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Brightness and contrast controllable image enhancement based on histogram specification

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ABSTRACT

Histogram based image enhancement techniques are widely used for performing contrast enhancement in images. However, most histogram based image enhancement methods have insufficient capability to freely tune the brightness and contrast of enhanced image. In this paper, two novel histogram based image enhancement algorithms are proposed. The proposed algorithms provide the way to control the brightness and contrast of enhanced image by adjusting two parameters. The principles for parameter selection are also discussed in this paper. Experimental results demonstrate a better performance of the proposed methods in both perceptual quality and image quality assessment metrics than the existing histogram based methods.

1. Introduction

Image enhancement that improves the visual effect of the image is an important image pre-processing technique in machine vision applications. Brightness and contrast [9] are two distinctive and objective image quality metrics in image enhancement. In the past few years, several methods have been introduced to improve the contrast of an image. These methods can be broadly divided into two groups: direct method and indirect methods. Direct methods define a contrast measure and find a solution to improve it [10–13]. While indirect methods enhance the contrast through enlarging the dynamic range of pixel values or specified region without defining a contrast measure. Indirect methods can further be divided into two sub-groups: 1) decomposition based and, 2) histogram based techniques [14]. Decomposition based techniques attempt to recover the intrinsic properties or find representations of the input image [1,6]. On this basis, the input image is decomposed into different components. Through modifying the magnitude of the desired decomposed component, the enhanced image can be obtained. Low-rank methods are widely used in data decomposition, and it is an efficiency way in performing image reconstruction [2–5]. The learning based sparse representation methods are also widely used in image decomposition [6–8].

Since the simplicity and high efficiency, histogram-based techniques are widely used in image enhancement. Histogram based image enhancement techniques can be divided into two categories, histogram equalization and specification. Histogram equalization aims to find a transformation so that the output image has a uniform histogram [14]. When image enhancement is applied on local regions, some local histogram equalization methods are developed [15–18]. The local histogram equalization methods use a small window that slips through every pixel sequentially and the histogram of current position within a window is equalized. Local histogram equalization methods sometimes over enhance some regions of the image and produce undesirable checkerboard effects. In order to improve the performance of histogram equalization, some bi-histogram and multi-histogram [19–22] equalization methods have been introduced. The bi and multi-histogram equalization methods split the input image histogram into two or more sub-histograms, then those sub-histograms are independently equalized. Although these image equalization methods can achieve satisfactory contrast enhancement, the variation in the gray level distribution may result in annoying side effects [24].

Histogram specification (matching) is the approach to transform the input image into a similar image that has a pre-specified or desired shape of histogram. More generally, histogram equalization is a special case of histogram specification when the desired histogram is uniform distributed. Various global histogram specification methods have been proposed to specify the histogram of an

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input image. Gonzalez et al. [14] provided the conventional histogram specification algorithm. Rolland et al. [25] introduced the optimal cumulative distribution function matching algorithm for fast histogram specification. Sun et al. [26] proposed dynamic histogram specification algorithm to keep the histogram characteristics of the input image. On this basis, the exact histogram specification algorithms [27–29] are further proposed to transform the histogram of the input image exactly to the desired one. Compared to global histogram specification methods, the local histogram specification can avoid the problem of seeking the desired histogram for the entire image. Therefore, some local histogram specification algorithms [30–32] applied the global histogram specification in local regions to produce favorable image qualities. Similar with the local histogram equalization algorithms, the computational complexity and undesirable checkerboard effects still are the problems that local histogram specification algorithms faced. The two dimensional histogram can counts the pairs of adjacent pixels with gray levels and represent the gray level difference between the pixels of an input image and their neighbors [23]. Recently, by using the mutual information between each pixel and its neighboring pixels, two dimensional histogram equalization (2-D HE) [24] and specification [33] algorithms have been developed and have shown superiority in image contrast enhancement.

All the aforementioned approaches enhanced the brightness and contrast of the input image automatically. However, in some image enhancement applications, particularly in consumer electronics, users always want the brightness and contrast of enhanced image be controllable, e.g. restraining the brightness and enhancing image contrast for power saving. Is it possible to employ the histogram based image enhancement technologies to satisfy this requirement? Moreover, can we attach the spatial information in images histogram to make the enhanced image has more details on the basis of above requirement? In this paper, we introduce the 2-D histogram to provide contextual information around each pixel and use 1-D and 2-D Gaussian distribution as desired histogram in specification. We tune the brightness and contrast of enhanced image by involving two parameters to adjust the shape of probability density function of 1-D and 2-D Gaussian distribution. The proposed algorithm firstly calculates the original mean and variance of the histogram of the input image. Secondly, two parameters are introduced to tune the mean and variance by multiplication. Thirdly, the desired 1-D and 2-D Gaussian distributions are estimated by the tuned mean and variance. At last, we use the probability density functions of desired 1-D and 2-D Gaussian distribution to specify the original 1-D and 2-D histogram respectively, and finally get the enhanced image. Compared with several state-of-the-art histogram based image enhancement algorithms, the proposed algorithms not only produce better performance in both visual effect and image quality assessment metric, but also provide an approach for users to tune the brightness and contrast of enhanced image by adjusting two parameters. Moreover, in some non-manual intervention applications, the two controllable parameters can be automatically estimated by the environment brightness or which achieve the highest image quality assessment.

The rest of the paper is organized as follows. Section 2 presents the 1-D and 2-D histogram specification algorithms using 1-D and 2-D Gaussian distribution. The connection between these two algorithms is also discussed in this section. Section 3 verifies the brightness and contrast controllability of the proposed methods. The subjective and quantitative comparisons of the proposed algorithm with several state-of-the-art histogram based image enhancement techniques are provided in this section. The discussion on parameters selecting is also provided in this section. Section 4 concludes the paper.

2. Proposed algorithms

2.1. 1-D histogram specification (1-D HS)

Consider an input image $X = \{x(i, j) | 1 \le i \le M, 1 \le j \le N\}$ and assume that has a dynamic range of $[x_{\min}, x_{\max}]$ (i.e. $x(i, j) \in [x_{\min}, x_{\max}]$. The main objective of the proposed algorithm is to generate an enhanced image $Y = \{y(i, j) | 1 \le i \le M, 1 \le j \le N\}$ and $y(i, j) \in [0, Z^+]$, which has a better visual quality than X.

Let $\chi = \{x_1, x_2, ..., x_k\}$ be the sorted of k distinct gray-levels of the input image X and satisfies $x_1 < x_2 < \cdots < x_k$, $x_1 = x_{\min}$, $x_k = x_{\max}$, thus, the 1-D histogram can be expressed as

$$H_x = \{h_x(m) | m = 1, ..., k\} \tag{1}$$

where $h_x(m) \in \mathbb{R}^+$ is computed as

$$h_x(m) = {scr(m)} \Big/ {\sum_{i=1}^{k} scr(x_k)} \tag{2}$$

scr（m）表示整个图像中灰度级m的像素数

with $scr(m)$ denotes the number of the pixels of gray-level m in the whole image. Fig. 1(a) and (b) shows the “Lena” image and its 1-D histogram according to Eq. (2). Based on the histogram, the mean value of the gray-level of the input image is

$$a = \sum_{i=1}^{k} x_i h_x(x_i) \tag{3}$$

And the variance of the gray-level of the input image is

$$u = \left[\sum_{i=1}^{k} (x_i - a)^2 h_x(x_i) \right]^{1/2} \tag{4}$$

Moreover, since image histograms are samples of probability distribution function, for a given 1-D histogram $h_x(m)$ in Eq. (2), the cumulative distribution can be obtained as

$$P_x = \{p_x(m) | m = 1, ..., k\} \tag{5}$$

where

$$p_x(m) = \sum_{i=1}^{m} h_x(i) \tag{6}$$

For a given output image $Y = \{y(i, j) | 1 \le i \le M, 1 \le j \le N\}$, and assume that Y has a dynamic range of $[y_{min}, y_{max}]$. Let $\gamma = \{y_1, y_2 \ldots y_l\}$ be the sorted set of l distinct gray-levels of the output image, and satisfies $y_1 < y_2 < \cdots y_l, y_1 = y_{min}, y_l = y_{max}$. In order to map the elements of χ to the elements of γ, one needs to find a 1-D density function and cumulatively histogram. In this section, we use probability density function of 1-D Gaussian distribution as the desired distribution/histogram

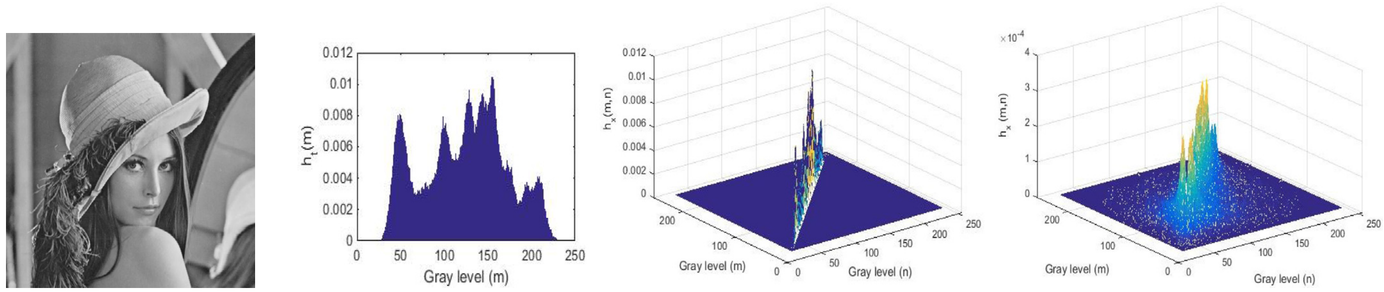
$$H_t = h_t(m') = \frac{1}{\sqrt{2\pi k_2 u}} e^{-\frac{(m' - k_1 a)^2}{2(k_2 u)^2}} | m' = 1, ..., l \tag{7}$$

From Eq. (7), we can find that, the mathematical expectation and variance of desired distribution are set as $k_1 a$ and $k_2 u$, with a and u denote the mean and variance of the histogram of the input image defined in Eqs. (3) and (4) respectively. k_1 and k_2 are the two parameters that control the mathematical expectation and variance of desired histogram in Eq. (7). Consequently, the desired cumulative distribution function obtained by the desired probability distribution function $h_t(m')$ can be written as

$$P_t = \{p_t(m') | m' = 1, \ldots, l\} \tag{8}$$

where

$$p_t(m') = \sum_{i=1}^{m'} h_t(i) \tag{9}$$



(a) (b) (c) (d)

Fig. 1. The “Lena” image (a) and its 1-D histogram (b), as well as its 2-D histogram with w=1 (c) and w=3 (d).

According to the Single Mapping Law (SML) [14] in histogram specification, the gray-levels of the input image are transformed to the output gray-levels for a given output range of $[y_{min}, y_{max}]$ using the cumulative distribution functions $p_x(m)$ and $p_t(m')$. The input gray-level x_m is mapped to the output gray-level $y_{m'}$, by finding an index m' for a given index m according to:

$$m' = \underset{i \in \{1,2,\ldots,L\}}{\arg\min} |p_x(m) - p_t(i)| \tag{10}$$

By using Eq. (10), each distinct gray-level of the input image X is mapped to a corresponding output gray-level to create an enhanced output image Y. The corresponding algorithm is provided in Algorithm 1.

Algorithm 1 1D-HS.

Input: input image X, parameters k_1, k_2
Output: output image Y

```
Initialize expectation a = 0, variance u = 0, image histogram h,
  destination histogram dest, enhanced image Y, pixel intensity y
compute the histogram h by Eq. (2)
for each pixel intensity m in X do
    a := m · h(m) + a
for each pixel intensity m in X do
    u := (m − a)^2 · h(m) + u
u := u × k2, a := a × k1
compute the destination histogram dest by Eq. (7)
compute the cumulative distribution functions p_t(m') of destination histogram by Eq. (9)
compute the cumulative distribution functions p_x(m) of histogram of input image by Eq. (6)
for each pixel intensity m in X do
    y(m') := min(abs(p_t(m') − p_x(m)))
for each pixel intensity m in X do
    for each row do
        for each column do
            if X(row, column) is equal to m then
                Y(row, column) := y(m')
return Y
```

2.2. 2-D histogram specification (2-D HS)

Similar with 1-D histogram defined in Section 2.1, letting $\chi = \{x_1, x_2, \ldots, x_k\}$ be the sorted of k distinct gray-levels of the input image $X = \{x(i,j) | 1 \le i \le M, 1 \le j \le N\}$, the 2-D histogram of the input image can be defined as

$$H_x = \{h_x(m,n) | m = 1, \ldots, k; n = 1, \ldots, k\} \tag{11}$$

where $h_x(m,n) \in \mathbb{R}^+$ is computed as:

$$h_x(m,n) = \frac{scr_w(m,n)}{\sum_{i=1}^{k}\sum_{j=1}^{k} scr_w(i,j)} \tag{12}$$

with

$$\begin{aligned} scr_w(m,n) = \textstyle\sum_{\forall i}\sum_{\forall j}\sum_{k=-[w/2]}^{[w/2]}\sum_{l=-[w/2]}^{[w/2]} \phi_{m,n}(x(i,j), \\ x(i+k, j+l))(|x_m - x_n| + 1) \end{aligned} \tag{13}$$

In Eq. (13), w is an odd integer number introduced for determining a square $w \times w$ neighborhood around each pixel. $\phi_{m,n}(x(i,j), x(i+k, j+l)) \in \{0,1\}$ is a binary function involved in identifying the occurrence of the gray-levels x_m and x_n at the spatial locations of (i, j) and $(i+j, j+l)$

$$\phi_{m,n}(x(i,j), x(i+k, j+l)) = \begin{cases} 1 & \text{if } x_m = x(i,j) \text{ and} \\ & \quad x_n = x(i+k, j+l) \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Fig. 1(c) and (d) shows the 2-D histogram of the Lena image according to Eq. (12) with w=1 and 3 respectively. Similar with 1-D HS defined in the above subsection, we use the probability density function of 2-D Gaussian distribution as the desired histogram, and also introduce two parameters k_1 and k_2 to control the mean and variance of 2-D Gaussian distribution

$$H_t = h_t(m', n') = \frac{1}{2\pi (k_2 u)^2} e^{-\frac{(m'-k_1 a)^2 + (n'-k_1 a)^2}{2(k_2 u)^2}} | m' = 1, \ldots, l; n' = 1, \ldots, l \tag{15}$$

Substituting Eq. (15) to Eqs. (5) and (8), the corresponding 2-D cumulative distribution function can be written as

$$P_x = \{p_x(m) | m = 1, \ldots, k\} \tag{16}$$

where

$$p_x(m) = \sum_{i=1}^{m}\sum_{j=1}^{k} h_x(i,j) \tag{17}$$

and the desired probability distribution function

$$P_t = \{p_t(m') | m' = 1, \ldots, l\} \tag{18}$$

where

$$p_t(m') = \sum_{i=1}^{m'}\sum_{j=1}^{l} h_t(i,j) \tag{19}$$

At last, by replacing P_x and P_t with the above 2-D cumulative distribution functions in SML (defined in Eq. (10)), the input gray-level x_m is mapped to the output gray-level y_m. Each distinct gray-level of the input image X is transformed to a corresponding output gray-level to create an enhanced/output image Y. The corresponding algorithm is provided in Algorithm 2.

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Algorithm 2 2D-HS.

Input: input image X, parameters k_1, k_2
Output: output image Y

Initialize expectation $a = 0$, variance $u = 0$, two-dimensional image histogram h_2, image window size w, destination histogram *dest*, enhanced image Y, pixel intensity y
compute the histogram h by Eq. (2)
for each pixel intensity m in X **do**
    $a := m \cdot h(m) + a$
for each pixel intensity m in X **do**
    $u := (m - a)^2 \cdot h(m) + u$
$u := u \times k_2$, $a := a \times k_1$
compute the two-dimensional image histogram h_2 by Eq. (12)
compute the destination histogram *dest* by Eq. (15)
compute the cumulative distribution functions $p_t(m')$ of destination histogram by Eq. (19)
compute the cumulative distribution functions $p_x(m)$ of histogram of input image by Eq. (16)
for each pixel intensity m in X **do**
    $y(m') := min(abs(p_t(m') - p_x(m)))$
for each pixel intensity m in X **do**
    for each row **do**
        for each column **do**
            if $X(row, column)$ *is equal to* m **then**
                $Y(row, column) := y(m')$
return Y

2.3. The connection between 1D-HS and 2-D HS

From Eqs. (7) and (15), we can have the conclusion that, by controlling the mean and variance of the histogram of output image, parameters k_1 and k_2 can tune the brightness and contrast of output image in both 1-D HS and 2-D HS. If k_1 and k_2 are larger than 1, the brightness and contrast of output image are enhanced, otherwise, the brightness and contrast of output image are restrained.

There is an extra parameter w in 2-D HS defined in Eq. (12). From Fig. 1, it can be seen that the diagonal of Fig. 1(c) (i.e., 2-D histogram with $w = 1$) has the same distribution with Fig. 1(b) (i.e., 1-D histogram). Thus, the 2-D histogram is equivalent to the 1-D histogram when $w = 1$. This means that, when $w = 1$, the 2-D HS will have the same effect with 1-D HS. Moreover, From Eq. (13), we can find that, the value of w associates with the contextual information utilization and computation time in 2-D HS. The larger value of parameter w is, the more contextual information is utilized in 2-D histogram, but more computation time is consumed. Therefore, in the followed experiments, $w = 3$ is selected in 2-D HS to achieve a well-balanced tradeoff between the utilization of contextual information and computation complexity.

3. Experimental results and analysis

In this section, five experiments are designed to test the performance of our proposed algorithms. Experiment in Section 3.1 is designed to test the brightness controllability in both 1-D and 2-D HS by varying parameter k_1 . Experiment in Section 3.2 is provided to test the contrast controllability in 1-D and 2-D HS by varying parameter k_2 . Experiment in Section 3.3 tests both the brightness and contrast controllability by varying k_1 and k_2 simultaneously. In order to show the superiority and applicability of the proposed algorithm, a comparison with some state of art histogram based image enhancement methods is given in Section 3.4. Section 3.5 provides the discussion on parameters selection of the proposed algorithm. To evaluate the enhanced results, some objective image quality assessments (IQAs) which overcome the shortcoming of artificial factors and take advantage of image statistics properties to establish a steady standard of performance evaluation are used. In this paper, four widely used no-reference IQAs, i.e., Spatial-frequency (SF, in [34]), Average-gradient (AG, in [35]), Edge-intensity (EI, in [36]) and Measurement of enhancement by entropy (EME, in [37]) are employed to measure the quality of enhanced images.

3.1. Brightness enhancement

As we discussed above, the proposed algorithms can tune the brightness and contrast of enhanced image by adjusting parameters k_1 and k_2 in both 1-D HS and 2-D HS. In this experiment, the testing on brightness controllability of proposed 1-D HS and 2-D HS is provided. The classic and widely used "Pollen" image is selected as input image. The enhanced images using 1-D HS and 2-D HS under different k_1 are listed in Fig. 2. Table 1 shows the brightness, contrast and IQAs of these enhanced images. Form Fig. 2 and Table 1, we can find that, for each method, the brightness of enhanced image is about k_1 times larger than the input image, while the contrast, SF, AG and EI stay almost the same. Therefore, we can draw a conclusion that, changing k_1 in 1-D HS and 2-D HS can proportional tunes the brightness of enhanced image, and makes the contrast of enhanced image basically unchanged. Moreover, compared with 1-D HS, 2-D HS performs better in restraining the brightness and enhancing the contrast due to the contextual information is utilized. This makes the images enhanced by 2-D HS have better perceptual quality than 1-D HS.

3.2. Contrast enhancement

In this experiment, testing on contrast controllability of proposed 1-D HS and 2-D HS is provided. We still take the "Pollen" image as input image, the enhanced images using 1-D HS and 2-D HS under different k_2 are shown in Fig. 3. Table 2 presents the corresponding brightness, contrast and IQAs. It can be seen from Fig. 3 that, images in Fig. 3(b)–(d) and (e)–(g) shows significant contrast enhancement visually. The corresponding histograms in Fig. 3 also have larger gray-level range than original histogram. Moreover, form the input to output gray-level mapping functions shown in Fig. 3(h) and the IQAs in Table 2, we can find that, changing k_2 in both 1-D HS and 2-D HS can proportional increases the contrast of enhanced image. The larger value of k_2 is, the higher contrast in enhanced image can be achieved. In addition, 2-D HS obtains larger contrast than 1-D HS under the same value of k_2. This means that 2-D HS generates higher perceptual quality than 1-D HS since the contextual information around each pixel is used in the processing of 2-D HS.

3.3. Both brightness and contrast enhancement enhancement

Usually, in some image enhancement applications, particularly in consumer electronics, the users prefer to tune both brightness and contrast simultaneously. In this experiment, we provide the testing on both brightness and contrast controllability of the proposed 1-D HS and 2-D HS. Fig. 4 shows the enhanced images by 1-D HS and 2-D HS under different value of k_1 and k_2. Table 3 shows the corresponding IQAs, brightness and contrast of enhanced images. Form Fig. 4 and Table 3, we can find that, the brightness and contrast of enhanced images increase proportionally with k_1 and k_2 increased. This means that both brightness and contrast controllability can be achieved in the proposed 1-D HS and 2-D HS. Similar with the above experimental results, 2-D HS obtains better performance in both perceptual quality and IQAs than 1-D HS under the same value of k_1 and k_2. This can explained that 2-D

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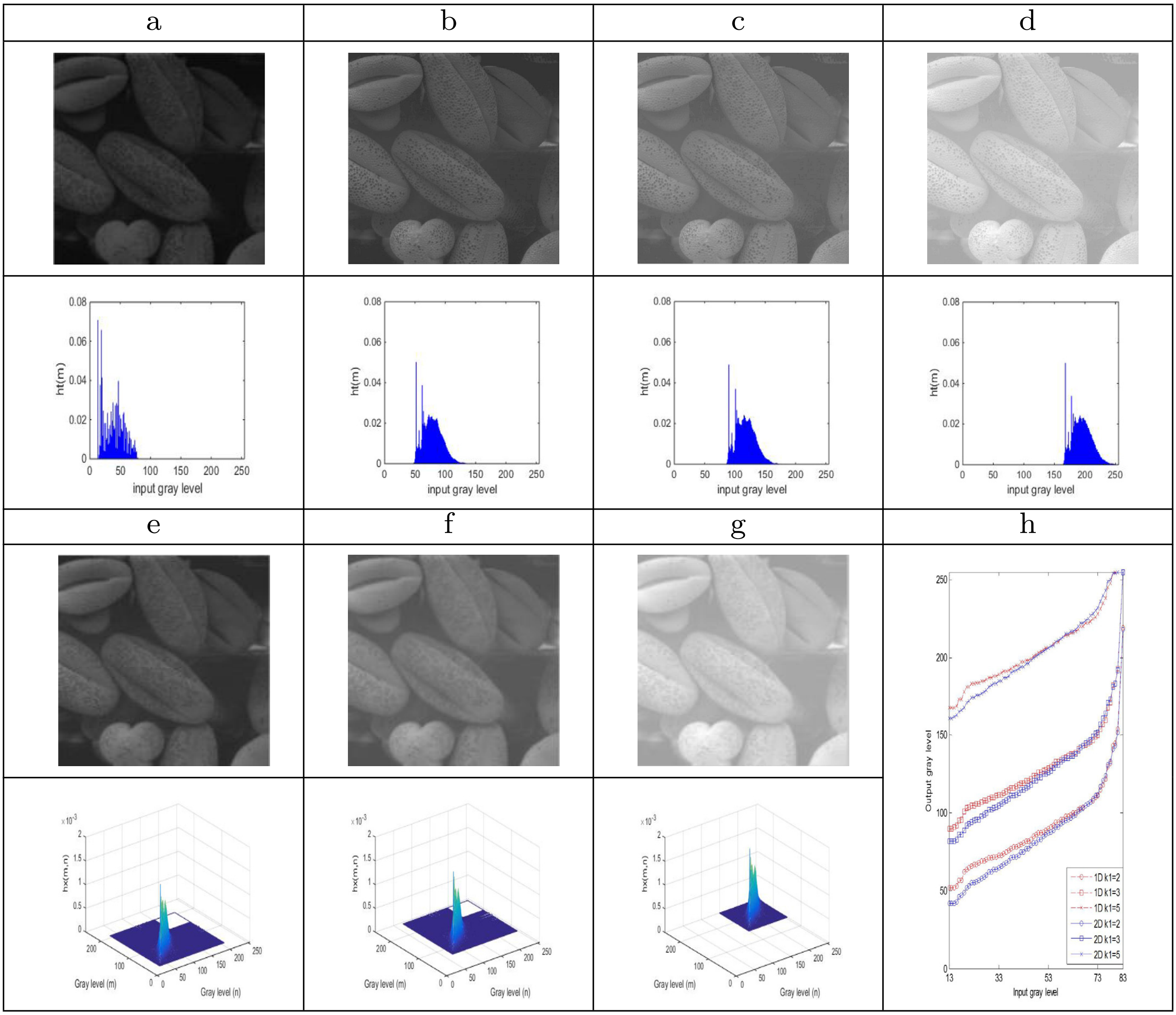


Fig. 2. Brightness enhancement for image "Pollen". (a) the input image and its histogram; (b–d) brightness enhanced images and the corresponding 1-D histogram by using 1-D HS with $k_1 = 2, 3$ and 5; (e–g) brightness enhanced images and the corresponding 2-D histogram by using 2-D HS with $k_1 = 2, 3$ and 5; (h) input to output gray-level mapping functions.

Table 1
IQAS in brightness enhancement.

	Input image	1-D HS			2-D HS		
		$k_1 = 2$	$k_1 = 3$	$k_1 = 5$	$k_1 = 2$	$k_1 = 3$	$k_1 = 5$
SF	5.15	5.24	5.26	5.22	6.18	6.19	6.10
AG	2.19	2.15	2.16	2.16	2.59	2.60	2.59
EI	22.39	21.70	21.86	21.78	26.34	26.31	26.24
Brightness	38.75	78.25	117.00	194.55	71.70	111.51	190.88
Contrast	91.79	80.64	82.09	82.39	122.35	121.75	122.48
EME	8.97	4.21	2.86	1.68	5.63	3.62	2.12

HS utilizes contextual information around each pixel while 1-D HS only use the gray value of each pixel itself.

3.4. Compared with some existing methods

3.4.1. Gray level image enhancement

In this experiment, the comparative analysis of proposed 1-D HS and 2-D HS on gray-level image enhancement with some state of art histogram based image enhancement methods are provided. We compare the enhancement results of our proposed methods with classical histogram equalization method (1-D HE, in [14]), 2-D histogram equalization method (2-D HE, in [24]) well performed power-constrained contrast enhancement method (PCCE, in [43]), recent proposed spatial entropy-based contrast enhancement method (SECEDCT, in [38]) and fuzzy-contextual based contrast enhancement method (FCCE, in [39]. The parameters k_1 and k_2 in 1-

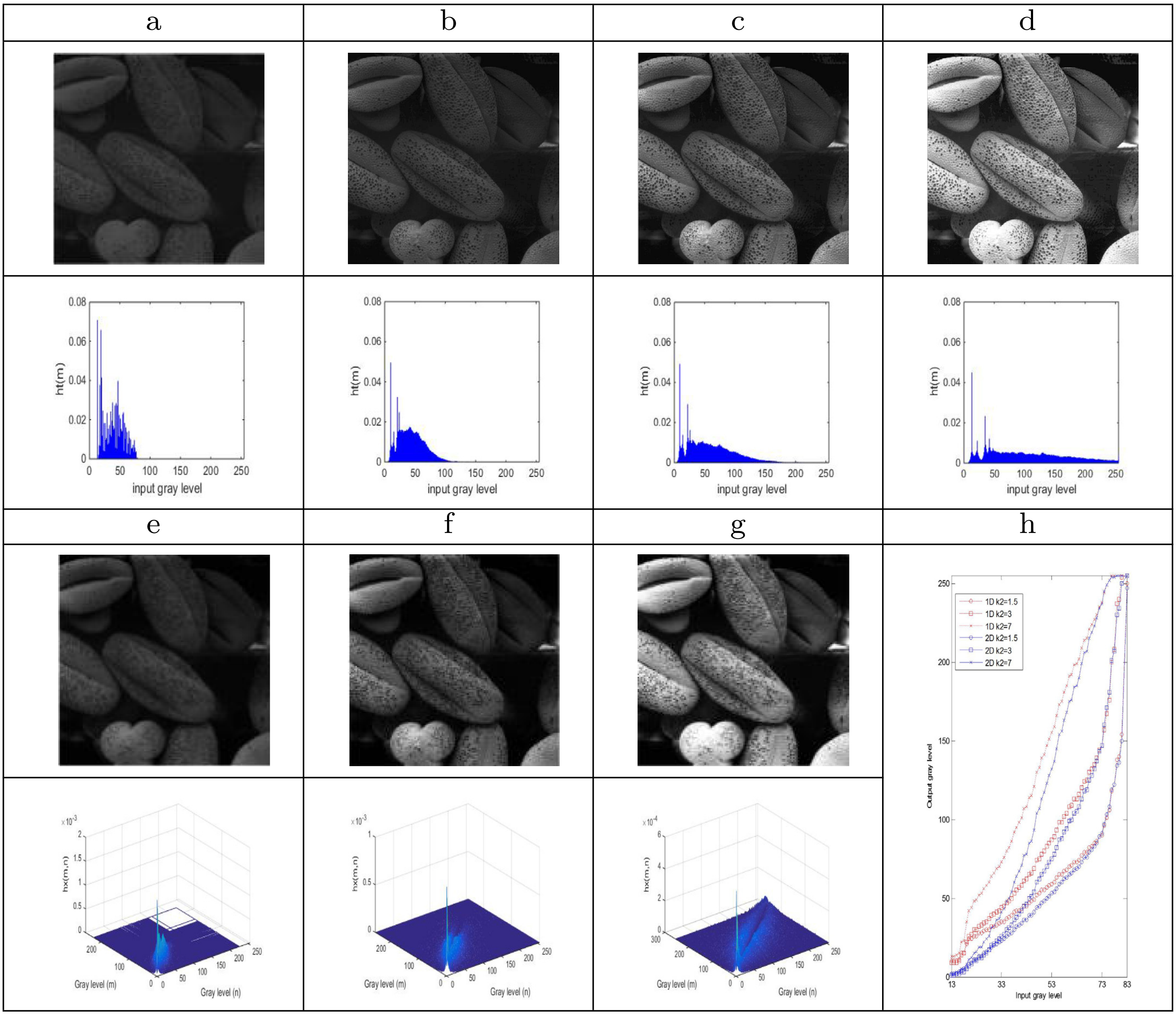


Fig. 3. Contrast enhancement for image "Pollen". (a) the input image and its histogram; (b–d) contrast enhanced images and the corresponding 1-D histogram by using 1-D HS with $k_2 = 1.5, 3$ and 7; (e–g) contrast enhanced image and the corresponding 2-D histogram by using 2-D HS with $k_2 = 1.5, 3$ and 7; (h) input to output gray-level mapping functions.

Table 2
IQAS in contrast enhancement.

	Input image	1-D HS			2-D HS		
		$k_2 = 2$	$k_2 = 3$	$k_2 = 5$	$k_2 = 2$	$k_2 = 3$	$k_2 = 5$
SF	5.15	7.41	13.26	20.97	8.43	14.82	23.88
AG	2.19	3.01	5.31	8.71	3.44	5.81	9.55
EI	22.39	30.45	53.74	88.72	34.93	58.97	97.38
Brightness	38.75	43.32	60.44	102.98	34.03	46.85	79.12
Contrast	91.79	153.19	462.99	1286.51	203.17	555.19	1512.68
EME	8.97	11.03	14.14	14.52	18.96	24.14	24.04

D HS and 2-D HS are set as $[k_1 = 2, k_2 = 3]$ and $[k_1 = 3, k_2 = 9]$. Moreover, for space saving, in the following tables, "B" represent for brightness and "C" for contrast are used, and only one digit after the decimal point of all IQAs is retained. Tables 4 and 5 show the enhanced results and the corresponding IQAs by different methods for "Pollen" and "Elaine" images. From those tables we can find that, 1) the IQAs of enhanced image by our proposed methods can be absolutely controlled. This property offers the users to tune the enhanced result according to their preference, environment brightness and so on; 2) the proposed 1-D HS and

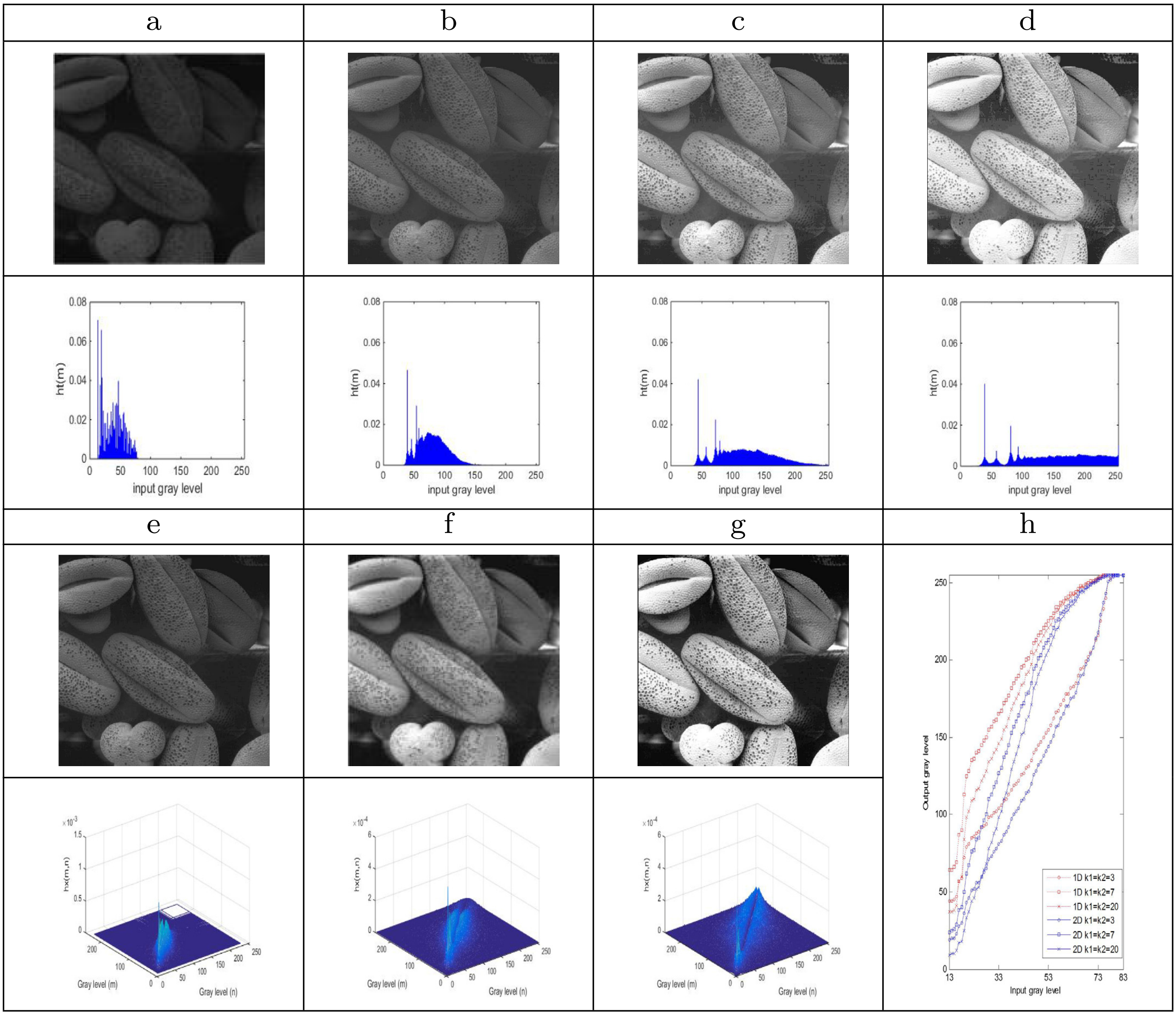


Fig. 4. Effects of both brightness and contrast enhancement. (a) the input image; (b) enhanced image and its 1-D histogram using 1-D HS with$k_1 = 2$, $k_2 = 1.5$; (c) using 1-D HS with $k_1 = k_2 = 3$; (d) using 1-D HS with $k_1 = 5$, $k_2 = 7$; (e) enhanced image and its 2-D histogram using 2-D HS with $k_1 = 2$, $k_2 = 1.5$; (f) using 2-D HS with $k_1 = k_2 = 3$; (g) using 2-D HS with $k_1 = 5, k_2 = 7$; (h) input to output gray-level mapping functions.

Table 3
IQAS in both brightness and contrast enhancement.

	Input image	1-D HS			2-D HS		
		$k_1 = 2$	$k_1 = 3$	$k_1 = 5$	$k_1 = 2$	$k_1 = 3$	$k_1 = 5$
		$k_2 = 1.5$	$k_2 = 3$	$k_2 = 5$	$k_2 = 1.5$	$k_2 = 3$	$k_2 = 7$
SF	5.15	7.86	14.65	18.58	9.23	17.26	23.05
AG	2.19	3.24	6.17	7.69	3.89	7.34	9.54
EI	22.39	32.73	62.52	78.27	39.45	73.66	97.62
Brightness	38.75	78.86	120.06	152.56	68.57	100.41	122.29
Contrast	91.79	183.34	666.30	1195.84	270.58	961.58	1776.27
EME	8.97	6.23	8.02	8.95	9.18	12.73	16.00

2-D HS have better performance in brightness restraining while contrast enhancement. This means that the proposed methods provide high image contrast and good perceptual quality while reducing power consumption; 3) 2-D HS still has better performance in both IQAs and perceptual quality than 1-D HS since the contextual information around each pixel is used in 2-D HS.

3.4.2. Color image enhancement

The proposed algorithms can be straightforwardly extended to color image enhancement by applying the algorithms to the luminance component and maintain the chrominance component. In this experiment, the input color image is transformed into CIE Lab color space and only “L” component is taken for enhance-

Table 4
Comparative analysis on image enhancement by different methods for gray-level "Pollen" image.

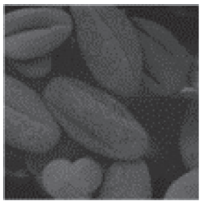
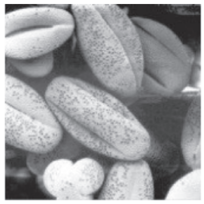
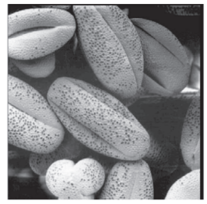
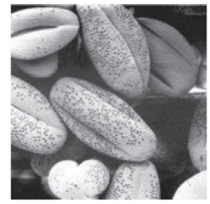
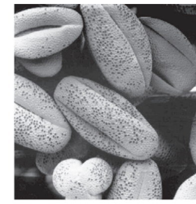
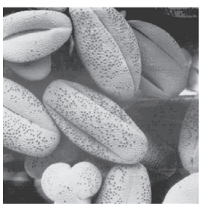
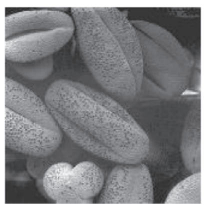
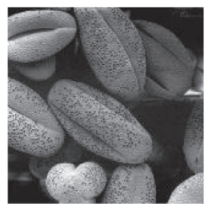
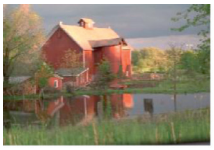
Input image	1-D HE	PCCE	2-D HE	SECEDCT
				
SF:5.2;AG:2.2; EI:22.4;B:38.8; C:91.8;EME:8.97	SF:22.1;AG:9.2; EI:94.0;B:127.9; C:1634.0;EME:15.0	SF:20.2;AG:8.7; EI:88.9;B:105.2; C:1397.2;EME:15.6	SF:23.8;AG:9.9; EI:101.4;B:116.2; C:1785.0;EME:16.1	SF:21.8;AG:5.9; EI:73.4;B:92.2; C:1253.0;EME:12.1
FCCE	1-D HS ($k_1 = 2, k_2 = 3$)	2-D HS ($k_1 = 2, k_2 = 3$)	1-D HS ($k_1 = 3, k_2 = 9$)	2-D HS ($k_1 = 3, k_2 = 9$)
				
SF:16.3; AG:8.2; EI:73.4; B:100.8; C:1055.1; EME:19.5	SF:14.3; AG:6.0; EI:61.4; B:86.8; C:607.1; EME:11.5	SF:17.1; AG:7.1; EI:72.6; B:70.5; C:850.0; EME:18.3	SF:20.8; AG:8.8; EI:90.4;B:128.9; C:1430.4; EME:13.1;	SF:25.7; AG:10.5; EI:107.0;B:101.5; C:1908.0; EME:20.1

Table 5
Comparative analysis on image enhancement by different methods for gray-level "Elaine" image.

Input image	1-D HE	PCCE	2-D HE	SECEDCT
				
SF:11.3;AG:4.4; EI:43.1;B:135.4; C:639.1;EME:6.9	SF:18.8;AG:7.0; EI:68.5;B:127.6; C:1676.0;EME:13.2	SF:14.3;AG:5.5; EI:55.6;B:127.0; C:1160.1;EME:11.5	SF:17.9;AG:6.6; EI:63.6;B:157.5; C:1210.3;EME:10.6	SF:10.9;AG:4.5; EI:51.6;B:123.5; C:1011.3;EME:7.6
FCCE	1-D HS ($k_1 = 2, k_2 = 3$)	2-D HS ($k_1 = 2, k_2 = 3$)	1-D HS ($k_1 = 3, k_2 = 9$)	2-D HS ($k_1 = 3, k_2 = 9$)
				
SF:12.6; AG:4.7; EI:53.3;B:152.5; C:1022.4;EME:7.3	SF:18.2; AG:6.7; EI:64.3;B:163.5; C:1224.4;EME:9.9	SF:18.1; AG:6.5; EI:62.9;B:173.7; C:1166.0;EME:9.5	SF:18.7; AG:6.9; EI:67.9;B:137.5; C:1585.4;EME:12.9	SF:19.3; AG:7.1; EI:69.0;B:149.5; C:1579.3;EME:12.4

ment. After that, inverse transform is employed to get the enhanced color image. A public color image database, which available on [41] are used for testing. The color images in this database are widely employed in image enhancement applications [24,40]. Table 6 lists the enhanced results by different methods for the "House" image. From this table, we can find that, 1-D HS and 2-D HS with $[k_1 = 2, k_2 = 5]$ and $[k_1 = 3, k_2 = 9]$, the enhanced image show more details than 1-D HE, PCCE, 2-D HE, SECEDCT and FCCE, i.e., the texture of the "wall" and the "small tree" in the front of house. Moreover, it is undeniable that the users can proportionally tune the brightness and contrast of enhanced image in 1-D HS and 2-D HS according to their visual preference. Table 7 lists various

Table 6
Comparative analysis on image enhancement by different methods for gray-level "House" image.

Input image	1-D HE	PCCE	2-D HE	SECEDCT
				
SF:18.7;AG:6.0; EI:57.6;B:107.6; C:659; EME:10.2	SF:33.7;AG:11.2; EI:107.0;B:116.8; C:1742; EME:17.7	SF:21.9;AG:6.9; EI:66.4;B:74.3; C:912; EME:15.8	SF:32.4;AG:10.3; EI:98.1;B:93.4; C:1667; EME:20.7	SF:33.5;AG:7.3; EI:57.1;B:103.4; C:1543; EME:12.7
FCCE	1-D HS ($k_1 = 2, k_2 = 3$)	2-D HS ($k_1 = 2, k_2 = 3$)	1-D HS ($k_1 = 3, k_2 = 9$)	2-D HS ($k_1 = 3, k_2 = 9$)
				
SF:32.1;AG:10.4; EI:63;B:110.1; C:1073; EME:15.7	SF:34.1;AG:11.4; EI:109;B:125.1; C:1751; EME:18.7	SF:34.1;AG:11.2; EI:107.9;B:133.0; C:1685; EME:17.8	SF:35.6;AG:11.5; EI:109.8;B:105.8; C:1922; EME:20.2	SF:35.5;AG:11.5; EI:110.4;B:114.9; C:1863; EME:19.4

enhanced results on the Flower" image by 1-D HS, 2-D HS with different value of k_1 and k_2 . It can be seen that, with the increments of k_1 and k_2, the brightness and contrast of output image are enhanced. If the users want to find more information in the whole image, they can increase the two parameters simultaneously and vice versa. For example, when $[k_1 = 2, k_2 = 3]$ or $[k_1 = 3, k_2 = 3]$ are selected, the "flower" and the background are highlighted in the enhanced image. On the contrary, if the users hold the parameter k_1 and only increase parameter k_2, the texture on the surface of "flower" is enhanced (such as $[k_1 = 1, k_2 = 9]$ or $[k_1 = 2, k_2 = 9]$).

3.4.3. Average performance of the proposed algorithm

In order to verify the average performance of the proposed methods, a public database includes 27 images and provided by NASA [42] (illustrated in Table. 8) are used for testing. The parameters k_1 and k_2 in both 1-D HS and 2-D HS are also shown in Table 8. Table 9 lists the average performance of six IQAs on NASA database. It can be seen that, the proposed 2-D HS and 1-D HS perform better than other methods with respect to six IQAs. 2-D HS still has better performance than 1-D HS since 2-D HS introduces the contextual information around each pixel in the process of enhancement.

3.5. Parameter selection

The parameter w in 2-D HS has been discussed in Section 2, there have two parameters k_1 and k_2 in 1-D and 2-D HS. Although these two parameters exactly offer users a way to freely tune the brightness and contrast of enhanced image. Without loss of generality, in this section, we provide the discussions on optimize and automatic estimation of these two parameters in some non-manual intervention applications.

Although in contrast enhancement technique, the enhanced image is supposed to has better contrast than input image, in our experiments, the largest contrast value not always reflects the best visual pleasing results (e.g., as shown in Figs. 2–4). Therefore, we consider that utilize the EME value, which reflects the degree of enhancement, to assessment enhanced results. As shown in Table 1, for the "Pollen" image, with the increment of k_1 values, the EME values decreased. And the enhanced image with largest EME value has the most acceptable result. We can also find the same results from Tables 2 to 3, the enhanced image with largest EME value has the most visual pleasing. Thus, in parameters selection, we suggest to select k_1 and k_2 that correspond to highest EME value, e.g., $[k_1 = 5, k_2 = 7]$ as the optimize parameters for the "Pollen" image. Furthermore, as we have discussed above, the parameter k_1 tunes the brightness of enhanced image. The higher value k_1 is, the brighter output image is achieved. Usually, we can adjust the parameter k_1 to make the brightness of enhanced image close to an accepted perceptual quality value or the median brightness. For example, in the application of gray-level image enhancement, $k_2 \approx 2$ can be chosen if the brightness of the input image is 64. Moreover, in some real world applications such as surveillance, TV, mobile phone and other consumer electronics, the optimal selection of k_1 can be determined by the environment brightness which can be obtained by brightness sensor or camera in those equipment. We can turn down k_1 to make the enhanced image dark if the consumer electronics are under a bright environment and vice versa. Parameter k_2 tunes the contrast of enhanced image. The larger value of k_2 is, the higher contrast in output image can be achieved. Ideally, for a gray image, when a suitable k_1 is chosen to make the brightness of enhanced image close to 128, and the parameter k_2 tends to infinity, the corresponding Gaussian distribution will becomes a uniform distribution. This means that, under the above situation, the proposed 1-D HS and 2-D HS are equal to 2-D HE and 2-D HE respectively. Its worth to note that, the highest contrast or highest brightness of enhanced image is not the acceptable perceptual quality for users. However, in our proposed methods, users can own the chance to have preference brightness and contrast of enhance image only by adjusting the two parameters k_1 and k_2.

4. Conclusion

In this paper, two brightness and contrast controllable histogram specification algorithms for image enhancement are proposed. The main contribution of this paper relies on the following aspects: (1) the proposed algorithms can tune the brightness

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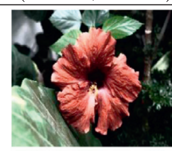
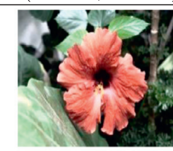
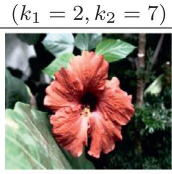
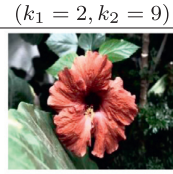
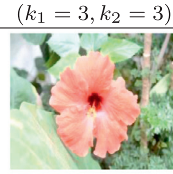
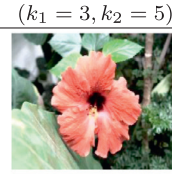
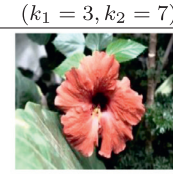
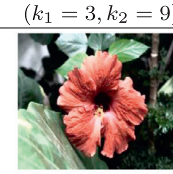
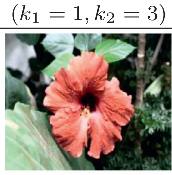
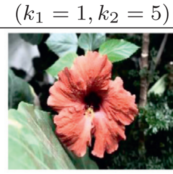
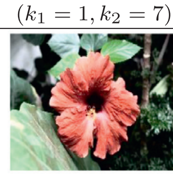
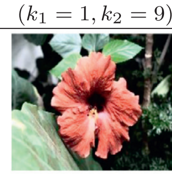
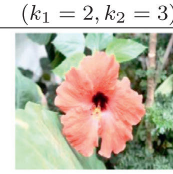
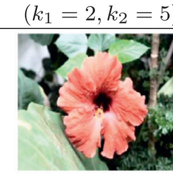
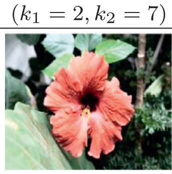
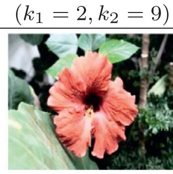
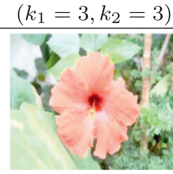
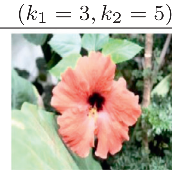
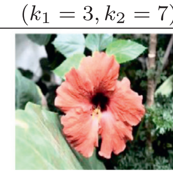
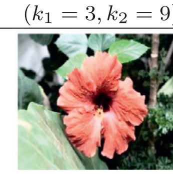
Table 7
Comparative analysis on image enhancement by different methods for gray-level "Flower" image.

Input image	1-D HE	PCCE	2-D HE	SECEDCT	FCCE
					
SF:7.2; AG:2.8; EI:29.1;B:81.6; C:624; EME:8.2	SF:14.8; AG:5.4; EI:55.8;B:116.2; C:1688; EME:11.6	SF:9.7; AG:3.6; EI:37.7;B:75.1; C:843; EME:11.7	SF:16.1; AG:5.7; EI:58.2;B:116.8; C:1944; EME:13.8	SF:15.4;AG:4.4; EI:37.5;B:125.1; C:1068; EME:11.4	SF:16.3;AG:4.2; EI:37.9;B:133.0; C:1143; EME:12.8
1-D HS $(k_1 = 1, k_2 = 3)$	1-D HS $(k_1 = 1, k_2 = 5)$	1-D HS $(k_1 = 1, k_2 = 7)$	1-D HS $(k_1 = 1, k_2 = 9)$	1-D HS $(k_1 = 2, k_2 = 3)$	1-D HS $(k_1 = 2, k_2 = 5)$
					
SF:16.2; AG:5.5; EI:57.0;B:80.9; C:1595; EME:15.9	SF:17.2; AG:5.7; EI:58.9;B:77.1; C:1710; EME:16.6	SF:17.6; AG:5.8; EI:59.5;B:75.7; C:1745; EME:16.7	SF:17.8; AG:5.8; EI:59.7;B:75.1; C:1758; EME:16.7	SF:12.7; AG:4.9; EI:50.9;B:141.4; C:1551; EME:9.3	SF:16.2; AG:5.8; EI:59.6;B:104.8; C:1879; EME:14.5
1-D HS $(k_1 = 2, k_2 = 7)$	1-D HS $(k_1 = 2, k_2 = 9)$	1-D HS $(k_1 = 3, k_2 = 3)$	1-D HS $(k_1 = 3, k_2 = 5)$	1-D HS $(k_1 = 3, k_2 = 7)$	1-D HS $(k_1 = 3, k_2 = 9)$
					
SF:17.0;AG:5.9; EI:60.5;B:90.5; C:1869; EME:15.9	SF:17.4;AG:5.9; EI:60.6;B:84.1; C:1848; EME:16.3	SF:9.5; AG:3.8; EI:40.2;B:175.1; C:1023; EME:5.8	SF:14.6; AG:5.4; EI:55.9;B:129.7; C:1777; EME:11.8	SF:16.5; AG:5.9; EI:60.3;B:105.3; C:1927; EME:14.7	SF:17.0; AG:5.9; EI:60.9;B:93.2; C:1909; EME:15.7
2-D HS $(k_1 = 1, k_2 = 3)$	2-D HS $(k_1 = 1, k_2 = 5)$	2-D HS $(k_1 = 1, k_2 = 7)$	2-D HS $(k_1 = 1, k_2 = 9)$	2-D HS $(k_1 = 2, k_2 = 3)$	2-D HS $(k_1 = 2, k_2 = 5)$
					
SF:16.4;AG:5.7; EI:58.0;B:105.4; C:1840; EME:15.2	SF:16.9;AG:5.8; EI:60.1;B:102.7; C:1989; EME:15.6	SF:17.2; AG:5.9; EI:60.7;B:101.7; C:2036; EME:15.7	SF:17.6; AG:5.9; EI:60.9;B:101.2; C:2049; EME:15.7	SF:11.9; AG:4.5; EI:47.5;B:159.6; C:1451; EME:8.5	SF:15.6; AG:5.5; EI:57.4;B:128.9; C:1969; EME:13.6
2-D HS $(k_1 = 2, k_2 = 7)$	2-D HS $(k_1 = 2, k_2 = 9)$	2-D HS $(k_1 = 3, k_2 = 3)$	2-D HS $(k_1 = 3, k_2 = 5)$	2-D HS $(k_1 = 3, k_2 = 7)$	2-D HS $(k_1 = 3, k_2 = 9)$
					
SF:16.6; AG:5.8; EI:59.8;B:116.2; C:2066; EME:14.8	SF:17.0; AG:5.9; EI:60.5;B:110.1; C:2079; EME:15.1	SF:9.4; AG:3.5; EI:37.3;B:186.9; C:894; EME:5.4	SF:14.1; AG:4.9; EI:51.8;B:150.2; C:1700; EME:10.7	SF:16.3; AG:5.6; EI:57.8;B:129.4; C:2004; EME:13.6	SF:17.1; AG:5.8; EI: 59.7;B:118.8; C:2078; EME:14.7

and contrast of enhanced image by using two parameters. This enable the users obtaining their preferable brightness and contrast in real-world applications. (2) It is easy to restrain brightness while enhance contrast for power saving by using the proposed method. (3) To the best of our knowledge, the proposed methods are the first attempt to tune the brightness and contrast of enhanced image using histogram based technologies. (4) The proposed 2-D HS holds more detail information in the process of enhancement than 1-D histogram based methods since the contextual information is utilized in 2-D histogram.

Experimental results show that, when the suitable parameters are selected, the proposed methods have better performance than some state of art histogram based image enhancement methods in both perceptual quality and image quality assessments. Although we proposed a principle on parameters selection to obtain the most visual pleasing enhanced image, the selections are based on contrast and EME measure of enhanced image, which is a time-consuming process. In our future work, how to select the suitable parameters, and how to select parameters automatically and efficiently are the topics we mainly focused on.

Table 8
NASA image database for enhancement

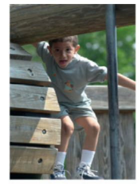
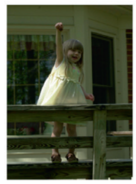
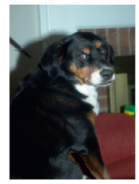
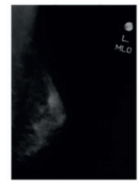
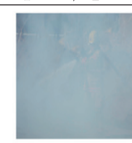
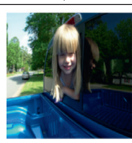
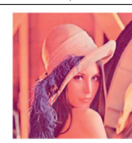
							
1-D HS	$k_1 = 2, k_2 = 2$	$k_1 = 3, k_2 = 2$	$k_1 = 2, k_2 = 2$	$k_1 = 2, k_2 = 2$	$k_1 = 2, k_2 = 2$	$k_1 = 2, k_2 = 2$	$k_1 = 2, k_2 = 2$
2-D HS	$k_1 = 4, k_2 = 5$	$k_1 = 3, k_2 = 4$	$k_1 = 2, k_2 = 4$	$k_1 = 2, k_2 = 7$	$k_1 = 2, k_2 = 4$	$k_1 = 5, k_2 = 4$	$k_1 = 5, k_2 = 5$
							
1-D HS	$k_1 = 3, k_2 = 5$	$k_1 = 3, k_2 = 5$	$k_1 = 4, k_2 = 6$	$k_1 = 4, k_2 = 3$	$k_1 = 3, k_2 = 2$	$k_1 = 3, k_2 = 5$	$k_1 = 4, k_2 = 6$
2-D HS	$k_1 = 2, k_2 = 5$	$k_1 = 2, k_2 = 4$	$k_1 = 2, k_2 = 3$	$k_1 = 4, k_2 = 4$	$k_1 = 5, k_2 = 9$	$k_1 = 5, k_2 = 5$	$k_1 = 4, k_2 = 8$
							
1-D HS	$k_1 = 4, k_2 = 6$	$k_1 = 3, k_2 = 5$	$k_1 = 3, k_2 = 7$	$k_1 = 4, k_2 = 6$	$k_1 = 3, k_2 = 3$	$k_1 = 2, k_2 = 2$	$k_1 = 2, k_2 = 2$
2-D HS	$k_1 = 3, k_2 = 8$	$k_1 = 3, k_2 = 5$	$k_1 = 4, k_2 = 5$	$k_1 = 3, k_2 = 5$	$k_1 = 4, k_2 = 3$	$k_1 = 3, k_2 = 3$	$k_1 = 2, k_2 = 3$
							
1-D HS	$k_1 = 4, k_2 = 3$	$k_1 = 4, k_2 = 6$	$k_1 = 4, k_2 = 6$	$k_1 = 3, k_2 = 5$	$k_1 = 4, k_2 = 7$	$k_1 = 3, k_2 = 5$	
2-D HS	$k_1 = 3, k_2 = 3$	$k_1 = 5, k_2 = 7$	$k_1 = 2, k_2 = 6$	$k_1 = 2, k_2 = 5$	$k_1 = 2, k_2 = 3$	$k_1 = 4, k_2 = 9$	

Table 9
Average of six IQAs by different methods on NASA database.

	2-D HS	1-D HS	1-D HE	2-D HE	PCCE	SECEDCT	FCCE
SF	15.46	16.20	13.51	11.62	6.29	7.31	10.22
AG	5.17	4.63	4.16	3.63	1.81	2.21	4.03
EI	53.49	45.91	40.30	35.59	18.65	36.22	38.13
Brightness	114.38	136.46	122.50	95.48	54.54	100.21	106.13
Contrast	1787.33	1375.83	1569.70	1407.20	595.45	1102.12	1434.11
EME	12.98	10.68	6.42	7.84	5.72	6.13	9.14

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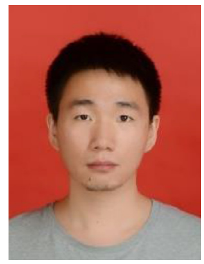

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