Journal of King Saud University – Computer and Information Sciences 34 (2022) 1172–1182

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

A novel joint histogram equalization based image contrast enhancement

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ARTICLE INFO

Article history:
Received 14 March 2019
Revised 15 May 2019
Accepted 30 May 2019
Available online 31 May 2019

Keywords:
Contrast enhancement
Histogram equalization
Joint histogram
Image processing

ABSTRACT

The limitation to the most commonly used histogram equalization (HE) technique is the inconsideration of the neighborhood info near each pixel for contrast enhancement. This gives rise to noise in the output image. To overcome this effect, a novel joint histogram equalization (JHE) based technique is suggested. The focus is to utilize the information among each pixel and its neighbors, which improves the contrast of an image. The suggested method is developed in a truly two-dimensional domain. The joint histogram is constructed using the original image and its average image. Further, it does not require a target uniform distribution for generating the output. The two-dimensional cumulative distribution function (CDF) is utilized as a mapping function to get the output pixel intensity. Extensive experiments are performed using 300 test images from BSD database. The experimental analysis indicates that the procedure produces better results than the state-of-the-art HE based contrast enhancement algorithms. More significantly, it produces the best results even for images having a narrow dynamic range. The implementation simplicity of the proposed algorithm may attract researchers to explore the idea for new applications in image processing.

1. Introduction

Presently, high-quality digital cameras are indeed the most widely used devices to acquire images. They are extensively used in cell phones, personal digital assistants, robots, medical systems and surveillance, and home security systems. Over the years, the quality of the images acquired has significantly improved due to the development of technology. Still, there are varieties of problems that need to be addressed regarding the quality of the images. Some of the problems include contrast defects, chromatic anomalies, noise, geometrical distortions, focus defects, etc. Many image-processing techniques are reported in the literature to address such problems (Gonzalez and Woods, 2009). In this paper, we are primarily concerned with image enhancement or contrast enhancement to be more specific. Image enhancement entails the modification of an image such that the output image is either more pleasing to the human eye, or contains more information and less noise, useful for further processing. Image enhancement techniques are used either as preprocessing steps or as post-processing steps to generate a visually desirable image. This includes various contrast enhancement techniques to enhance the edges of the image. Image enhancement finds application in numerous areas, for instance, medical imaging, remote sensing, television, microscopic imaging, etc.

One of the main quality impairment of a digital image is low contrast. Low contrast is caused by many factors such as uneven illumination, the addition of noise during transmission, analog to digital transformations, etc. Several algorithms for contrast enhancement are proposed in the literature. Based on the information available in the literature (Tang et al., 2003), contrast enhancement algorithms are classified into two categories: transform domain and spatial domain. The transform domain algorithms partition an input image into various sub-bands of frequency components. The image is then enhanced by modifying the magnitude of frequency components locally or globally. Such calculations are computationally complex and time-consuming. Moreover, to produce an output image free from distortions and visual artifacts, such algorithms require proper settings of the related parameters. The strategy accomplishes both global and local contrast improvement with an appropriate parameter choice.

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.jksuci.2019.05.010
1319-1578/

Even though transform domain algorithms have produced satisfying results in the specific applications field, the spatial domain algorithms are widely used for their computational simplicity and faster implementation. Among spatial domain algorithms, histogram equalization (HE) is mostly used for contrast enhancement due to its simplicity and satisfactory results. It is based on the one-dimensional (1D) histogram modification. The basic idea in HE is to modify the histogram of the enhanced image such that it is uniformly distributed exploiting the dynamic range of the image (Gonzalez and Woods, 2009). It uses the cumulative distribution function (CDF) as the mapping function to derive the output pixel intensity. Such a mapping technique expands the grey levels with high pixel occurrences to a wider range of intensity levels. The intensity levels with fewer pixel occurrences are compressed into smaller ranges. However, the HE technique does not utilize contextual information surrounding a pixel and modifies a grey level irrespective of the grey level distribution around a pixel. This tends to enhance the noise present in the input image. HE also tends to over enhance the input images having narrow dynamic ranges and high peaks in the histogram leading to an unnatural looking noisy output (Gonzalez and Woods, 2009).

In general, it is impossible to design a contrast enhancement method that produces a visual artifact free output. Choosing an appropriate contrast enhancement algorithm is difficult because of the absence of trustworthy and dependable measures to evaluate the quality of the output image. Moreover, enhancement algorithms generally depend on the legitimate parameter choice, which also experiences the absence of the tried and true measures.

This has motivated us to propose a new joint histogram equalization (JHE) based contrast enhancement method that utilizes the grey level distribution around each pixel in an image instead of directly using the grey levels. A joint histogram is formed by choosing a group of local pixel attributes and building a multidimensional histogram. The individual entry in it represents the number of pixels in the image expressed by a certain combination of the attribute values. The information in the neighborhood surrounding each pixel is used as a feature to obtain the joint histogram (Pass and Zabih, 1999). In contrast to the popular histogram equalization method, this algorithm calculates a new intensity value for a particular grey-level according to the neighborhood grey-level distribution around it. It modifies only a few selected instances of the grey-level according to the probability distribution instead of modifying all the occurrences of the grey-level. Thus, this method results in a more natural looking output image as compared to the global histogram equalization method. Since this method considers the grey-level distribution around a pixel as a feature to compute the histogram, it is named joint histogram equalization. Here, the JHE method is also extended to color images to enhance the contrast. The algorithm is applied to the luminance component only in color images, thereby preserving the color information in them. To the best of our knowledge, the concept of joint histogram-based contrast enhancement method is not found in the image processing literature. The joint histogram is constructed using the original image and its average image. The proposed idea is a special case of the 2D histogram. However, the present formulation is completely different from the two-dimensional histogram equalization (2DHE) method. It uses the grey level pixel pairs, instead of the grey level differences, for contrast improvement. It does not require a target uniform distribution for generating the output. By contrast, the two-dimensional cumulative distribution function (CDF) is used as a mapping function to get the output pixel grey level.

The paper has been organized as follows. Section 2 discusses the related work in contrast enhancement. The proposed methodology is explained in Section 3. Section 4 discusses the outcomes obtained. Finally, Section 5 draws a conclusion.

2. Related work

Some common algorithms that enhance the contrast by improving the performance of HE are local histogram equalization (Dale-Jones and Tjahjadi, 1993; Kim et al., 1998), brightness preserving bi-histogram equalization (Kim, 1997), minimum mean brightness error bi-histogram equalization (Chen and Ramli, 2003), dualistic sub-image histogram equalization (Wang et al., 1999), recursive mean-separate histogram equalization (Chen and Ramli, 2003) and weighted threshold histogram equalization (Wang and Ward, 2007).

Singh et al. (2015) used a recursive histogram equalization algorithm for enhancement of low exposure images. The authors claimed that their suggested methods are successful for images captured under a low light condition such as underwater sequences or night vision images. They first used the recursive exposure based sub-image histogram equalization that iteratively implements the exposure-based sub image histogram equalization (ESIHE) technique. Then they used recursively separated, exposure-based sub image histogram equalization that recursively implements the separation of an image histogram. However, the inappropriate sub-divisions may not give natural looking output images. Furthermore, the decision on the number of divisions may degrade the algorithm performance. Similar work was carried out in Zhuang and Guan (2017).

Menotti et al. (2007) used minimum within-class variance multi-histogram equalization (MWCVMHE) technique for contrast improvement. The technique divides the histogram of the input image into multiple sub-histograms based on minimum within-class variance. Next, HE is applied to each sub-histogram independently. They used dynamic programming for optimization of the objective function. The authors concluded that their method achieved brightness preservation, but resulted in an output image having low-contrast. Wang et al. (2008) used convex optimization in flattest histogram specification with accurate brightness preservation (FHSABP) for enhancement. They used the exact histogram specification procedure to maintain brightness. However, the method fails to produce a good contrast image when the average brightness is either too low or too high.

Arici et al. (2009) used a histogram modification framework for contrast enhancement. They used penalty terms in the optimization technique to address the noise and stretching problem. However, the parameters used in the process need to be manually tuned for achieving a better result. Hashemi et al. (2010) suggested GA to maximize edge information for contrast enhancement. Because of the limitations of GA based algorithms, the enhanced image is not spatially smooth and the process is computationally intensive. Jabeen et al. (2016) suggested a weighted transformation function for image contrast enhancement. The modified histograms are used to obtain different transformation functions. Then weights are assigned to the functions consistent with their similarity/dissimilarity from the mean value. As a result, bins having very small contributions in the histogram are discarded. Hongbo and Xia (2014) incorporated the grey level co-occurrence matrix (GLCM) for the modification of the conventional histogram equalization approach. Their approach provided a combination of weighted and conditional histogram equalization for enhancing the given grey level with respect to their spatially adjacent grey levels. However, the computation of GLCM increases the complexity and the method involves many parameters for tuning.

Wei et al. (2014) presented an entropy maximization HE scheme by modifying the global histogram equalization (GHE) approach. The authors divided the GHE technique into pixel population mergence and grey level distribution. In the grey level distribution, the log-based distribution function is employed to control the enhancement level. However, the parameters: mergence times and transformation function need to be tuned. Any variation in the values may not yield desired output images. Ling et al. (2015) proposed an adaptive extended piecewise histogram equalization algorithm. The approach subdivides the original image into piecewise histograms and adaptive histogram equalization is applied to each sub-image for contrast boosting and intensity level preservation. Lastly, a weighted fusion of these equalized sub-images is employed to obtain the enhanced image. The method seems to combine many stages making it complex. The variance used in the method needs to be tuned properly for better output. Parihar and Verma (2016) proposed an entropy-based dynamic sub-histogram equalization technique for contrast enhancement. The approach iteratively divides the histogram based on the entropy by equally dividing into sub-histograms. A new dynamic range is assigned to each sub-histogram based on the number of used and missing intensity levels in the sub histogram.

It is observed that almost all the approaches discussed above are based on the 1D histogram. They use the histogram equalization approach or its modification to achieve the contrast enhancement. One of the major constraints with HE based approaches is that they produce noisy images when the input images are dark and have a narrow dynamic range. They use the one-dimensional histogram of the image, where info surrounding each pixel is not considered. The 1D histogram reflects the pixel intensity and not spatial distribution. Further, very different images may have the same 1D histogram.

Inspired by the concept of HE, we suggest a new joint histogram equalization (JHE) based contrast enhancement. Here, a joint histogram is generated which is two-dimensional and the concept is developed in a truly two-dimensional domain. The details of the suggested technique are given in Section 3. Results are compared with the state-of-the-art HE based techniques along with 2DHE (Celik, 2012) technique. It is observed that our technique yields better results as compared to the other approaches.

3. Proposed methodology

The proposed method uses the correlation between the intensity of a pixel and the average intensity value of its neighborhood to improve the contrast of the image. The correlation is achieved by building the joint histogram. A joint histogram is created by choosing a group of local pixel attributes and building a multidimensional histogram. The individual cells in the joint histogram matrix represent the number of pixels in the image expressed by a certain combination of attribute values. For instance, consider a joint histogram that combines the pixel intensity information of an image with the pixel neighborhood average intensity information from another image.

A given pixel in an image has intensity levels $\{0,\dots,L-1\}$ and its neighborhood average intensity levels $\{0,\dots,L-1\}$. The joint histogram will contain $L\times L$ entries. Each value corresponds to a particular pixel intensity value and its corresponding neighborhood average intensity value at the same location. The value stored here is the number of times the intensity pair occurs in the two images. More precisely, we can develop a joint histogram with a given set of k attributes, where the l^{th} attribute has n_l possible values. A joint histogram is a k-dimensional matrix so that each element represents the number of pixels in an image expressed by a k-tuple of attribute values. The dimension of the joint histogram matrix is, therefore $n=\prod_{l=1}^{k} n_l$, the number of feasible permutations of the values of each attribute (Dale-Jones and Tjahjadi, 1993).

Let I represent a grey scale image of size $M\times N$ with L intensity levels $G=\{0,1,\dots,L-1\}$. Let $f(x,y)$ be the grey value of the pixel at the location (x,y) where $x\in\{1,2,\dots,M\}$, $y\in\{1,2,\dots,N\}$. The total number of pixels is $M\times N$. Let $\bar{I}$ represent the average image derived from I. The size of $\bar{I}$ is the same as I with L intensity levels. Let $g(x,y)$ be the grey value of the pixel at the corresponding location (x,y) in $\bar{I}$. The $g(x,y)$ is computed in a w^2 neighboring window, expressed as

$$g(x,y)=\left\lfloor \frac{1}{w\times w}\sum_{m=-k}^{k}\sum_{n=-k}^{k} f(x+m,y+n)\right\rfloor, \tag{1}$$

where $k=\lfloor w/2\rfloor$, $\lfloor.\rfloor$ indicates the integer part of a number "$\cdot$". Note that $w<\min(M,N)$. w is typically set as an odd value. Here, it is taken as three. However, researchers can use any other values of w for computing the average image. Now $f(x,y)$ (from image I) and $g(x,y)$ (from image $\bar{I}$) are taken as a feature to construct the joint histogram. Let $h(i,j)$ be the count of the number of times the pair $(i,\ j)$ appears, where $f(x,y)=i$ and $g(x,y)=j$. Now utilizing (i,j) and $h(i,j)$, the joint histogram is formed.

The conventional approach for image enhancement is to replace individual pixel intensities with the required intensity values by forming a one-dimensional (1D) histogram of the input image. Then the required intensity values are computed from the corresponding probability distribution. The 1D histogram equalization technique uses a discrete transformation function as defined below to generate the output pixel intensity.

$$S_v=T(r_v)=(L-1)\sum_{k=0}^{v} p(r_k),\quad v=0,1,2,\dots,L-1 \tag{2}$$

where S_v represents the equalized grey level in the output image, r_v is the grey level of the pixel in the input image. $T(\cdot)$ represents the transformation operator. $p(r_k)$ represents the probability of occurrence of grey level r_k. It is to be noted that the probability of occurrence of grey level r_k is represented as,

$$p(r_k)=\frac{1}{MN}\sum_{k=0}^{v} n_k,\quad v=0,1,2,\dots,L-1 \tag{3}$$

Note that this equation is not used in any of our calculations. However, it is presented here for the sake of completeness. Such an approach does not consider the information contained around each pixel while constructing the histogram. The joint histogram takes into account the local neighborhood information around each pixel. In order to construct the joint histogram, the average intensity value around each pixel is calculated. This histogram takes into consideration the correlation existing between intensity values in a small neighborhood of the image, which the conventional approaches ignore. The joint histogram is expressed as:

$$H=\{h(i,j)\ |\ 0\le i\le L-1,\quad 0\le j\le L-1\}. \tag{4}$$

The term $h(i,j)$ is the number of occurrences of the grey level pair $f(x,y)$ and $g(x,y)$ at the same spatial location (x,y) of the images I and $\bar{I}$ respectively. It represents the count function. As i and j can take any possible integer value between 0 and L-1, the number of pixel pair combinations possible are $L\times L$. Therefore, the joint histogram H will contain $L\times L$ entries. The joint histogram (of dimension $L\times L$) for an example *island* image is shown in Fig. 1.

Fig. 1 represents the joint histogram concept. The original island image is taken. Its average image is obtained using (1). Here the window size is taken three. The 1D histogram is shown for comparison. The joint histogram is formed using (4). The joint histogram is shown as a matrix. The horizontal axis #1 ($f(x,y)=i$) represents the grey levels of the original image and the horizontal axis #2 ($g(x,y)=j$) represents the grey levels of the average image in the 3D plot. The entries of the joint histogram $h(i,j)$ (count function) show the

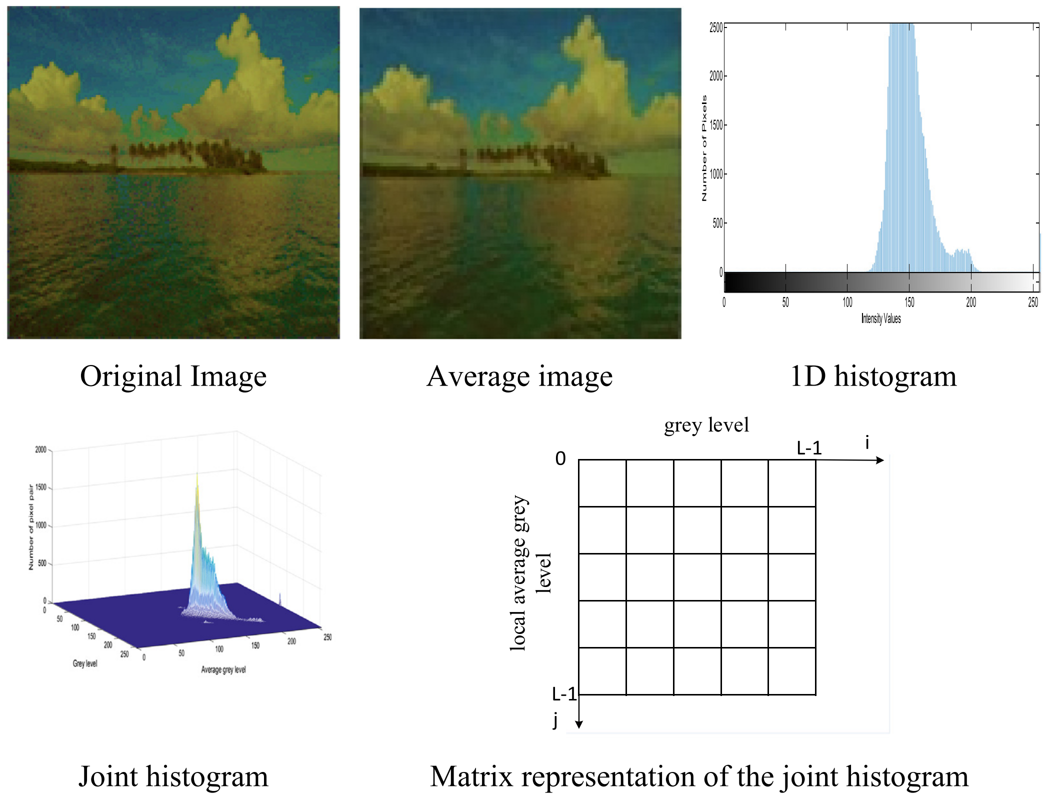

Fig. 1. Representation of joint histogram concept.

number of times the pixel pair (i,j) appears and are represented by the vertical axis of the 3D plot.

The two-dimensional (2D) cumulative distribution function (CDF) is obtained from the count function as given below:

$$CDF(i,j) = \sum_{m=0}^{i} \sum_{n=0}^{j} h(m,n). \tag{5}$$

Note that the computation of CDF does not depend on the size (M, N) of the images.

In this paper, we use this 2D CDF value to generate the contrast-enhanced output pixel intensity. The equalized value of the intensity pairs (i, j) in the output image using the proposed method is obtained as:

$$h_{eq}(i,j) = round\left(\frac{L-1}{MN-1}\left(CDF(i,j) - CDF(i,j)_{\min}\right)\right). \tag{6}$$

where $CDF(i,j)_{\min}$ is the minimum non-zero value of the CDF computed using (5). Here, the size of the image (MN) appears in the denominator so that the equalized intensity levels remain within the range $\{0,\ldots,L\text{-}1\}$. The equalized joint histogram matrix is now represented as:

$$H_{eq} = \{\, h_{eq}(i,j) \mid 0 \le i \le L-1,\ 0 \le j \le L-1\}. \tag{7}$$

It is to be noted that the dynamic range of entries of the equalized joint histogram matrix is extended. Then the original intensity values $f(x,y) = i$ are replaced by $h_{eq}(i,j)$ at all the occurrences of i with j only. Note that $f(x,y) = i$ may have multiple occurrences in the original sub-image. Separately for each $g(x,y) = j$, the original values of $f(x,y) = i$ are replaced by the equalized values. This is further explained in the example given below. It gives the enhanced image whose dynamic range is $\{0,\ldots,L\text{-}1\}$. A schematic block diagram of our suggested technique is shown in Fig. 2.

The algorithm for the suggested technique consists of the following processing steps.

Step #1 Consider the input image I and compute the average image $\bar{I}$ using (1) where each pixel intensity value is substituted by the average intensity value of its neighboring pixels.

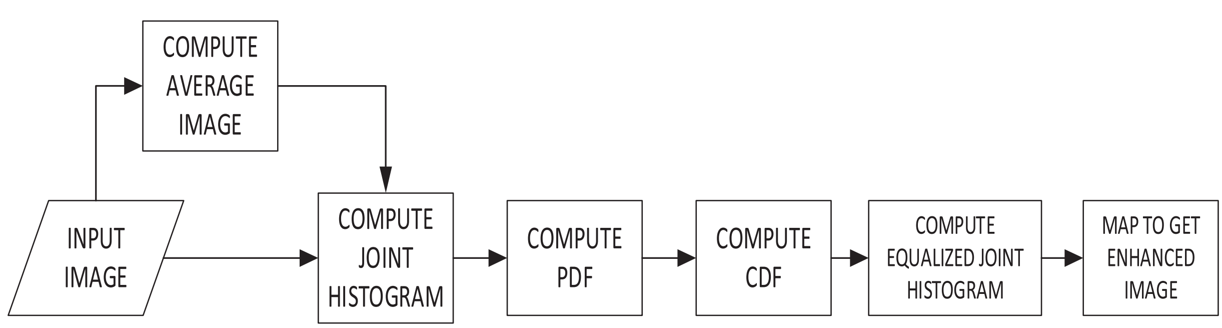

Fig. 2. Schematic block diagram of the suggested technique.

Step #2 Compute the joint histogram by comparing the input image I and the average image $\bar{I}$ using (4).

Step #3 The joint histogram count function is then used to obtain the two-dimensional cumulative distribution function using (5).

Step #4 The output pixel intensity is calculated using (6) and the original intensity values $f(x, y) = i$ are mapped to the equalized ones $h_{eq}(i, j)$ at all occurrences of pair (i, j) only. The final mapping produces the output image with a dynamic range that spans a wider range of grey-level scale.

To explain the proposed method, a small sub-image matrix is considered and the results are shown below in Fig. 3. Let an 8-bit grey scale sub-image I of size 6×6 have intensity values as shown in Fig. 3 (a). The average sub-image $\bar{I}$ obtained using (1) is shown in Fig. 3 (b). The window size is taken as three. The pixel pairs are formed according to the location. For instance, (143,63) forms a pixel pair at the location (1,1) in both the input image and its average image. Similarly, (137,93) forms another pixel pair at the location (2,1) in both the input image and its average image. The pixel pairs are sorted in increasing order in the example used below.

The joint histogram is represented by the count field which takes into consideration the intensity level pair. The size of the joint histogram matrix is 256×256. The pixel pair values having a zero count are excluded to conserve the size. The CDF shows that the minimum value pixel pair is (112, 93) and the maximum value pixel pair is (164, 98). The equalized joint histogram value is obtained by using (6). Note that the value of $CDF(i,j)_{\min}$ is 1 here. For example, the CDF of (149, 149) pixel pair is 24. The equalized value becomes

$$h_{eq}(149,149) = round\left(\frac{24-1}{35} \times 255\right) = round(0.65714 \times 255) = 167.$$

This value replaces the intensity value (149) in the original sub-image i.e. I at all the occurrences of the pixel pair (149,149) only. It does not replace the value (149) anywhere else in the original sub-image such as the pixel pair (149,99). The resulting image is the equalized image shown in Fig. 3(d). It is to be noted that the minimum intensity value (112) in I is now (0) and the maximum value (164) is now (255). In general, the grey levels of the output equalized image span a wider range of intensity scale.

143	145	149	154	150	135
137	143	149	155	152	139
133	141	149	158	154	142
130	140	150	160	156	145
112	146	156	148	140	132
148	164	158	136	122	134

a

63	96	99	100	98	64
93	143	149	152	148	96
91	141	149	153	151	98
89	139	149	152	148	96
93	144	150	147	141	92
63	98	100	95	90	58

b

Intensity Level Pair		Count	CDF	$h_{eq}(i,j)$	Intensity Level Pair		Count	CDF	$h_{eq}(i,j)$
I	$\bar{I}$				I	$\bar{I}$			
112	93	1	1	0	146	144	1	19	131
122	90	1	2	7	148	63	1	20	138
130	89	1	3	14	148	147	1	21	145
132	92	1	4	21	149	99	1	22	153
133	91	1	5	29	149	149	2	24	167
134	58	1	6	36	150	98	1	25	174
135	64	1	7	43	150	149	1	26	182
136	95	1	8	51	152	148	1	27	189
137	93	1	9	58	154	100	1	28	196
139	96	1	10	65	154	151	1	29	204
140	139	1	11	72	155	152	1	30	211
140	141	1	12	80	156	148	1	31	218
141	141	1	13	87	156	150	1	32	225
142	98	1	14	94	158	100	1	33	233
143	63	1	15	102	158	153	1	34	240
143	143	1	16	109	160	152	1	35	247
145	96	2	18	123	164	98	1	36	255

c

102	123	153	196	174	43
58	109	167	211	189	65
29	87	167	240	204	94
14	72	182	247	218	123
0	131	225	145	80	21
138	255	233	51	7	36

d

Fig. 3. Example sub-image to demonstrate joint histogram equalization. (a) Sample sub image matrix, (b) Average sub image matrix, (c) Joint histogram equalization, (d) Equalized sub image matrix.

4. Results and validations

The suggested approach is investigated using both grey scale and colored images from (www/http://sipi.usc.edu/database/S, 2018; www/http://r0k.us/graphics/kodak/S, 2018). The simulation is performed on a core i5 machine running with 8 GB RAM on Windows 10 using MATLAB. The results are compared with HE (Pass and Zabih, 1999), MWCVMHE (Wang et al., 2008), FHSABP (Arici et al., 2009), HMF (Hashemi et al., 2010), CEBGA (Jabeen et al., 2016) and 2DHE (Celik, 2012). The images used for testing have wide variations in intensity and contrast.

An example *cameraman* grey scale image and its contrast enhanced results using different methods are presented in Fig. 4. The cameraman image shown has bright and dark areas. The background contains a light colored sky and building. The unequalised joint histogram confirms the concentration of intensity values near the origin. The output images found with HE, MWCVMHE and FHSABP methods look similar. However, the sky and cameraman's face looks degraded. HMF method gives a better contrast with minor deformations on the sky area and somehow darkens the whole image. CEBGA also gives a light enhancement because of high contrast (between the object and the background). 2DHE gives a better output in terms of contrast and details. However, the sky portion is not evenly enhanced. But the results obtained with the proposed method are clear and evenly enhanced. The suggested scheme provides an improved output in terms of enhancing the contrast and preserving the brightness. The equalized joint histogram confirms the extension of the dynamic range of the intensity values.

An example *Lighthouse* color image and its contrast-enhanced results using different methods are shown in Fig. 5. The proposed methodology is applied to the luminance component only for enhancement. The input color image (in RGB) is converted to CIE *L a b* (color space) and only the *L* component is used. Then an inverse transformation gives the RGB enhanced image. The unequalised joint histogram is concentrated towards the origin with a very low dynamic range. It is observed that the output images obtained with HE, MWCVMHE and FHSABP are similar. Many regions are not properly enhanced, particularly the sky, cliff and the water area, thereby losing information. On the other hand, the enhanced image obtained with HMF removes the deficiency to a large extent, but the overall contrast looks low. The output images obtained with CEBGA and 2DHE are much better, but some regions, such as the sky and cliff are not evenly enhanced. The suggested technique gives a much better output in terms of preserving the color, brightness and contrast. The details in the image, particularly the rocky area, are also clearer in comparison to the other methods. This confirms that the joint histogram approach performs better. The equalized joint histogram also correctly extends the dynamic range of intensities. The reason for the significant improvement is due to the incorporation of the contextual information.

Quantitative assessment of different methods is also performed with the help of three quantitative measures: edge based contrast measure (EBCM), absolute mean brightness error (AMBE), and discrete entropy (DE).

$$DE_n = \frac{1}{1+\frac{\log(256)-DE(O)}{\log(256)-DE(I)}}. \tag{9}$$

The EBCM is computed on the basis of the sensitivity of human perception mechanisms to contours (or edges). The intensity values of the object are found by calculating the weighted mean value of the pixel grey values (Beghdadi and Negrate, 1989).

Contrast $con(x,y)$ is defined in this context as:

$$con(x,y) = \left|\frac{i(x,y)-e(x,y)}{i(x,y)+e(x,y)}\right|, \tag{10}$$

$$e(x,y) = \frac{\sum_{(k,l)\in N(x,y)} g(k,l)\, i(k,l)}{\sum_{(k,l)\in N(x,y)} g(k,l)}$$

Here, $N(x,y)$ represents the neighboring pixels of the pixel located at (x,y) and $g(k,l)$ represents the edge value of the pixel located at(k,l). It is to be noted that, for a 3×3 neighboring window, $g(k,l)$ represents the image gradient magnitude calculated using the Sobel operator. The EBCM for an image is then calculated as average contrast value, i.e.

$$EBCM = \sum_{x=1}^{M}\sum_{y=1}^{N}\frac{con(x,y)}{MN}. \tag{11}$$

Then the normalized contrast measure CM_n is given as:

$$CM_n = \frac{1}{1+\frac{1-EBCM(O)}{1-EBCM(I)}}. \tag{12}$$

Note that the sample images used for comparison are represented as follows.

Im∼1–	Plane image,	Im∼2–	Tank image,	Im∼3–	Cameraman image,	Im∼4	Baboon image,
Im∼5–	Cessna image,	Im∼6–	Lighthouse image,	Im∼7–	Beach image,	Im∼8–	Island image.

The objective measurement utilized to evaluate the performance of the approaches in preserving the original brightness of the input image is AMBE. This is expressed as the absolute difference between the average values of the input and the output images as Wang and Ward (2007);

$$AMBE(I,O) = \frac{1}{1+|E(I)-E(O)|}, \tag{8}$$

here, I and O represent the input and output image, respectively. Note that $E(\cdot)$ represents the statistical mean value. A higher AMBE value shows improved brightness preservation.

Discrete Entropy is a statistical quantity of randomness which is utilized to describe the textural characteristics of the input image. It determines the content in an image. A higher value indicates richer details. It is expressed as $DE(I) = -\sum_{k=0}^{L-1} p(r_k) * \log(p(r_k))$ where $p(r_k)$ is the probability of pixel intensity r_k computed from the normalized histogram of the input image I. Note that $DE(O) = -\sum_{k=0}^{L-1} p(r_k) * \log(p(r_k))$ where $p(r_k)$ is the probability of pixel intensity r_k computed from the normalized histogram of the output image O. Then the normalized DE for the input image I and the corresponding output image O is defined as Shannon (1948);

The FHSABP method outperforms all other methods in terms of average AMBE as shown in Table 1. The visual display shows that it maintains the AMBE value at the expense of visual quality. Although the proposed method gives a lower value of AMBE, the visual quality is much better than all other methods. Excepting FHSABP and MWCVMHE, the proposed method is clearly the winner as compared to the other methods.

The average DE_n value, as shown in Table 2, obtained with the proposed method is the best as compared to other methods. HE, MWCVMHE and FHSABP behave similarly, thus producing identical results. The values obtained with HMF are relatively high since it preserves the total entropy of the output. CEBGA gives the lowest value among all, as it maps the same grey levels in the input and output image. The values obtained with 2DHE are high as it considers the contextual information. However, the values obtained with the proposed method are highest as the joint histogram is constructed using the neighboring pixels only. The entire process retains the information until the output image is obtained.

The CM_n values, as shown in Table 3, obtained with HE are the best in most of the cases. However, the average CM_n value obtained with the proposed method is the best as compared to other methods. Even it is better than 2DHE and FHSABP in most of the cases.

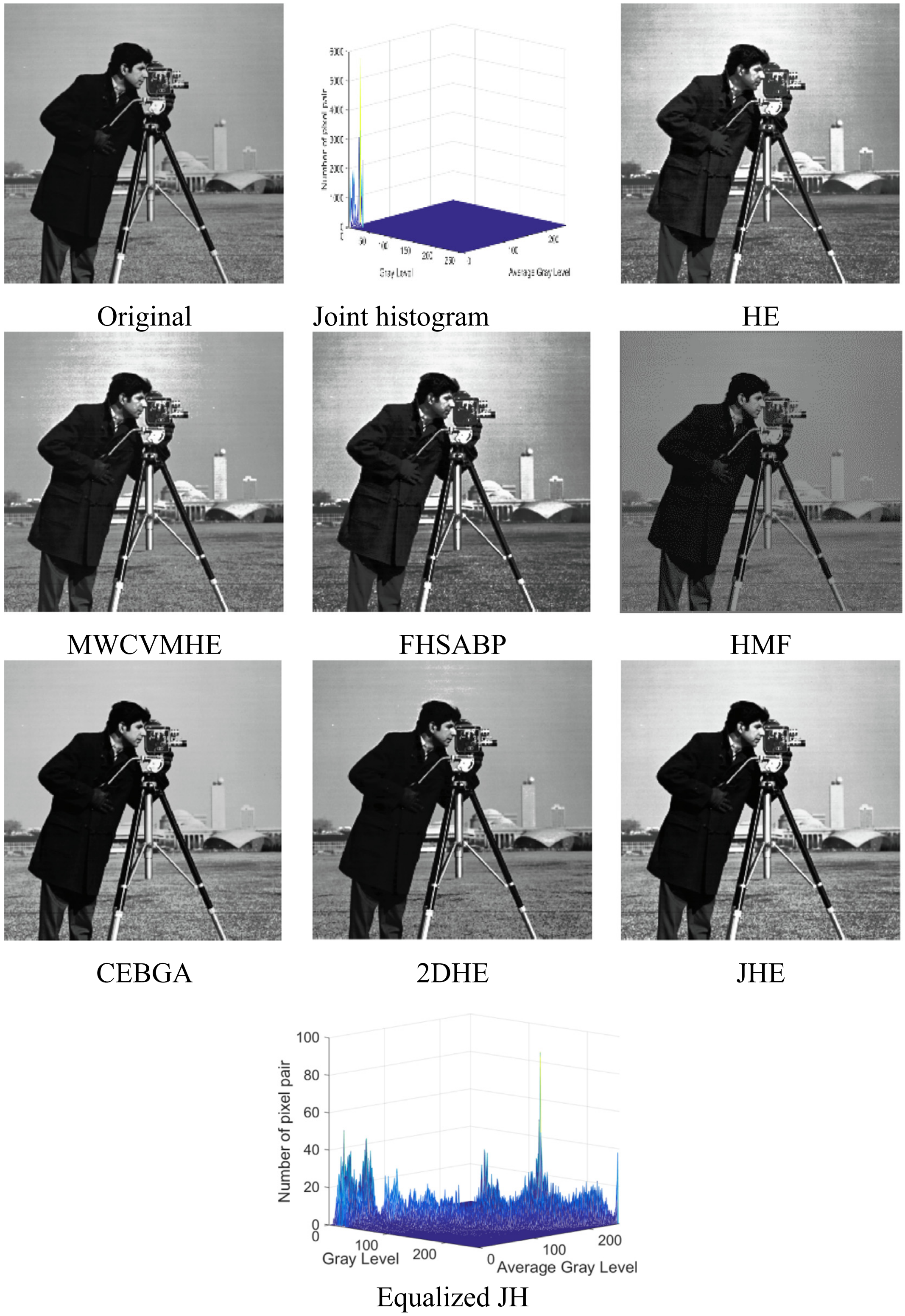

Fig. 4. Results of contrast enhancement for cameraman image using different methods.

To further evaluate the robustness of the proposed method, it is applied to 300 test images from BSD (Martin et al., 2001) database. The average values of the performance metrics are presented in Table 4. A similar trend is observed in the results. As discussed, FHSABP gives the highest average value of AMBE. The proposed method is the second contestant. However, the proposed method is a clear winner in terms of average DE and EBCM values.

Some latest evaluation indices of contrast enhancement, such as QRCM (Celik, 2016) and PCQI (Wang et al., 2015) are also computed to validate the proposed method. Table 5 shows the

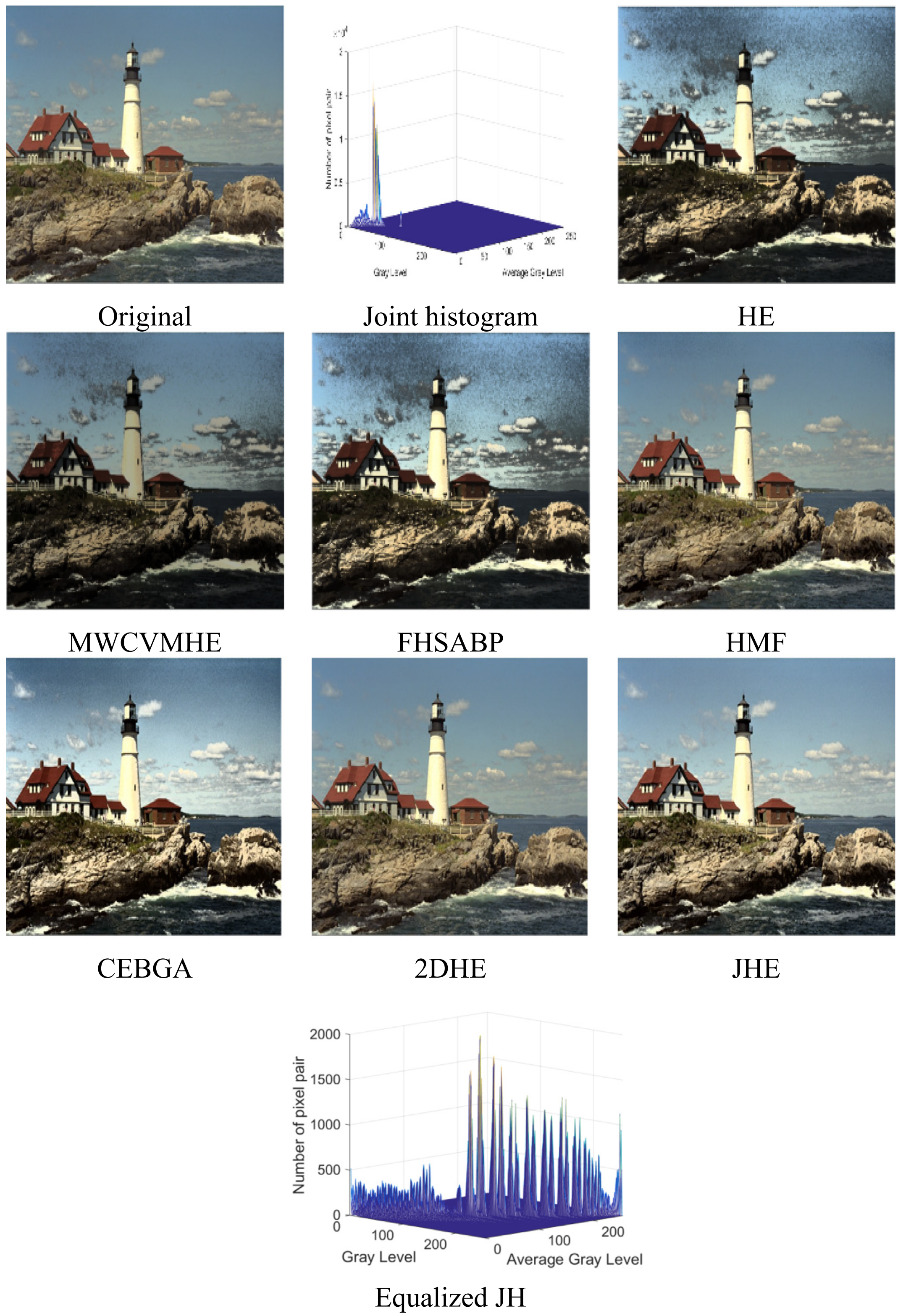

Fig. 5. Results of contrast enhancement for Lighthouse image using different methods.

variation of QRCM for the different methods. It is observed that the average QRCM value achieved using the proposed scheme is better than the other methods.

Table 6 shows the variation of PCQI measure for the different methods. It is observed that the average PCQI value achieved using the proposed scheme is better than the other methods.

In order to support our claim, the narrow dynamic range images are better enhanced, few example images are presented in Fig. 6. The first row shows the narrow dynamic range images of house and beach. The second row shows the corresponding enhanced images using the proposed method. It is to be noted that the dynamic range of the input house image is 27 and the dynamic

Table 1
Comparison of AMBE for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
Im~1	0.0260	0.0824	0.1246	0.2328	0.0330	0.3269	0.3291
Im~2	0.4928	0.1039	0.2140	0.0661	0.0239	0.0360	0.2639
Im~3	0.0944	0.1471	0.5470	0.2601	0.0782	0.0473	0.1653
Im~4	0.3618	0.4936	0.7338	0.0938	0.0564	0.1276	0.2487
Im~5	0.0197	0.2926	0.2308	0.0392	0.2225	0.5973	0.6108
Im~6	0.1141	0.7862	0.5283	0.1587	0.4376	0.0973	0.2099
Im~7	0.0198	0.1603	0.6743	0.0467	0.0371	0.0245	0.1712
Im~8	0.2495	0.5470	0.5625	0.0932	0.1524	0.1873	0.2461
Average	0.1723	0.3266	**0.4519**	0.1238	0.1301	0.1805	0.2806

Table 2
Comparison of DE_n for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
Im~1	0.4920	0.4909	0.4973	0.4935	0.4975	0.4990	0.5117
Im~2	0.4880	0.4867	0.4895	0.4945	0.4525	0.4951	0.5211
Im~3	0.4458	0.4516	0.4432	0.4585	0.3876	0.4812	0.4951
Im~4	0.4572	0.4630	0.4588	0.4785	0.3197	0.4802	0.4992
Im~5	0.4623	0.4690	0.4558	0.4522	0.4560	0.4815	0.4923
Im~6	0.4502	0.4597	0.4538	0.4847	0.3625	0.4866	0.4961
Im~7	0.4528	0.4630	0.4501	0.4619	0.4389	0.4767	0.4931
Im~8	0.4532	0.4573	0.4517	0.4843	0.3787	0.4670	0.5009
Average	0.4627	0.4677	0.4625	0.4760	0.4117	0.4830	**0.5012**

Table 3
Comparison of CM_n for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
Im~1	0.5540	0.5138	0.5268	0.5299	0.5050	0.5264	0.5296
Im~2	0.5556	0.5197	0.5524	0.5296	0.5112	0.5351	0.5563
Im~3	0.5128	0.5060	0.5165	0.5071	0.5099	0.5158	0.5267
Im~4	0.5422	0.5096	0.5103	0.5103	0.5031	0.5266	0.5301
Im~5	0.5220	0.5040	0.5064	0.5064	0.5067	0.5103	0.5225
Im~6	0.5348	0.5078	0.5103	0.5103	0.5049	0.5192	0.5281
Im~7	0.5305	0.5061	0.5191	0.5191	0.5097	0.5164	0.5219
Im~8	0.5256	0.5072	0.5189	0.5189	0.5124	0.5234	0.5772
Average	0.5347	0.5093	0.5253	0.5164	0.5079	0.5217	**0.5365**

Table 4
Average performance metrics results (for 300 images from BSD database).

Parameter	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
AMBE	0.1034	**0.5014**	0.5468	0.1182	0.1746	0.2052	0.2249
DE_n	0.4496	0.4651	0.4531	0.4572	0.3610	0.4822	**0.4952**
CM_n	0.5253	0.5064	0.5231	0.5141	0.5103	0.5263	**0.5382**

Table 5
Comparison of QRCM for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
Im~1	0.0697	0.1221	0.1512	0.1527	0.1143	0.1621	0.1845
Im~2	0.3223	0.2124	0.3318	0.2577	0.2457	0.3404	0.4107
Im~3	0.0504	0.0451	0.0377	0.0363	0.0657	0.1208	0.1413
Im~4	0.2246	0.0773	0.2262	0.1174	0.0820	0.1983	0.2440
Im~5	−0.2411	0.0040	−0.1471	−0.2143	0.0412	0.0620	0.1040
Im~6	0.1331	0.0444	0.1498	0.0515	0.0489	0.1493	0.1846
Im~7	0.0051	0.0270	0.0606	0.0583	0.0179	−0.0213	0.0532
Im~8	0.1099	0.0485	0.1056	0.0699	0.0859	0.1223	0.1419
Average	0.0843	0.0726	0.1145	0.0662	0.0877	0.1417	**0.1830**

range of the enhanced image is increased to 254. Similar behavior is witnessed with the other images shown.

The theoretical time complexity of the proposed algorithm is computed as in Cao et al. (2018). The computation time required to construct the joint histogram for a 'b-bit' grey scale image of size $M \times N$ is $O(2MN)$. The mapping function using two dimensional CDF requires time $O(2^b)$. The mapping requires $O(MN)$ time. Hence, the total time complexity is $O(3MN + 2^b)$. It is to be noted that the time complexity of the proposed technique may be slightly higher than the conventional HE technique. However, it is very effective while enhancing narrow dynamic range images and reduces the noise in the enhanced image.

Table 6
Comparison of PCQI for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	JHE
Im~1	1.2175	1.1967	1.2589	1.2362	1.0166	1.2457	1.2135
Im~2	1.3147	1.2584	1.3178	1.2436	1.1444	1.2377	1.2986
Im~3	1.0661	1.0409	1.0837	0.9953	0.9314	1.0150	1.0926
Im~4	1.2210	1.0821	1.2216	1.1089	1.0304	1.1991	1.2161
Im~5	0.6086	0.9194	0.7295	0.7283	0.9685	0.9668	0.8158
Im~6	0.9906	0.9949	1.0050	0.9865	0.9821	1.0103	1.1049
Im~7	0.9249	0.9615	1.0246	0.8810	0.8440	0.7994	1.0983
Im~8	1.0285	1.0018	1.0253	0.9562	0.9466	0.9696	1.0947
Average	1.0464	1.0569	1.0833	1.0170	0.9830	1.0554	**1.1168**

Fig. 6. Results of contrast enhancement for narrow dynamic range images using the JHE method.

5. Conclusion

In this work, a truly two dimensional (domain) concept is employed to develop the suggested technique. The suggested joint histogram equalization scheme utilizes the intensity distribution surrounding each pixel in an image to improvise the contrast. It is implemented for both the grey and colored images. The experimental analysis shows that the algorithm produces better or competitive results with respect to most of the state-of-the-art algorithms. The joint histogram equalization produces the best results for images having a narrow dynamic range. Different quantitative assessment metrics are used to validate the algorithm.

The joint histogram concept used in the proposed method may pave the way for investigation of more sophisticated contrast enhancement algorithms. Optimization techniques can be used to determine the best neighborhood size for a given input image. Further, this method can also be used along with other techniques to achieve both global and local contrast enhancement. The suggested technique is very simple but useful for contrast enhancement. It does not require a target uniform distribution and uses the CDF as the mapping function to generate the output image.

Declaration of Competing Interest

None declared.

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