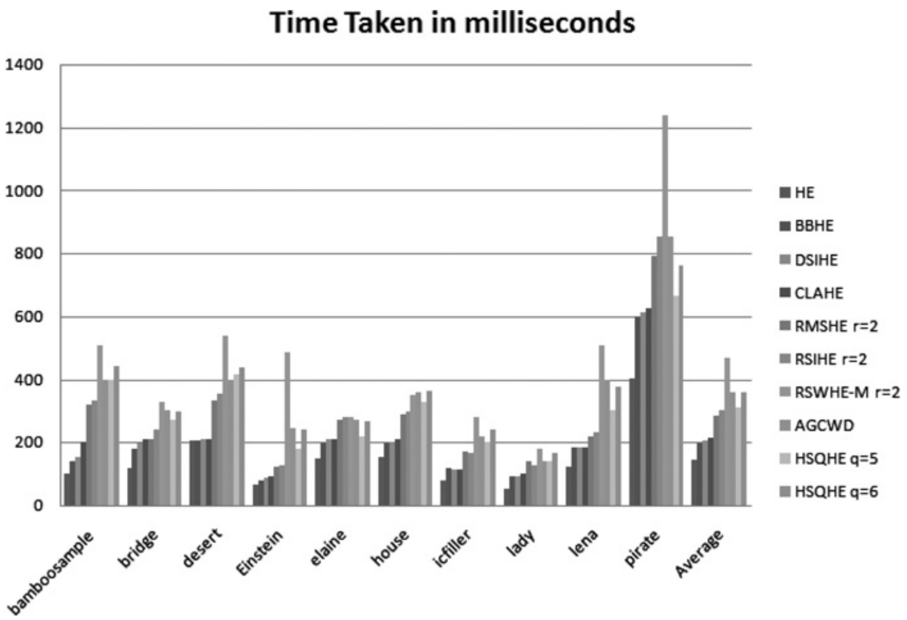

Fig. 4 *Graphical representation of time taken by various methods in milliseconds on given set of images*

important HE-based methods including CLAHE, BBHE, DSIHE, RMSHE, RSIHE, AGCWD and RSWHE-M. Here, we implement these methods on the ten test images bamboo sample, bridge, desert, Einstein, elaine, house, icfiller, lady, lena and pirate, which have been previously used in many of these methods to show their performances.

To evaluate the effectiveness of our method, we choose four metrics, peak signal-to-noise ratio (PSNR), AMBE, image entropy (H) and time taken (in milliseconds for enhancement).

5.1 Assessment of time

In Fig. 4, we compare the time required (in milliseconds) for contrast enhancement by various methods. It is clear from Fig. 4 that the proposed method requires less time as compared with all the other methods that separate input image histogram into sub-histograms recursively and then performs some form of histogram modification on each segmented sub-histograms. The proposed method performs faster, as segmentation process is not recursive as it is in the other methods. For measuring processing speed, time taken to enhance given image is taken as base criteria in some of the previously developed methods of Wang *et al.* [17] and Ming [18], these methods prove that they are faster than other methods.

We have implemented all methods (including HSQHE) in Java programming language without using any third party application programming interface, to calculate the processing time we have executed these algorithms 1000 times and then we calculated average processing time. This time is displayed in Fig. 4.

As we already know that the previously developed methods use recursive processing for histogram segmentation. The term 'recursion' allows multiple activation-records [19] of a procedure to exist in main memory, and hence it requires more memory and more computations. On the other hand, the proposed method uses linear segmentation of input image histogram and it does not have any recursive mechanism for that. This is why it is computationally less expensive than other methods. In favour of this claim, in Fig. 5 we are again showing results of time taken in milliseconds for 60 standard test images [20] of size 256 × 256. In Fig. 5, we are comparing the proposed method processing time with the widely used RSWHE-M method. The RSWHE-M method also uses some form of histogram weighting module before applying histogram equalisation process, and hence it is somehow similar to the proposed method.

Fig. 5 clearly shows that how the linear segmentation process reduces the processing time (in Fig. 5, x-axis represents the segmentation level from 1 to 128 and y-axis represents processing time in milliseconds). Another advantage of the proposed HSQHE method is that it provides the complete control on the level of enhancement. As in all previously developed methods, number of sub-histograms after the rth recursion are 2^r, that is, after the third recursion eight sub-histogram and then in the next levels 16, 32 and so on. In many cases, we required to preserve image brightness up to certain level, for example,

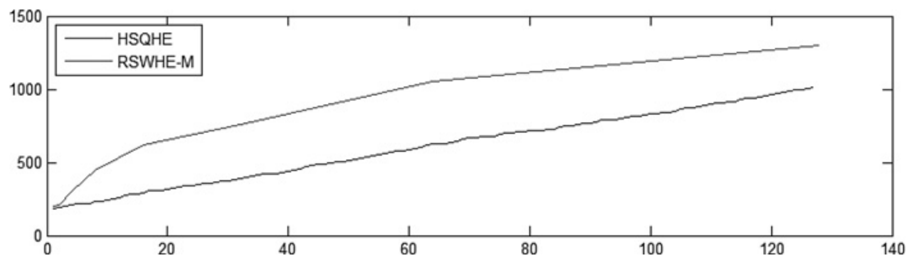

Fig. 5 *Graphical representation of time taken by RSWHE-M and the proposed method in milliseconds on standard test images*

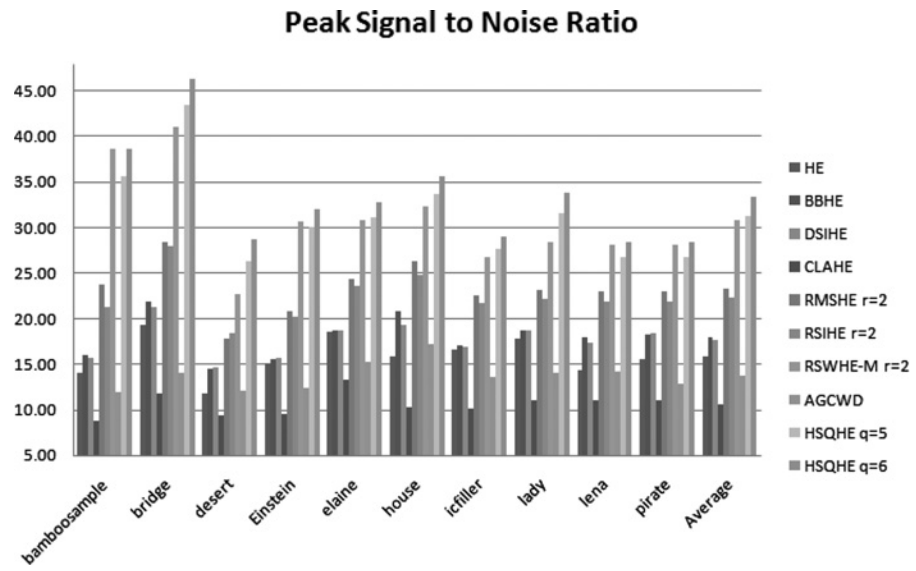

Fig. 6 *Graphical representation of PSNR values by each method on given set of images*

let in a situation we require to achieve brightness preservation up to a level L, and this level can achieve above 16 and below 32 histogram segmentation of given image X. Then the required level (L) of brightness preservation cannot be achieved by previously developed methods, whereas in case of our method any value in between 1 and 255 (for images where single pixel intensity value is stored in 8 bit) can be taken to carry out same task that will meet our current requirement of brightness preservation up to level L.

5.2 Assessment of contrast enhancement

In this sub-section, we demonstrate the performance of the proposed HSQHE method in comparison with the other methods in terms of PSNR and entropy. The PSNR and entropy are widely user measured for comparing the contrast enhancement methods.

5.2.1 Peak-signal-to-noise ratio: PSNR is an approximation to human perception of reconstruction quality of an image. A higher PSNR generally indicates that the reconstruction is of higher quality [8, 9, 21, 22]. To calculate PSNR between two images (each image is having L discrete grey levels in the range $\{X_0, X_1, \ldots, X_{L-1}\}$), mathematical expression is given as

$$\text{PSNR} = 10 \log_{10} \frac{(L-1)^2}{\text{MSE}} \tag{19}$$

where MSE is mean square error, is defined as

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |X(i, j) - Y(i, j)|^2 \tag{20}$$

Practically the MSE allows us to compare the 'true' pixel values of our original image to our degraded image. The MSE represents the average of the squares of the 'errors' between our actual image and our noisy image. The error is the amount by which the values of the original image differ from the degraded image. The proposal is that the higher

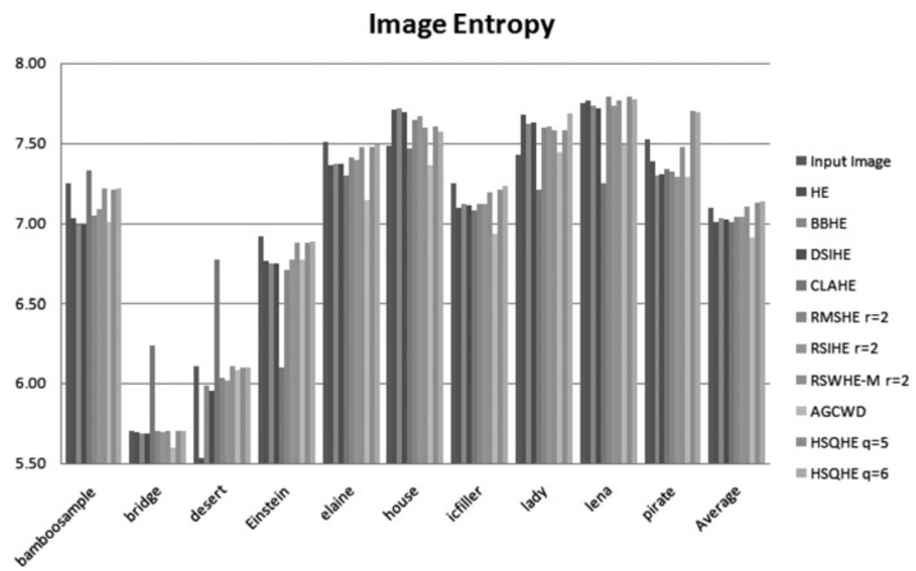

Fig. 7 *Graphical representation of entropy values by each method on given set of images*

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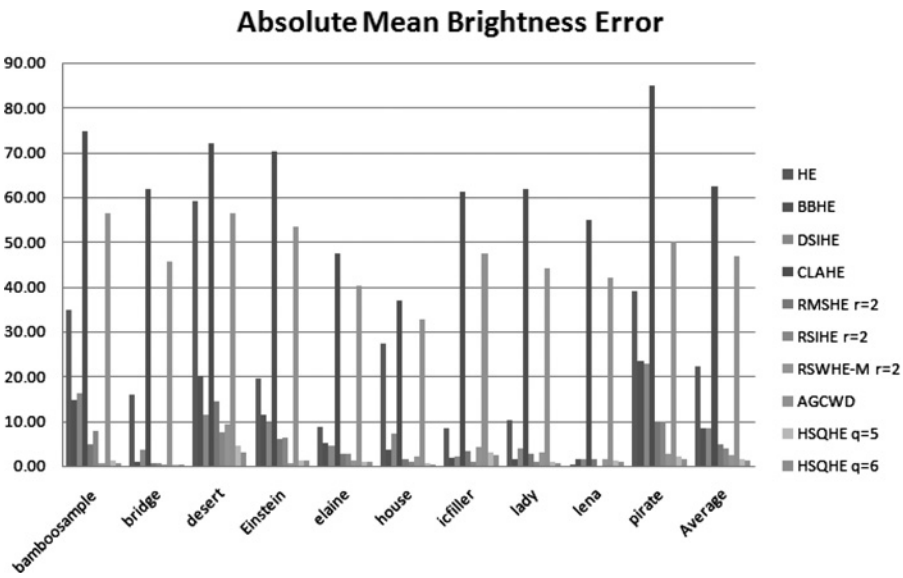

Fig. 8 *Graphical representation of AMBE values by each method on given set of images*

the PSNR, the better degraded image has been reconstructed to match the original image and the better the reconstructive algorithm. This would occur because we wish to minimise the MSE between images with respect the maximum signal value of the image [23].

Fig. 6 gives the comparison of PSNR between the proposed HSQHE method and other methods on ten test images. It is clear from Fig. 6 that the proposed HSQHE method with $q = 6$ has highest PSNR for all the test images. In addition, for $q = 5$ the proposed HSQHE method has higher PSNR for seven out of ten images. The average PSNR values are given in the right most plot of Fig. 6. The average PSNR values of other methods are smaller than those of HSQHE, which shows that HSQHE outperforms other existing methods in terms of the PSNR.

5.2.2 Entropy: In general, the higher the entropy is, the richer details and information the image holds [9]. Mathematical expression to calculate entropy of an image is given as

$$\mathrm{Ent}[P] = -\sum_{k=0}^{L-1} P(k) \log_2 P(k) \tag{21}$$

where $P(k)$ is PMF of histogram of given image.

Fig. 7 gives the comparison of entropy between the proposed HSQHE method and other methods on same set of ten test images. It is clear from Fig. 7 that the proposed HSQHE method has higher entropy for six out of ten images. The average entropy values are given in the right most plot of Fig. 7. The average entropy values of other methods are smaller than those of HSQHE, which shows that on an average HSQHE is better than the other existing methods in terms of the entropy also.

5.3 Assessment of brightness preservation

This section shows the efficiency of the proposed HSQHE method to deal with 'mean-shift' problem.

The AMBE is used to measure difference in mean brightness between two images. Mathematical expression to calculate AMBE between two images is given as

$$\mathrm{AMBE} = |X_{\mathrm{M}} - Y_{\mathrm{M}}| \tag{22}$$

where X_{M} and Y_{M} are mean brightness of input and processed image, respectively.

Based on results of Fig. 8, it can be observed that HSQHE ($q = 5$) has least values in eight images as compared with that of HE, BBHE, DSIHE, CLAHE, RMSHE and RSIHE and it has least values in six out of ten from that of RSWHE-M. For HSQHE ($q = 6$), observations in Fig. 7 show that the proposed HSQHE method produces best results from all other methods in comparatively less time. The average of AMBE of all the ten test images is given in the right most plot of Fig. 7. The average of AMBE of the proposed HSQHE method is significantly smaller than the other methods.

In the following Table 1, we are showing average results of PSNR, AMBE and image entropy (H) for 60 standard test images.

Based on results of Table 1, it is clear the proposed method performs well on standard test images and it gives more contrast to input image and preserves image brightness more accurately than many other methods.

5.4 Inspection of visual quality

From quantitative evaluation, it is clear that our method produces comparatively better results as compared with other important existing methods. There are situations when

Table 1 Average results of AMBE, PSNR and H for standard test images

Methods	AMBE	PSNR	Image entropy (H)
HE	22.65	15.45	7.00
BBHE	8.53	18.31	7.03
DSIHE	8.59	18.43	7.02
RMSHE	4.47	23.65	7.04
RSIHE	4.69	24.03	7.04
CLAHE	63.09	12.15	7.01
RSWHE-M	1.78	31.88	7.10
AGCWD	47.79	13.27	6.91
HSQHE $q = 5$	1.42	31.97	7.10
HSQHE $q = 6$	0.93	32.13	7.11

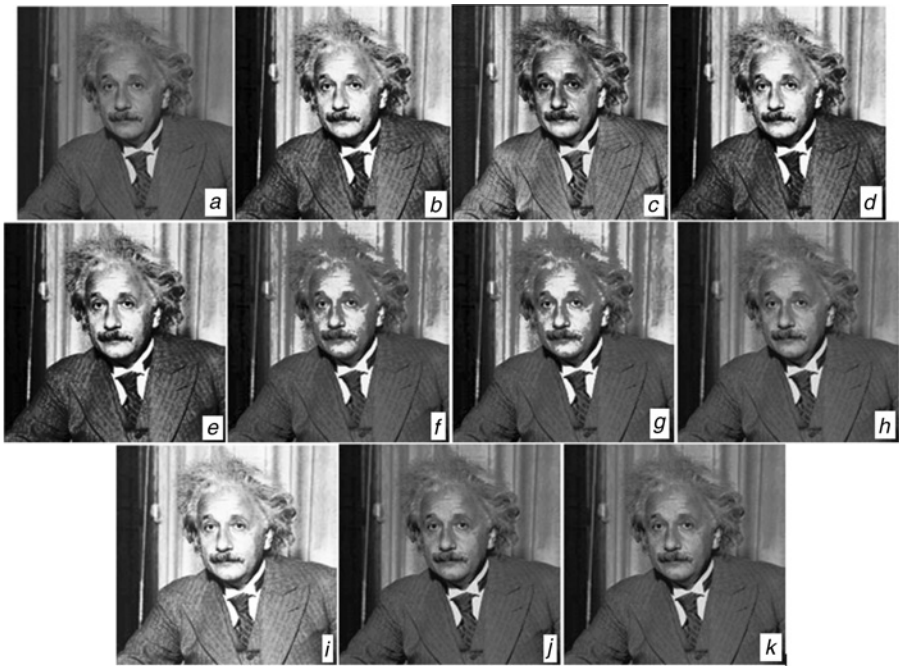

Fig. 9 *Enhancement results for Einstein image*

a Input image
b Result of HE
c Result of CLAHE
d Result of BBHE
e Result of DSIHE
f Result of RMSHE
g Result of RSIHE
h Result of RSWHE-M
i Result of AGCWD
j Result of HSQHE $q = 5$
k Result of HSQHE $q = 6$

we required qualitatively assessment of the image after contrast enhancement, which can be done by judging the visual acceptance and natural appearance of processed image.

Fig. 9 shows results of various methods on Einstein image for visual quality inspection.

From Fig. 9, it is clear that result produced by HSQHE looks more natural as compared with other methods. This shows that the proposed method produces images without losing their natural appearance.

6 Conclusion

In this paper, we propose HSQHE; this method is developed to enhance image contrast without much affecting the mean brightness of input image. In addition, HSQHE is designed such that it takes less time as compared with other methods, as in the proposed method we have quantile-based histogram segmentation that does not need recursive segmentation of the histogram. Another advantage of quantile-based histogram segmentation is that it provides chance to every part of grey-level spectrum to play their role in the enhancement process. Experimental results show that HSQHE preserves image brightness more accurately than other existing HE-based methods and produces image with better contrast in comparatively less time, without producing unwanted artefacts.

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