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Non-parametric modified histogram equalisation for contrast enhancement

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Abstract: Histogram equalisation has been a much sought-after technique for improving the contrast of an image, which however leads to an over enhancement of the image, giving it an unnatural and degraded appearance. In this framework, a generalised contrast enhancement algorithm is proposed which is independent of parameter setting for a given dynamic range of the input image. The algorithm uses the modified histogram for spatial transformation on grey scale to render a better quality image irrespective of the image type. Added to this, two variants of the proposed methodology are presented, one of which preserves the brightness of original image while the other variant increases the image brightness adaptively, giving it a better look. Qualitative and quantitative assessments like degree of entropy un-preservation, edge-based contrast measure and structure similarity index measures are then applied to the 500 image data set for comparing the proposed algorithm with several existing state-of-the-art algorithms. Experimental results show that the proposed algorithm produces better or comparable enhanced images than several algorithms.

1 Introduction

Image enhancement is a process of applying a transformation on the image so that the resultant image is better than the original for a specific application [1]. The main aim of applying this technique is to improve the perception of information in images for visual inspection or machine analysis, without any knowledge of the source degradation model.

There are several techniques used for improving the contrast of an image, and they are basically categorised as: (i) spatial techniques that operate directly on pixels, (ii) transform domain techniques. In spatial techniques, the most prevalent approach for improving the contrast is to modify the grey levels, to increase the dynamic range of the resultant image. Global histogram equalisation (HE) is one of the simplest techniques, which obtains its transformation function from the cumulative distribution function (CDF) of the input image. Although this transformation leads to an image with a uniform distribution and wider spread than the original image, it creates an undesirable effect and an over-enhancement of the image [2].

To overcome this problem, different local HE (LHE) techniques were proposed. LHE divides the input image into an array of sub-images and then performs HE on each of them independently [3]. However, LHE based methods have higher computational cost and results in over-enhancement in certain portion of the image at times [4].

A group of researchers took particular interest in preserving the mean brightness of an image by modifying the method of applying HE to the input image. It not only maintains a natural look in the output image but reduces saturation effect in it as well. Mean brightness preserving HE (MBPHE) methods separate the input histogram into non-overlapping disjoint sections and equalise them independently. Bisections MBPHE and multi-sections MBPHE are two primary groups under the MBPHE methods [5–8]. Although these methods provide decent enhancement in certain cases, they are preferred only for images with quasi-symmetrical distribution around its separating point [7].

Multi-sections MBPHE methods divide the input histogram into R (any positive integer) sub-histograms and equalise them individually [9, 10]. Although these methods provide good brightness preservation, they suffer from the drawback of being ineffective when R is too-large [11]. Dynamic HE (DHE) [12] first smoothens the input histogram using a one-dimensional smoothing filter and then splits it into sub-histograms based on the local minimums. Brightness preserving DHE (BPDHE) [13] uses the Gaussian kernel for smoothing the input histogram and avoids re-mapping of peaks unlike DHE. This technique does not take imprecision of grey-values while processing crisp histograms [14]. Brightness preserving dynamic fuzzy HE (BPDFHE) [14] is a further improvement of BPDHE and applies fuzzy histogram to handle inaccuracy in grey-levels.

Since, most of these techniques of multi-sections MBPHE require complicated algorithms and high computation time [2], few researchers studied the use of optimisation-based techniques for contrast enhancement. Brightness preserving HEs with maximum entropy (BPHEME) [11] intends to a histogram with utmost entropy using a variational approach under the constraint of mean brightness. Although entropy maximisation concurs to contrast stretching, it does not always result in contrast enhancement [15]. In order to overcome this problem, flattest histogram specification with accurate brightness preservation (FHSABP) [15] proposes a convex optimisation for finding the flattest histogram for contrast improvement under the mean brightness constraint. Since the cumulative distribution functions are not exactly invertible, FHSABP uses an exact histogram specification method [16] for an assured discrete histogram. However, this technique may produce a low-contrast image, when the average brightness is too low or too high, because of its mean brightness preservation constraint. Arici *et al.* [17] suggested a histogram modification framework, which aimed to minimise a cost function to improve the contrast of an image with the least possible addition of noise. This algorithm could enhance the images to a good level, but requires manual tuning of many parameters. Furthermore, a contrast enhancement method based on genetic algorithm [18] is applied to find a target histogram that maximises a contrast measure based on edge information. Although this technique was non-parametric, it had the disadvantages of GA-based methods [4]. In order to address the artefacts introduced by HE, clipped HE methods were implemented in HE with bin underflow and bin overflow (BUBOHE) [19] and weighted and thresholded HE (WTHE) [20]. WTHE preserves the low-probability grey levels by using a normalised power law function, with index between '0' and '1'. However, WTHE and BUBOHE are limited by the fact that it necessitates the user to set the parameter manually.

Transform based techniques, modify the magnitude of the desired coefficients of the image by decomposing the input image into different sub-bands [21, 22]. These algorithms enable simultaneous global and local contrast enhancement by transforming the signal in the appropriate bands.

The above mentioned techniques are mostly parametric and create distortions in smooth regions of the image after modification. Moreover, time complexity becomes an important aspect of enhancement techniques when real time applications are considered. In order to overcome these issues, a non-parametric enhancement method is proposed in this paper. It can well preserve the shape of the histogram even after the transformation. Added to this, two more variants of the proposed algorithm are suggested, one of which preserves the average brightness of the original image while the other one increases the brightness of the image in a regulated manner.

The remaining part of the paper is organised as follows: Section 2 presents the necessary background related to modified HE. Section 3 presents the proposed technique for enhancement of the image. Section 4 presents the objective and subjective assessment for the image generated by the proposed techniques and benchmarks with other state-of-the-art techniques. Finally, Section 5 concludes the paper.

2 Histogram modification framework

HE is one of the most widely adopted approaches to enhance low contrast images. The HE technique obtains a mapping function to modify the original image to be as close as possible to a uniform distribution. Let us consider an input image, that is, $I = \{I(i, j) | 1 \le i \le M, 1 \le j \le N\}$, of size $M \times N$ pixels, where $I(i, j) \in \mathbb{R}$ the probability density function (PDF) of the image is given by

$$p(k) = n_k / J, \quad \text{for } k = 0, 1, \ldots, L-1 \tag{1}$$

where, n_k is the no. of pixels with intensity k and J, the total number of pixels in the image. The cumulative distribution function (CDF), $c(k)$ is given by (2) as

$$c(k) = \sum_{i=0}^{k} p(i) \tag{2}$$

The transformation mapping, $T(k)$, is a single valued and monotonically increasing function, which maps each input grey-level to a modified grey-level in the interval $[0, \ldots, L-1]$, where $L = 256$ for an 8-bit image. $T(k)$ for HE is obtained by multiplying $c(k)$ with the maximum intensity level of the output image. For a b-bit image, there are $2^b = L$ intensity levels and the transformation function is given by

$$T(k) = \lfloor (L-1)c(k) + 0.5 \rfloor \tag{3}$$

For the algorithm described by (1)–(3), the increment in output level $T(k)$ is directly related to the probability of occurrence of the kth grey-level such that

$$\Delta T(k) = T(k) - T(k-1) \cong (L-1)p(k) \tag{4}$$

After this discussion on HE, a general framework of different modification methods for HE has been presented in the following sub-sections.

2.1 Adjustable uniform mapping

HE tends to over enhance the image in its attempt to distribute the pixels uniformly among all grey levels. Histogram spikes occur because of the existence of large no. of pixels with same grey level as their neighbours. This results in a transformation mapping function that will map a narrow range of pixel values to a wider range, introducing grainy noise in smooth portion of the image. This phenomenon can be restrained by adjusting the mapping function, such that, it is an optimisation between the uniformly distributed histogram (u) and the mapping function of HE [17]. This optimisation problem can be formulated as

$$\min (\|h - h_i\| + \gamma \|h - u\|) \tag{5}$$

where h_i is the original histogram for the given image, h, the modified histogram and γ, the problem parameter which varies between $[0, \infty)$. For $\gamma = 0$, the solution of (5) corresponds to traditional HE modified image, and as γ goes to ∞ the solution starts converging to the original image [17]. A solution to this optimisation function can be written as

$$h = wh_i + (1-w)u \tag{6}$$

where w is a weighting factor between 0 and 1. However, this modification does not solve the spike problem to a great extent and requires few more parameters to be included in the optimisation problem.

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2.2 Histogram weighing

The smooth regions in an image are the main source of spikes in a histogram [17], resulting in few highly probable grey levels. This leads to a transformation function with a very high slope at these intensity levels.

Fig. 1*a* shows an image with large smooth regions at nearly same grey levels. The histogram of this image as shown in Fig. 1*b* is found to have a spike near an intensity level of 255. The transformation function shown in Fig. 1*c*, depicts the mapping of a narrow intensity range of [250, 255] to a wider intensity range of [150, 255] in the modified image. As a consequence, for an increment of each grey-level, there is an increment of nearly 21 grey-levels in the reconstructed image. This results in a very unrealistic look and increases artefacts in the processed image as shown in Fig. 1*d*.

Histogram weighing modifies the original histogram by a weighting factor of average local variance of all pixels with the same grey-level [17]. This modification imparts lesser weight to the grey-levels, which lie in the smooth region, and higher weight to ones which lie in the spatially varying region. The optimisation function for a weighted histogram is

$$\min (h - h_i)^{\mathrm{T}} W (h - h_i) \tag{7}$$

where $W(i, i)$ is the average local variance of pixels with the grey level i [17].

2.3 Histogram smoothing

This method smoothens the original histogram and prevents spikes in the histogram. However, this implementation requires adjustment in the level of smoothing based on the magnitude of the spike.

2.4 Clipped HE

This modification framework avoids histogram spike by clamping the original histogram to an upper threshold, such that the probability density value above a particular bound is replaced by this limiting value. It is expressed as

$$p(k) = T | p(k) > T, \quad \text{for } k = 0, 1, \ldots, L - 1 \tag{8}$$

where $p(k)$ is the probability of occurrence of kth grey-level and T is the threshold value which needs to be adjusted depending on the intensity distribution profile of the image.

These optimisation techniques discussed in Sections 2.1-2.4 are computationally complex [17] and requires manual parameter tuning. Thus, these methods are not suitable for automated image enhancement [5].

3 Automatic and parameter free spatial transformation

The proposed non-parametric modified HE (NMHE) enhancement method performs HE on a modified histogram which is explained here-after. Let us consider an input image I, with dynamic range [0-255], where $I(i, j) \in [0, 255]$. In order to proceed with NMHE, the spikes are removed from the original histogram as a first step. Arici *et al.* [17] proposed a method to compute the modified histogram (h_{mod}) by considering only those pixels which have dissimilarity with their neighbours thus removing spike from the histogram. This computation is very simple, intuitive and avoids solving any complex optimisation function. Modified histogram is thus obtained by adopting only those pixels that have a two-lagged horizontal

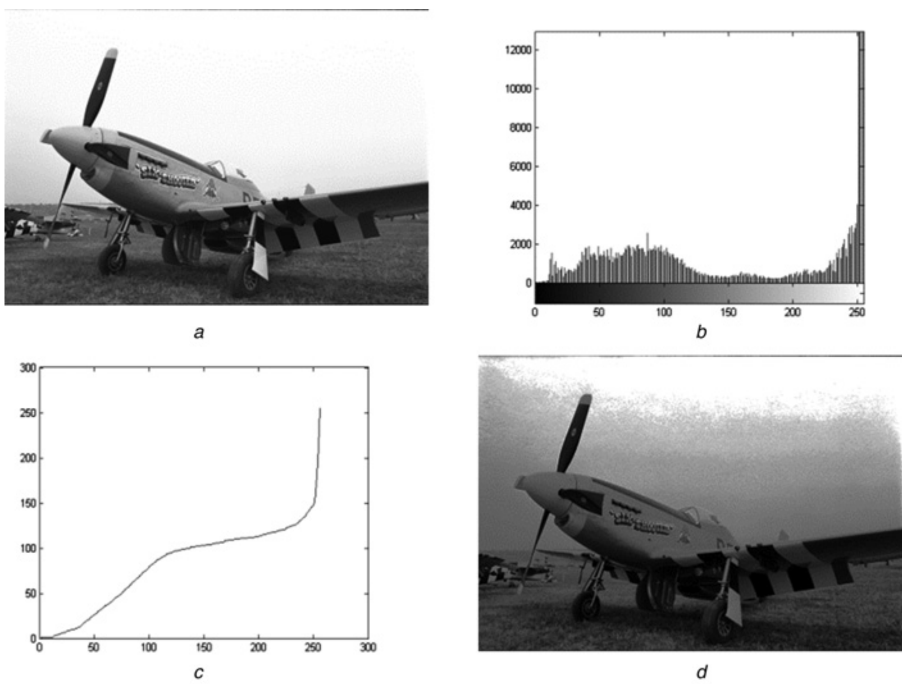

Fig. 1 *Histogram equalisation results for image Helicopter*

a Original grey-level image
b Histogram of original image
c Transformation mapping function obtained for HE
d Histogram equalised image with distortions

diversity greater than a threshold value, given by

$$h_{\text{mod}}(i) = p[i|C] \tag{9}$$

where $p[i|C]$ is the probability of occurrence of ith grey-level given the event C, where C denotes a horizontal contrast variation. C has been assigned a default value of six empirically and works fine with all sorts of image. The modified histogram is then normalised by the total no. of pixels considered in the above process to keep the value in between '0' and '1'.

A unique parameter is then calculated, which is used in (6) to weigh the uniform distribution and the modified histogram (h_{mod}). This factor is named as measure of un-equalisation (Mu) and is calculated from the original histogram (h_i) as follows.

Let us consider the original histogram (h_i) for any generic image as shown in Fig. 2*a*. This histogram is normalised and clipped to a value of ($1/L$) as shown in Fig. 2*b* defined by (11). It is then subtracted from a perfectly uniform probability density function (u) which is given as

$$u = \text{ones}(L, 1)/L \tag{10}$$

Clipped histogram obtained from h_i is given as

$$h_{\text{mod}\,c}(k) = \left\{ \begin{array}{ll} \left(\dfrac{1}{L}\right) & \text{if } h_i(k) > \left(\dfrac{1}{L}\right) \\ h_i(k) & \text{if } h_i(k) \leq \left(\dfrac{1}{L}\right) \end{array} \right\} \tag{11}$$

Measure of un-equalisation (Mu) is now calculated by the following equation

$$Mu = \text{sum}(u - h_{\text{mod}\,c}) \tag{12}$$

This value of Mu is an indicator of the degree to which the histogram of any given image does not follow a uniform distribution. It is then used as weighing factor in (6) to obtain the modified PDF given as

$$h_{\text{NMHE}} = (Mu)h_{\text{mod}} + (1 - Mu)u \tag{13}$$

The CDF of the image is obtained from this eventually redesigned histogram (h_{NMHE}) as

$$c_{\text{NMHE}}(k) = \sum_{i=0}^{k} h_{\text{NMHE}}(k) \tag{14}$$

The transformation function (T_{mod}) obtained by using c_{NMHE} is given below as

$$T_{\text{mod}}(k) = \lfloor (L-1)c_{\text{NMHE}}(k) + 0.5 \rfloor \tag{15}$$

From here, the output image produced by NMHE, $I_{\text{NMHE}} = \{I_{\text{NMHE}}(i, j)\}$, can be expressed as

$$I_{\text{NMHE}} = \{I_{\text{NMHE}}(i, j)\} = \{T(I(i, j)) | \forall I(i, j) \in I\} \tag{16}$$

This scheme performs excellent for images of all sorts, irrespective of the fact whether the image has high or low contrast. Results displayed in later section would give a clear picture of the proposed approach, but meanwhile there are few contradictory statements regarding brightness preservation which has been dealt by proposing two other variants of the same algorithm. Brightness preservation of the resultant modified image has always been the goal of many researchers [23], whereas another set of researchers commented on the insignificance of brightness preservation to maintain the natural quality of the image and the degree of enhancement is said to be high, if brightness variation is intense [24]. The human visual system is said to prefer images with elevated contrast and increased brightness, since it makes the object discernible [25]. The two variants of the above algorithm presented below, are again non-parametric and self-regulating.

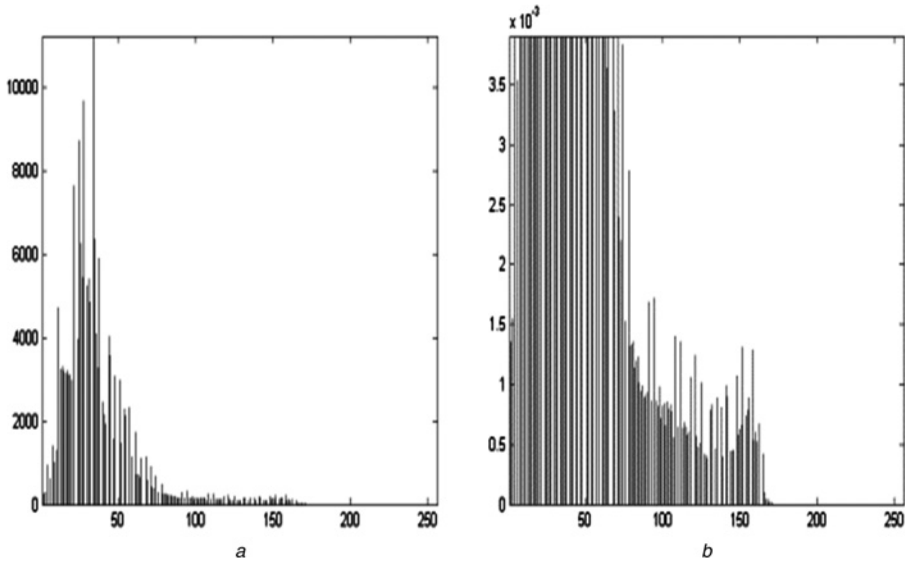

Fig. 2 *Histogram and its thresholding*

a Histogram of an image
b Clipped histogram at a maximum level of ($1/L$) where 'L' is the total no. of grey levels in the image

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3.1 NMHE with brightness preservation

Power-law transformation of the form given by (17) is implemented here with an adaptive gamma value

$$s = r^{\gamma} \tag{17}$$

where s is the transformed image, r is the original image and γ is the factor of transformation. 'γ' value higher than '1' tends to darken the image, whereas a value between '0' and '1' tends to brighten the image. This adaptive γ value is calculated from the mean-brightness value of the original image and the modified image, represented, by (18) as

$$\gamma = \log(\text{mean}(I)/255)/\log(\text{mean}(I_{\text{NMHE}})/255) \tag{18}$$

The mathematical form of (18) has been obtained empirically and shows promising result in preserving the brightness of the modified image. If the modified image has a higher mean brightness (MB) than the original image I, it tries to produce a gamma value greater than 1, reducing the overall brightness of the image. Similarly, when MB of the modified image is lesser than original image, it tries to produce a gamma value lower than 1, brightening the overall image. Although the brightness of the gamma corrected image is not exactly same as that of the original image, it lies very close to it.

3.2 NMHE with improved brightness

Power-law transformation of the form

$$s = r^{\gamma}, \quad 0 < \gamma < 1 \tag{19}$$

maps narrow range of dark input values into a wider range of output values, leading to an enhancement of dark areas in the image [1]. A self-regulating factor is devised for improving the brightness of the image obtained after executing NMHE algorithm. This factor adapts to the average intensity of the image and is given by the equation below as

$$\gamma = \log(\text{mean}(I\_\text{NMHE}))/\log(255) \tag{20}$$

The value of γ obtained by (20) which lies between 0 to 1, gets closer to '1' for brighter images and '0' for darker images. This adaptive correction is significant for dark image as compared to the bright image.

Finally, with these two variants of the proposed methodology, there are three versions of the modified histogram method, that is, (i) NMHE (without any power-factor), (ii) NMHE_BP (NMHE with brightness preserving factor) and (iii) NMHE_IB (NMHE with improved brightness). These algorithms are benchmarked with other existing state-of-the art algorithms in the next section. The flowchart for the complete methodology is depicted in Fig. 3.

The algorithm presented above is self-adaptive, and does not require any external parameters to be fed manually from image to image, and is the unique feature of the proposed methodology.

4 Results and analysis

In this section, the proposed algorithms are evaluated on data set comprising of images from [26–28]. The proposed algorithms are compared with HE [1], WTHE [20],

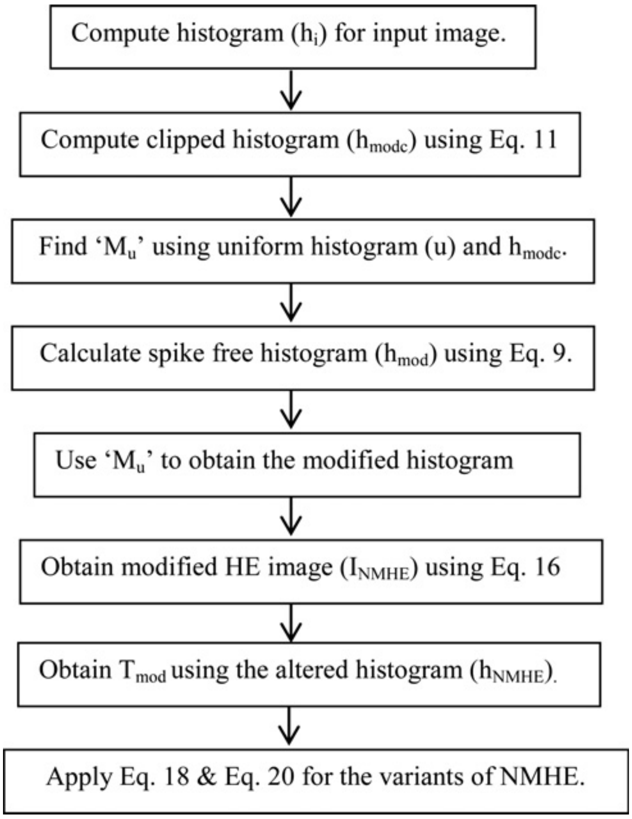

Fig. 3 *Non-parametric Histogram modification flowchart*

BPDFHE [14], smoothed HE (SHE) [29], FHSABP [15] and BPHEME [11]. There have been several attempts to quantitatively measure the enhancement in an image; which is a highly subjective issue and often very difficult to measure. Hence, it is desirable to have both quantitative and qualitative assessment of images enhanced by different algorithms. Later, the quantitative analysis of these algorithms has been presented by applying them on the Berkeley database of 500 images.

4.1 Qualitative assessments

In this section, a qualitative discussion on the image modified by different algorithms are presented.

4.1.1 Gray image: Three variants of the proposed algorithm NMHE, NMHE with brightness preservation (NMHE_BP) and NMHE with improved brightness (NMHE_IB) along with other benchmarking algorithms (HE, WTHE, BPDFHE, SHE, FHSABP and BPHEME) are implemented here for comparison. Sub-images in Figs. 4*a–j* correspond to the original image, and images modified by HE, NMHE, NMHE_BP, NMHE_IB, WTHE, BPDFHE, SHE, FHSABP and BPHEME, respectively. All implementations for WTHE have been done with the default value of $r = 0.5$ and $v = 0.5$. Similarly, for all implementations of BPDFHE, a Gaussian membership function with width of support 5 and spread factor 2 has been employed by default.

Fig. 4*b* shows the histogram equalised 'landscape' image of Fig. 4*a*. It can be noticed that HE gives a harsh and noisy look to the image. One can readily witness the brightening of ice covered mountain and darkening of the tree present in Fig. 4*b*. NMHE and NMHE_BP modified

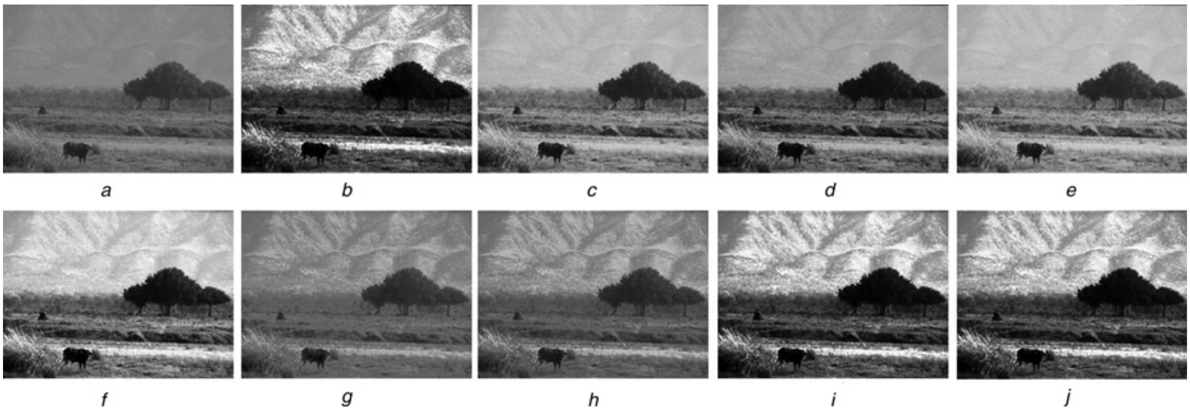

Fig. 4 *Test image landscape*

a Original image
Image enhanced by the following
b HE
c NMHE
d NMHE_BP
e NMHE_IB
f WTHE
g BPDFHE
h SHE
i FHSABP
j BPHEME

image has considerable improvement in contrast and even the structural information is seen to be preserved to a greater extent. NMHE_IB modified image shown in Fig. 4*e* seems to be visually more appealing than other modified images.

The histogram for Fig. 4*a*, modified by different algorithm is shown in Fig. 5. It can be seen in Figs. 5*c*–*e* that NMHE variants are able to preserve the shape of the histogram and stretches it to a regulated extent. Figs. 5*f*–*h* and *j* show the modified histogram obtained by applying WTHE, BPDFHE, SHE and BPHEME, respectively.

These algorithms attempt to redistribute highly probable grey-levels, stretching the pixel distribution to a large extent and are the main reasons for distortions induced in the images. FHSABP enhanced image shows a nearly uniform distribution of pixels in Fig. 5*i*, owing to the implementation of exact histogram specification giving it an artificial look as seen in Fig. 4*i*.

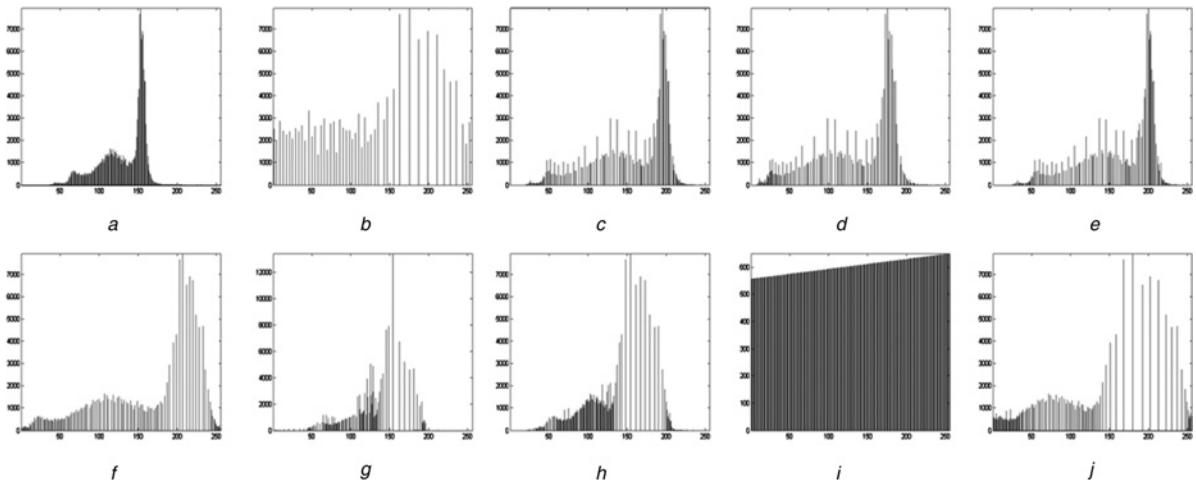

Fig. 5 *Histogram of images modified by different algorithm applied on Fig. 8*

a Original image
b HE
c NMHE
d NMHE_BP
e NMHE_IB
f WTHE
g BPDFHE
h SHE
i FHSABP
j BPHEME

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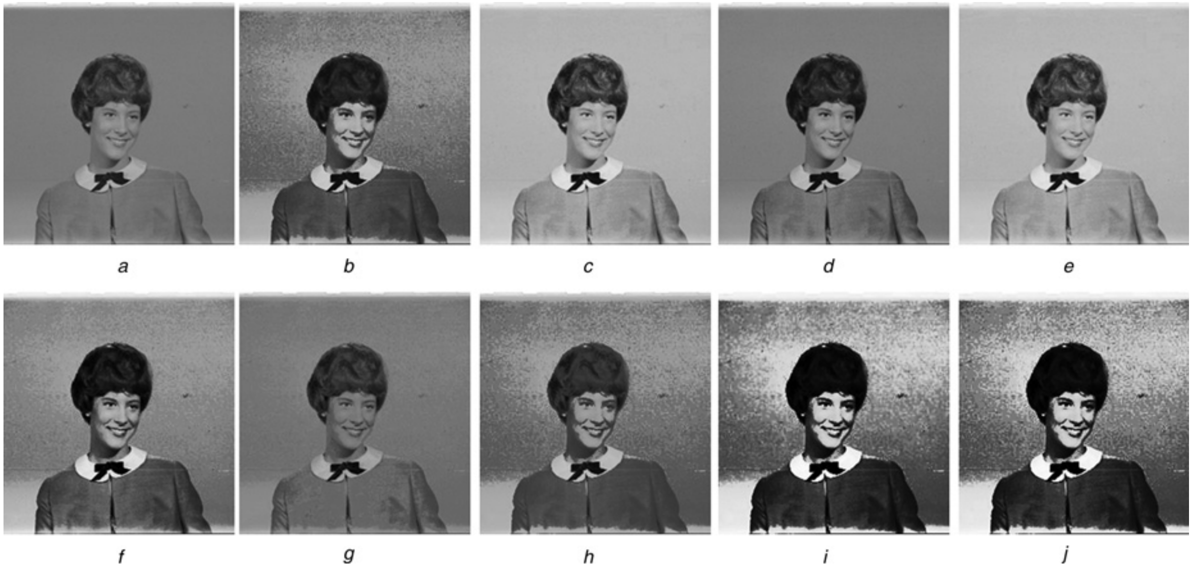

Fig. 6 *Test image girl*

a Original image
Image enhanced by the following
b HE
c NMHE
d NMHE_BP
e NMHE_IB
f WTHE
g BPDFHE
h SHE
i FHSABP
j BPHEME

4.1.2 Colour images: Contrast enhancement technique for colour images is applied only to the luminance (*L*) scale of the input image. This modified *L* matrix replaces the original *L* matrix in the colour image, while keeping the hue and saturation matrix constant. Fig. 6 gives a comparison of different algorithms applied on the image of 'girl'. Sub-images in Fig. 6, that is, *a–j*, correspond to the original image and images modified by HE, NMHE, NMHE_BP, NMHE_IB, WTHE, BPDFHE, SHE, FHSABP and BPHEME, respectively.

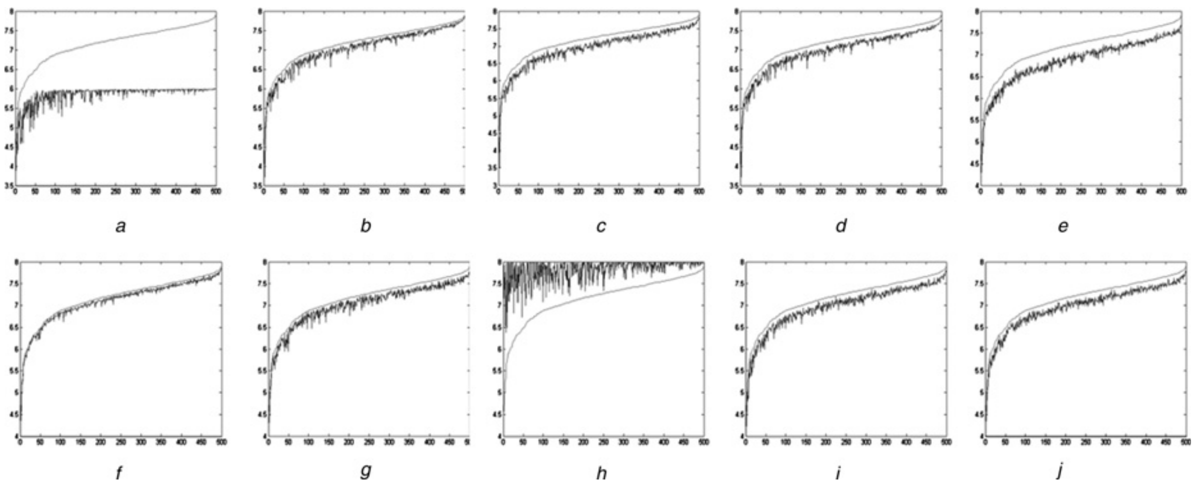

Fig. 7 *Entropy results on Berkeley image dataset for 500 images applied with following algorithms*

a HE
b NMHE
c NMHE_BP
d NMHE_IB
e WTHE
f BPDFHE
g SHE
h FHSABP with exact histogram specification
i FHSABP with traditional histogram specific
j BPHEME
Original image reference measurements (grey) and the processed image result (black)

The input image of 'girl' shown in Fig. 6*a* is a very special case of enhancement problem domain. This image has smooth regions for the spike formation in the histogram as well as have intensity values in both extremes. Since the average brightness of the input image is near to 127.5, HE, FHSABP and BPHEME perform similar. The HE maps smooth region of the image to different grey-levels giving it a very unpleasant look as shown in Fig. 6*b*. NMHE takes care of the uniform region and avoids taking them into consideration during histogram formation. Image enhanced by NMHE shows noticeable improvement in the processed image and has a better natural appearance. As seen in Fig. 6*g*, the image processed by BPDFHE is found to have distortion in smooth regions of the image and the output is not as satisfactory as the results obtained from NMHE. SHE enhanced image is not able to maintain the natural look of the image and has too many induced distortions.

These qualitative assessments were then validated with the visual quality score explained below.

4.2 Visual quality score

Although there are many parameters that aim to measure the quality of enhanced image, they are not always true indicators of image quality. In order to assign a visual quality score for each image in Figs. 4*b*–*j* and 6*b*–*j* enhanced by different algorithms, test subjects were asked to score from 0 to 5 depending on the following standard [4]. Test score value refers to an image with:

'0' – very high distortion and quality degradation;
'1' – distortion limited to certain areas;
'2' – slight distortion;
'3' – hardly any noticeable change;
'4' – noticeably higher quality; and
'5' – very high quality and significant enhancement.

The mean of the score given by 25 subjects and its standard deviation is shown in Table 1. The opinion score (OS) for both the images implemented with above discussed algorithms, supports the qualitative assessments done in Section 4.1. The OS value shows that NMHE_IB performs better than all other algorithms. NMHE has a higher OS value than WTHE while NMHE_BP does not perform as good as other algorithms. A low standard deviation indicates that the data points tend to be very close to the mean, and no significant variation exists from subject to subject.

4.3 Quantitative measures

Although there have been many approaches for measuring the enhancement of an image quantitatively; most of them do-not truly emulate human visual perception. The modified results have been compared based on entropy (E) [30], absolute mean brightness error (AMBE) [8], edge based contrast measure (EBCM) [31] and mean structural similarity index measure (MSSIM) [32]. AMBE has not been given much consideration, as there are many cases, in which enhancement is limited by brightness constraint and is presented here only for the sake of completion.

Table 1 OS for Figs. 4*b*–*j* and Figs. 6*b*–*j* applied with aforesaid algorithms

	Landscape	Girl
HE	1.6 ± 1.1	1.3 ± 1
NMHE	3.5 ± 1.3	3.7 ± 1.5
NM_BP	3.9 ± 0.7	3.5 ± 1.1
NM_IB	4.2 ± 1.1	4.2 ± 0.9
WTHE	3.4 ± 0.9	2.1 ± 0.7
BPDFHE	2.3 ± 1.2	2.4 ± 1.1
SHE	1.9 ± 1.2	1.4 ± 1.1
FHSAB	1.8 ± 1.4	1.9 ± 1.3
BPHEME	1.3 ± 0.6	1.6 ± 1.0

Entropy of an enhanced image normally remains lower than that of the original image, as no extra information is ever added to an image in a true sense. Nevertheless, targeting for an entropy to remain as close as possible to the original entropy, is always preferred, since the information content is further preserved by doing so. The image modified by the proposed approach shows a significant preservation of entropy without the introduction of any new distortion as compared to WTHE which although maintains entropy to a higher extent, but has an added distortion in smooth region of the image. FHSABP has a very high entropy value of 7.98 approaching to a value of 8.0, since it maps each grey level to a bin value, which was even not existing when Classical HE was implemented. BPHEME, with a similar framework as FHSABP utilises general HE for the transformation and has a reduced entropy value of 5.02.

AMBE value can be seen to be very high in HE, WTHE and in NMHE enhanced image of Fig. 6*a*. Although, NMHE_BP attempts to retain the MB value of the original image, it is not able to maintain the AMBE value as close to zero as other algorithms like BPDFHE, BPHEME and FHSABP does, but is still able to achieve the desired result to a promising extent, by applying the adaptive transformation developed in (18).

EBCM values for images modified by applying NMHE, NMHE_BP and NMHE_IB has increased to some extent as compared with its value for the original image, signifying an increase in the edges of an image, post applying the enhancement technique. However, the other techniques like FHSABP and BPHEME technique which have shown a significant change in EBCM value, are not just because of the increase in the edges but additional distortion in the smooth region of the image as seen in Figs. 4*i*–*j* and 6*i*–*j*.

Additionally, a SSIM index value has been implemented here, which indicates the structural similarity of the enhanced image as compared to the original image. This index is a very effective measure of the distortions induced in the image as a result of any transformation. A higher SSIM value indicates a higher degree of retaining structural information, which along with an improvement in edge content of the image has shown images with enhanced results in most of the cases. SSIM value for Fig. 6*a* enhanced by SHE, FHSABP, BPHEME and HE have reduced value as seen in Table 2, whereas the proposed methodology shows significant preservation of the structural content in the modified image.

In order to evaluate the performance of the above-mentioned algorithms further, they are applied to 500 test images of a wide range, from the Berkeley image database [27]. The measured values of Entropy, AMBE, EBCM and MSSIM are presented in Figs. 7–10, respectively, for all the algorithms discussed above.

Fig. 7 shows entropy values for different algorithms applied to the data set obtained from [27]. These graphs are plotted by sorting the parameters of original image in ascending order and indexing these images accordingly for

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Table 2 Quantitative measurement results on images I1 (landscape) and I2 (girl) on applying different algorithms

		Original	HE	NMHE	NMHE_BP	NMHE_IB	WTHE	BPDFHE	SHE	FHSABP	BPHEME
Entropy	I1	6.3	5.46	6.1	6.09	6.08	6.28	5.81	6.21	8	6.22
	I2	5.32	4.45	5.11	5.07	5.09	5.27	4.92	5.07	7.99	5.03
AMBE	I1	—	3.49	26.7	3.69	32.7	25.2	0.02	0.59	0	0.01
	I2	—	10	48.8	5.27	51.9	6.77	0.05	1.77	0.01	0.01
EBCM	I1	0.11	0.25	0.14	0.13	0.16	0.19	0.15	0.16	0.23	0.24
	I2	0.07	0.23	0.08	0.08	0.11	0.14	0.1	0.14	0.18	0.21
SSIM	I1	—	0.47	0.91	0.86	0.91	0.69	0.77	0.77	0.5	0.49
	I2	—	0.31	0.92	0.91	0.92	0.74	0.92	0.63	0.41	0.35

Table 3 Analysis result on Berkeley image data set and computational time comparison for different algorithms

Algorithms	DEU	AMBE	*P*-value	MSSIM_D	C_t
HE	1.321	26.14	0.998	0.26	0.001
NMHE	0.131	13.08	0.998	0.057	0.005
NMHE_BP	0.217	2.309	0.95	0.051	0.011
NMHE_IB	0.195	23.01	1	0.079	0.01
WTHE	0.301	13.08	0.998	0.123	0.001
BPDFHE	0.069	0.054	1	0.06	0.005
SHE	0.146	12.56	0.998	0.064	0.004
FHSABP	0.66	0.138	0.998	0.175	0.656
BPHEME	0.185	0.187	1	0.193	0.006

a better visualisation of plotted graphs. As seen in Fig. 7*h*, FHSABP has high entropy value as compared to the original image's entropy. This occurs because of the application of 'exact histogram specification' [16] used in its implementation. In all other cases, which employ CHE, one can see that the entropy of the resultant image never increases beyond the entropy of input image. In order to measure the difference in entropy between input and transformed image, a parameter called 'degree of entropy un-preservation' (DEU) has been calculated. It is obtained by averaging the difference in entropy between the processed and the input image, for the complete Berkeley image data set.

$$\text{DEU} = \frac{\text{sum}(|E(\text{original image set}) - E(\text{ processed image set})|)}{500} \tag{21}$$

The results obtained by applying this equation to different algorithms are presented in Table 3. As seen, HE has a very high value of DEU which clearly indicates that the entropy of the image has actually decreased in an attempt to enhance the quality of the image. Results obtained by NMHE, NMHE_BP NMHE_IB and SHE have very less DEU values and thus indicate a higher degree of entropy conservation as compared to WTHE. BPDFHE has a decent performance under this parameter and has a very small DEU value, while the performance of BPHEME is similar to NMHE_IB. FHSABP shows a very high difference because of its exact histogram implementation, whereas, if the same algorithm is applied with traditional HE, it gives a DEU value of 0.1879, and has values lower than the original image entropy, shown in Fig. 7*i*.

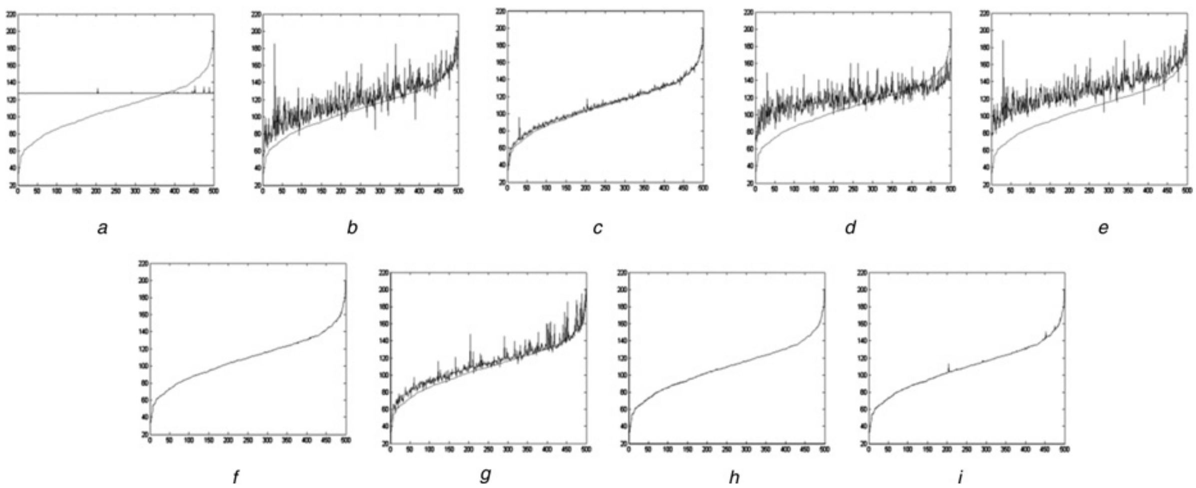

Fig. 8 *AMBE results on Berkeley image dataset for 500 images applied with following algorithms*

a HE
b NMHE
c NMHE_BP
d NMHE_IB
e WTHE
f BPDFHE
g SHE
h FHSABP with exact histogram specification
i BPHEME
Original image reference measurements (grey) and the processed image result (black)

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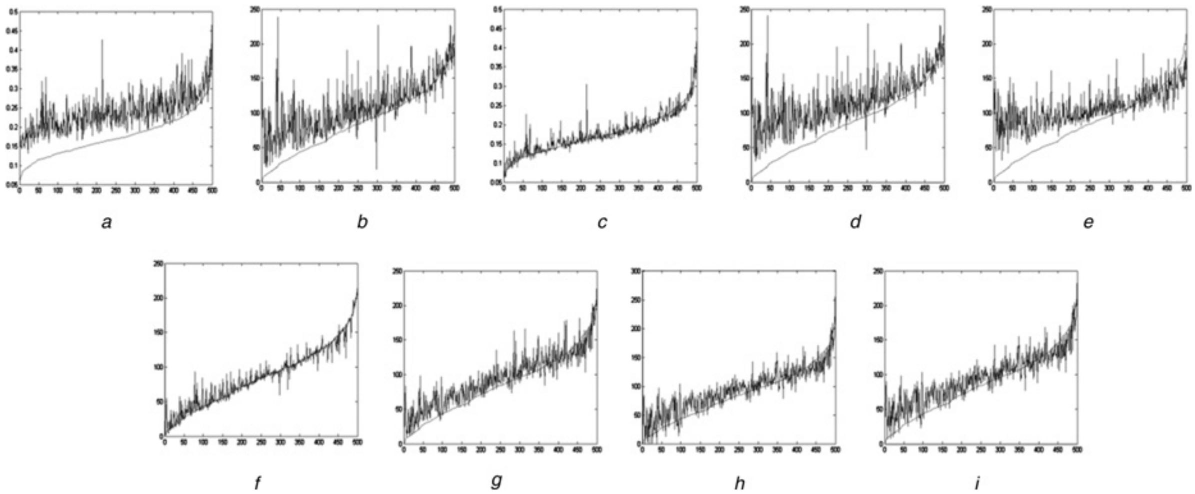

Fig. 9 *EBCM results on Berkeley image dataset for 500 images applied with following algorithms*
a HE
b NMHE
c NMHE_BP
d NMHE_IB
e WTHE
f BPDFHE
g SHE
h FHSABP with exact histogram specification
i BPHEME
Original image reference measurements (grey) and the processed image result (black)

Fig. 8 shows the AMBE value for different algorithms on applying it to the Berkeley image data set [27]. As one can see from the graphs, NMHE_BP preserves the brightness to a higher extent as compared to NMHE. Algorithms which are specifically meant for brightness preservation like BPDFHE, BPHEME and FHSABP shows excellent performance under this metric. NMHE, NMHE_IB and SHE do not perform well under this parameter and can be noticed from Table 3, and are not meant for brightness preservation. The values presented in this table depict the average AMBE value for the complete data set.

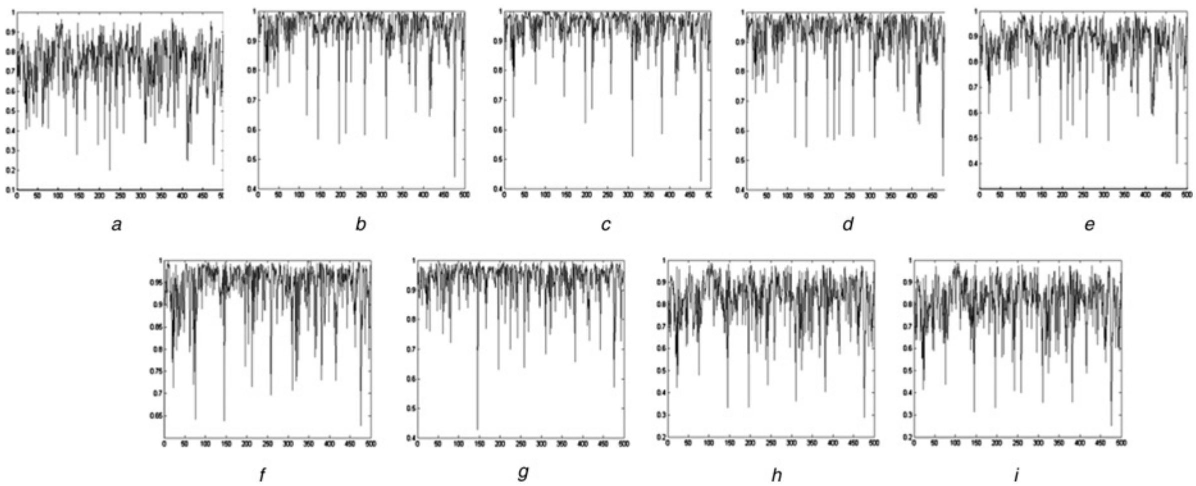

Fig. 10 *SSIM results on Berkeley image dataset for 500 images applied with following algorithms*
a HE
b NMHE
c NMHE_BP
d NMHE_IB
e WTHE
f BPDFHE
g SHE
h FHSABP with exact histogram specification
i BPHEME
Original image reference measurements (grey) and the processed image result (black)

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Fig. 9 shows EBCM values for images modified by different algorithms, when applied to the Berkeley data set. The images are also indexed in ascending order of EBCM value for better visualisation. Although an increased EBCM value is generally preferred, a high EBCM value does not always mean better and natural image enhancement [4]. A non-parametric two sample Kolmogorov–Smirnov test (KS-test) [33] is implemented for determining if the EBCM value of the output image is higher than the EBCM value of the input image. The hypotheses are given as

H_0: EBCM value has increased

H_1: EBCM value has not increased

The KS test has been specifically chosen here, since it does not make any assumption about the distribution of data. The hypothesis defined above, tests for the increase in EBCM value after applying a contrast enhancement algorithm, that is, EBCM (enhanced image) > EBCM (original image).

A higher *P*-value indicates a greater confidence level by which H_0 can be accepted. Results for the above test are presented by third column in Table 3. According to a confidence level of 95%, all algorithms produce results higher than 0.95, and do not reject in favour of H_0.

Fig. 10 shows the MSSIM index value for the data set. Although a high MSSIM value does not always indicate significant enhancement, it parameterises the visual artefact introduced in the process of enhancement. Images with an increased distortion will have lower SSIM value. As seen, NMHE_IB has a higher MSSIM value than WTHE, and NMHE has better performance as compared with other algorithms, and generates less distortion in the processed image. A measure of mean SSIM distortion (MSSIM_D) value has been presented in Table 3, given by (22)

$$\text{MSSIM\_D} = (500 - \text{sum(SSIM of images)})/500 \quad (22)$$

MSSIM_D measures the amount of distortions introduced into an image in the process of enhancement.

Thus for the Berkeley database, all the three variants of the proposed algorithm produces higher contrast image with least distortion introduced in the image as seen in the fourth column of Table 3.

4.4 *Computational time comparison*

Time complexities of the above-mentioned algorithms are also measured to check for its real time viability. According to the results shown in Table 3, NMHE takes a very small time of 5 ms for an image of size 250 × 256. NMHE_IB and NMHE_BP show a higher computational time because of extra calculation embedded in the algorithm. WTHE comparably takes a very small time frame to compute the algorithm, whereas FHSABP takes huge time in implementing the exact histogram specification. Time taken by BPDFHE and SHE is lesser, to a certain extent, than the proposed algorithm, whereas BPHEME takes marginally more time.

As a result of the previous analysis and discussion, it is observed that the proposed algorithm and its two variants are suitable for application in different scenarios as all of them perform well under different parameters. NMHE in general gives promising result as compared with all other algorithm, whereas NMHE_BP and NMHE_IB gives enhanced quality in brightness preserved enhancement and improved brightness aspects, respectively.

5 Conclusions

In this paper, a NMHE method has been proposed to improve the contrast of an image, which modifies the image by an adaptive transformation rather than solving any optimisation problem. The novelty of the technique lies in the use of image statistics to compute a spike free modified histogram, which is then equalised to render an image with better visual attribute. The two variants of the proposed algorithm offers a level of controllability to the user in obtaining images with varying brightness depending on application to application. Brightness preserved version of this algorithm (NMHE_BP) has shown satisfactory performance as compared with other contemporary algorithms, which enhances the image under brightness preserving constraint whereas the auto-brightness improved version of NMHE, that is, NMHE_IB, has demonstrated an enhanced visual quality image with distinctive features. The proposed algorithms can be applied for both grey level and colour images without any parameter tuning and applicable for wide variety of images and video sequence. Performance comparisons with state-of-the-art enhancement algorithms show that NMHE achieves reasonable image equalisation even under diverse conditions.

A higher degree of entropy preservation between the input and output images, has shown that NMHE can preserve the overall content of the image, while enhancing the image contrast. Using the test of significance on Berkeley image data set of 500 natural images, it has been shown that NMHE achieves contrast improvement under 99% confidence level. The mean SSIM index on these images has shown that the image enhanced by NMHE has minimal structural change in comparison to the original image.

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