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A Novel Filtered Bi-Histogram Equalization Method

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ABSTRACT

Here, we present a new framework for histogram equalization in which both local and global contrasts are enhanced using neighborhood metrics. When checking neighborhood information, filters can simultaneously improve image quality. Filters are chosen depending on image properties, such as noise removal and smoothing. Our experimental results confirmed that this does not increase the computational cost because the filtering process is done by our proposed arrangement of making the histogram while checking neighborhood metrics simultaneously. If the two methods, i.e., histogram equalization and filtering, are performed sequentially, the first method uses the original image data and next method uses the data altered by the first. With combined histogram equalization and filtering, the original data can be used for both methods. The proposed method is fully automated and any spatial neighborhood filter type and size can be used. Our experiments confirmed that the proposed method is more effective than other similar techniques reported previously.

Key words: Bi-histogram Equalization, Neighborhood Metric, Contrast Enhancement, Flat Histogram

1. INTRODUCTION

Image contrast enhancement methods are widely used in many fields, such as medical imaging, satellite imaging, consumer electronics, digital TV, digital cameras, and so forth. Many methods have been introduced for image enhancement, among which histogram equalization is the most commonly used due to its effectiveness and simplicity.

Global histogram equalization (GHE) transforms the result image to ensure a uniform distribution of gray levels [1]. This method flattens and stretches the dynamic range of the image's histogram, which results in overall contrast improvement [2-6]. Essentially, GHE maps the gray levels in the enhanced image through a transformation function that depends on the distribution of gray levels in the input image. This transformation function stretches the contrast of the high histogram region and compresses the contrast of the low histogram region. GHE achieves comparatively better performance on almost all types of image [7]. However, it changes the original image's brightness, while reducing the quality of the original image and in some cases causes a washout effect (Fig. 1).

To overcome the washout effect, brightness-preserving extensions of GHE have been developed, such as brightness-preserving bi-histogram equalization (BBHE) [8], dualistic sub-image histogram equalization (DSIHE) [9], and minimum mean brightness error bi-histogram equalization (MMBEBHE) [10]. These methods partition the histogram of the original image into sub-histo-

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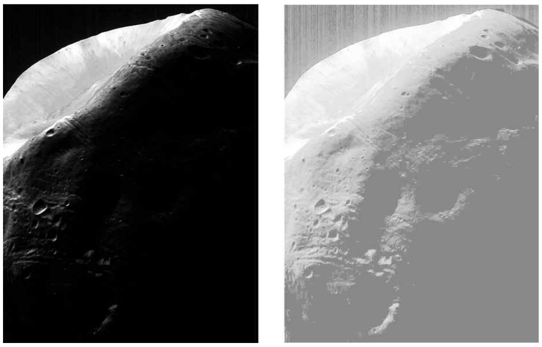
grams and then equalize each sub-histogram independently with GHE. In doing so, they equalize some sub-images over their ranges toward the mean and equalize others over their ranges away from the mean, depending on their respective histograms. Thus, the resulting equalized sub-images preserve the overall mean brightness. BBHE, DSIHE, and MMBEBHE divide the histogram into two sub- histograms as different dividing points. BBHE uses the mean value of the histogram, while DSIHE uses the median value. MMBEBHE first tests all possible values of the separation point from all gray levels. The differences between the mean value of the original image's histogram and the mean values of the sub-histograms are calculated for each separation point. The separation point is then chosen to achieve the minimum difference between the input and output means.

Another major drawback of GHE is that it cannot adapt the local information of the image. Although many methods have been developed to improve local contrast [11, 12], their computational complexity is very high and they sometimes cause over-enhancement, which may affect the characteristics of the original image.

Some methods have been developed to reduce these drawbacks [13-15]. These methods divide the input histogram bins into sub-bins using neighboring information, and can therefore enhance local contrast and prevent over-enhancement. However, these methods do not provide a great deal of enhancement.

Previous studies did not consider the enhancement of noisy images. Therefore, this paper presents a novel histogram equalization method, which is based on brightness-preserving methods and neighborhood metrics to improve local contrast. We also propose the use of filters to improve image quality [16]. This is expected to not only eliminate the above drawbacks of previous GHE methods but also to reduce noise from the input image. It is possible to use the filtering technique directly; however, our method saves time by combining the filtering process using neighboring information checked on each pixel in the neighborhood metric. The neighborhood metric is not efficient because neighboring information is changed from the original image after applying the filters, and therefore the filtering technique is applied simultaneously.

The remainder of this paper is organized as follows. Section 2 discusses related work and Section 3 presents the proposed method called filtered bi-histogram equalization method (FBHEM). Section 4 presents simulation results demonstrating the effectiveness of FBHEM compared to GHE, BBHE, DSIHE, and MMBEBHE. Section 5 concludes the paper.



(a) (b)

Fig. 1. Illustration of washout appearance: (a) Darker Mars image and (b) resultant image of GHE.

2. RELATED WORK

2.1 Global histogram equalization

Let h(i) be the -th bin of intensity level of original image f, and then p(i) be the probability that the gray level of any given pixel i ($0 \le i \le L-1$).

$$h(i) = n(i), \text{ for } i = 0,1,\dots,L-1.$$

$$p(i) = \frac{n(i)}{\sum_{i=0}^{L-1} n(i)} = \frac{n(i)}{N} \text{ and } \sum_{i=0}^{L-1} p(i) = 1. \quad (1)$$

where n(i) is the number of pixels of i-th intensity level in image f, N is the total number of pixels of image f, and L is the discrete intensity level. The cumulative distribution function (CDF) P(i) is defined as:

$$P(i) = \sum_{j=0}^{i} p(j), P(L-1) = \sum_{j=0}^{L-1} p(j) = 1 \quad (2)$$

GHE maps the original image to the resultant image using the intensity transformation function:

$$g(x,y) = T(f(x,y)), \quad (3)$$

where f and g are the original and resultant images, respectively, (x, y) are the 2D coordinates of the images, and T is the intensity transformation function, which maps the original image to the entire dynamic range [0, L-1], using CDF:

$$T(i) = (L-1) \cdot P(i), \qquad i = 0, \ldots, L-1 \quad (4)$$

2.2 Bi-histogram equalization

Let m be the mean of the image f and assume that m ∈ [0, L-1]. Based on m, the image is separated into two sub-images f^1 and f^2 as

$$f = f^1 \cup f^2, \quad (5)$$

where

$$f^1 = \{f(x,y) | f(x,y) \le m, \quad \forall f(x,y) \in f\} \quad (6)$$

and

$$f^2 = \{f(x,y) | f(x,y) > m, \quad \forall f(x,y) \in f\} \quad (7)$$

Next, we define the respective probability distribution functions of sub-images f^1 and f^2 as

$$p_1(k) = \frac{n_1(k)}{n_1}, \qquad k = 0,1,\ldots,m \quad (8)$$

and

$$p_2(k) = \frac{n_2(k)}{n_2}, k = m+1, m+2, \ldots, L-1 \quad (9)$$

in which $n_1(k)$ and $n_2(k)$ represent the respective values of k in the two sub-images f^1 and f^2, and n_1 and n_2 are the total values of f^1 and f^2, respectively. Here, $n_1 = \sum_{k=0}^{m} n_1(k)$, $n_2 = \sum_{k=m+1}^{L-1} n_2(k)$, and $n = n_1 + n_2$.

The respective CDFs are then defined as

$$P_1(k) = \sum_{j=0}^{k} p_1(j) \quad (10)$$

and

$$P_2(k) = \sum_{j=m+1}^{k} p_2(j) \quad (11)$$

Note that $P_1(m)=1$ and $P_2(L-1)=1$ by definition.

Let us similarly define the following transformation functions exploiting the CDFs

$$T_1(k) = m \cdot P_1(k) \quad (12)$$

and

$$T_2(k) = m + 1 + ((L-1) - (m+1)) \cdot P_2(k) \quad (13)$$

Then, the resultant image of the histogram can be expressed as

$$g(x,y) = T(f(x,y)), \quad (14)$$

in which

$$T(k) = \begin{cases} m \cdot P_1(k), & k \le m \\ m + 1 + ((L-1) - (m+1)) \cdot P_2(k), & \text{otherwise} \end{cases} \quad (15)$$

2.3 Histogram equalization with neighborhood metric

Let J be the number of sub-bins of the i-th bin, h(i), of intensity level of image f and J is produced by a neighborhood metric. The number of total sub-bins is R which equals J·L and the value of J depends on the chosen neighborhood metrics.

$$\lambda(r) = n_r, \text{ for } r = 0,1,\ldots,R-1.$$

$$p(r) = \frac{n(r)}{\sum_{r=0}^{R-1} n(r)} = \frac{n(r)}{N}, \text{for } r = 0,1,\ldots,R-1 \text{ and } \sum_{r=0}^{R-1} p(r) = 1 \quad (16)$$

where r=j+(J-1)·i, n(r) is the number of occurrences of the j-th sub-bin in i-th bin of image f, and N is the total number of pixels in image f. Then the CDF, P_r, is defined as:

$$P(r) = \sum_{r=0}^{R-1} p(r) \quad (17)$$

GHE maps the original image into the resultant image using the intensity transformation function:

$$g(x,y) = T_1(f(x,y)), \quad (18)$$

where f and g are the original and resultant images, respectively, (x, y) are the 2D coordinates of the images, and T_1 is the intensity transformation function, which maps the original image into the entire sub-bin's range, [0, R-1] using CDF:

$$T_1(r) = T_2(r) \cdot (L/R) \quad (19)$$

here

$$T_2(r) = (R-1) \cdot P(r) \quad (20)$$

3. PROPOSED METHOD

In the proposed method, the image histogram is divided into two sub-histograms to preserve the image brightness and each histogram bin of each sub-histogram is divided by a distinction metric into sub-bins [17-19]. Filtering of any drawbacks during the enhancement of image contrast requires rearrangement of the histogram when checking the neighborhood metric (Fig. 2). This rearrangement is described below, and all spatial neighborhood filter types are possible. To check all image pixels that have been neighbors, it is necessary to extend the input image.

3.1 Neighborhood metric

Let γ be the function that extends an image function surrounded by a “background” of zero padding:

$$\gamma(x,y) = \begin{cases} g(x,y), & (x,y) \in [0, N-1] \times [0, M-1] \\ 0, & \text{otherwise} \end{cases} \tag{21}$$

in which an image is N pixels by M pixels in size and g(x,y) is the intensity of image pixel (x,y).

The distinction metric is expressed by the following formula:

$$d_\Theta(x,y) = \sum_{(x',y') \in R_\Theta(x,y)} t(x,y,x',y') \tag{22}$$

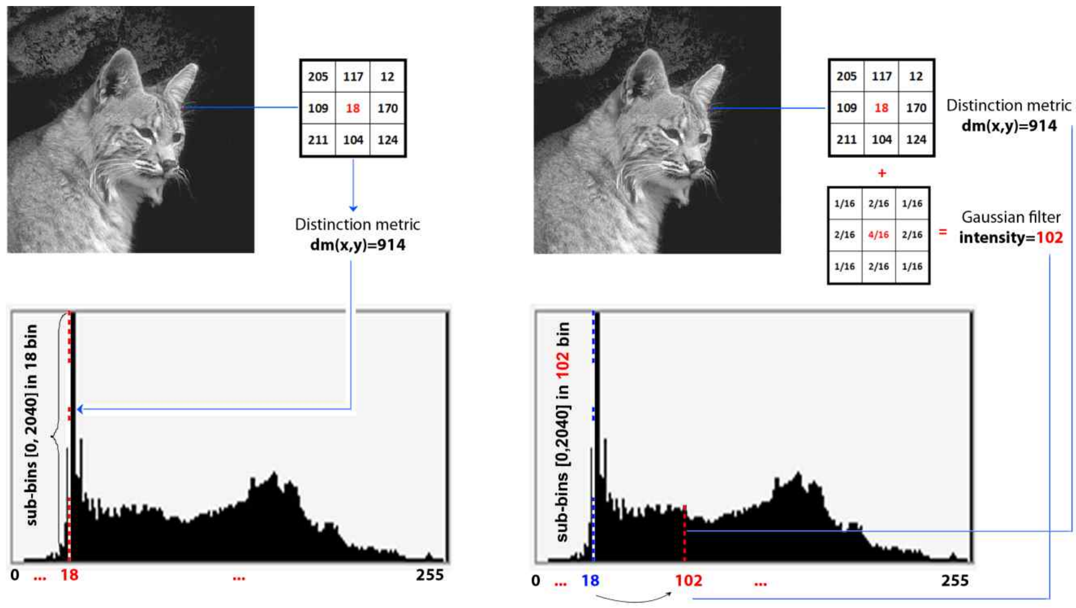
which requires the following distinction function:

$$t(x,y,x',y') = \begin{cases} \gamma(x',y') - \gamma(x,y), & \gamma(x,y) < \gamma(x',y') \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

in which the distinction metric, d_Θ, is defined by $R_\Theta(x,y)$, the set of pixels forming a square in the $\Theta\times\Theta$ square neighborhood centered on (x,y), (x′,y′), is a pixel of R_Θ and Θ is a positive odd integer.

3.2 Histogram arrangement

When making the histogram, every pixel’s neighborhood distinction metrics are computed with the Gaussian filtered values of the current pixel and its neighbors. While the distinction metric defines the current pixels sub-bin location of its histogram bin, the current pixel intensities are changed by the filtered values of its neighbors



(a) (b)

Fig. 2. Illustration of the neighborhood metric and filtering in a histogram bin. Pixels of equal intensity are arranged into sub-bins using neighborhood information (a) without filtering and (b) with filtering.

(Fig. 2). The reason of this rearrangement is that contrast enhancement and filtering processes can use an original image data simultaneously. This intensity rearrangement equals the filter applied directly to the image. However, it differs in that its distinction metrics are computed using the original image data. If we use the filtering process first, the distinction metrics that are computed as the changed neighbors of the filtered image and sub-bins created by the distinction metric do not use the original neighborhood information of the input image. Therefore, the histogram arrangement is performed with simultaneous computation of the neighborhood metric and filtering computations.

Fig. 3 shows the difference between direct filtering and simultaneous filtering with the neighborhood metric. As shown Fig. 3, although filtered (b) and GHE (c) results are small different, but contrast is not enough due to inhomogeneous intensities. However the proposed method solved that problem in Fig. 3 (d) and (e).

3.3 Filtered bi−histogram equalization method (FBHEM)

The number of total sub-bins is R-1, which equals r·L. The mean of the image f is denoted by m_r and $m_r \in [0. R-1]$. Based on m_r, the image is separated into two sub-images f^1 and f^2 as

$$f = f^1 \cup f^2 \tag{24}$$

where

$$f^1 = \{f(x,y) | f(x,y) \le m, \quad \forall f(x,y) \in f\} \tag{25}$$

and

$$f^2 = \{f(x,y) | f(x,y) > m, \quad \forall f(x,y) \in f\} \tag{26}$$

Next, we define the respective probability distribution functions of sub-images f^1 and f^2 as

$$p_1(k) = \frac{n_1(k)}{n_1}, k = 0,1,\ldots,m_r \tag{27}$$

and

$$p_2(k) = \frac{n_2(k)}{n_2}, k = m_r+1, m_r+2, .., R-1 \tag{28}$$

in which $n_1(k)$ and $n_2(k)$ represent the respective values of k in the two sub-images f^1 and f^2, and n_1 and n_2 are the total values of f^1 and f^2, respectively. Here, $n_1 = \sum_{k=0}^{m_r} n_1(k), n_2 = \sum_{k=m_r+1}^{R-1} n_2(k)$, and $n=n_1+n_2$.

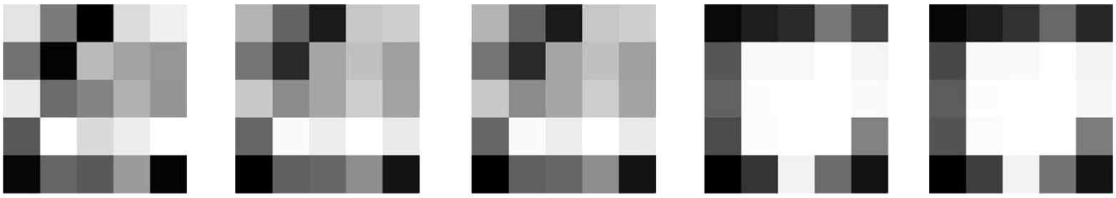
The respective CDFs are then defined as

$$P_1(k) = \sum_{j=0}^{k} p_1(j) \tag{29}$$

and

$$P_2(k) = \sum_{j=m_r+1}^{k} p_2(j) \tag{30}$$

Note that $P_1(m_r)=1$ and $P_2(R-1)=1$ by definition. Let us similarly define the following trans-



(a)

205	117	12	198	215
109	18	170	149	140
211	104	124	163	139
88	235	197	214	235
20	99	89	144	18

(b)

146	95	50	158	163
106	59	137	154	133
159	120	137	162	135
96	191	183	199	180
31	93	97	121	45

(c)

158	57	24	178	210
85	32	142	170	117
190	97	142	198	125
65	243	231	251	223
4	45	77	105	12

(d)

20	40	50	120	70
90	237	238	245	235
100	243	248	252	240
80	242	250	247	130
10	60	233	110	30

(e)

19	39	58	106	48
77	238	239	245	234
96	243	250	252	236
87	241	248	246	125
10	68	233	116	29

Fig. 3. Demonstration of differences using the neighborhood metric and filtering: (a) Original image and its intensities; (b) Gaussian filtered result of (a) and its intensities; (c) GHE result of (b) and its intensities; (d) FBHEM on (a) and its intensities; and (e) FBHEM on (b) and its intensities.

formation functions exploiting the CDFs

$$T_1(k) = m_r \cdot P_1(k), \qquad k = 0,1,\ldots,m_r \tag{31}$$

and

$$T_2(k) = (m_r+1) + ((R-1)-(m_r+1)) \cdot P_{m_2}(k),\ k = m_r+1, m_r+2,..,R-1 \tag{32}$$

Then, the resultant image of the histogram can be expressed as

$$g(x,y) = T_r(f(x,y)), \tag{33}$$

in which f and g are the original and resultant images, respectively, (x,y) are the 2D coordinates of the images, and T is the intensity transformation function, which maps the original image into the entire sub-bin's range, z, using CDF:

$$T \ = T_r \cdot (L/R), \tag{34}$$

where

$$T_r(k) = \begin{cases} T_1(k), & f(x,y) \le m_r, \left(P_1(k) - P_1(k-1)\right) < 2/m_r \\ T_2(k), & f(x,y) > m_r, \left(P_2(k) - P_2(k-1)\right) < 2/(R-m_r) \end{cases} \tag{35}$$

We used a slightly modified GHE method to consider the resultant image histogram "optimally full" [15]. That is, we never overfill a sub-bin by more than half its size.

4. EXPERIMENTAL RESULTS

In the experiment, we tested the proposed method on three images affected by Gaussian noise (3×3, σ=0.5) compared to the GHE, BBHE, DSIHE, and MMBEBHE methods. To define image brightness preservation, we used the absolute mean brightness error (AMBE) and flatness (σ).

$$\mathrm{AMBE} = |E(X) - E(Y)|; \tag{36}$$

where E(X) is the mean value of the test image, while E(Y) is the mean value of the corresponding output image. AMBE is the absolute difference between the input and output means.

To measure the flatness σ of a histogram h, we compute the variance of the bin sizes:

$$\sigma = \frac{\sum_{i=0}^{D-1}(|h_i| - \mu_h)^2}{D} \tag{37}$$

where $|h_i|$ is the size of the i-th bin of the image's histogram, μ_h is the mean histogram bin size, and D is the number of grey-level intensities. A smaller value of σ indicates a flatter histogram.

In experimental figures, the images in the first row were directly enhanced by the various methods and those in the second row were first treated with the Gaussian filter and then enhanced by the various methods. Although the former images were enhanced, noise remained in all result images, whereas those pretreated with the Gaussian filter were better. However, the results were not better than our proposed method. In Fig. 4, local and glob-

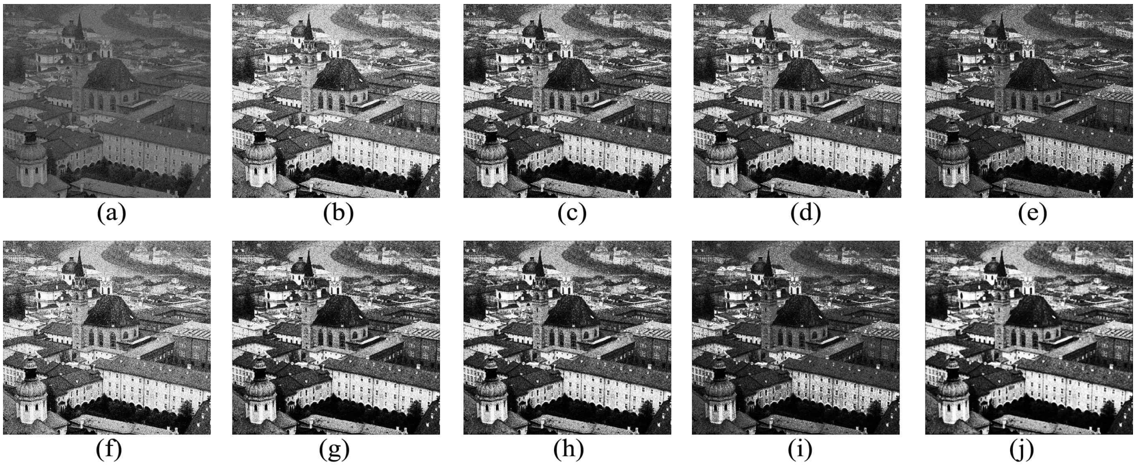


Fig. 4. Results for image I. First row; (a) original sample image I, (b) GHE image, (c) BBHE image, (d) DSIHE image, and (e) MMBEBHE image. Second row; first filtered original image then (f) GHE image, (g) BBHE image, (h) DSIHE image, (i) MMBEBHE image, and (j) proposed FBHEM image.

Table 1. AMBE obtained from three sample images

Method	Image I	Image II	Image III
GHE	45.0160	6.2856	2.5065
BBHE	20.7341	8.8849	15.0237
DSIHE	24.0591	6.3070	5.4366
MMBEBHE	4.3176	8.3722	14.7658
FHENM	22.0941	5.0070	3.1275

al contrast are improved simultaneously while reducing a noise effect. For example, the noise effect on wall of building is reduced more effective than that of various method results.

Table 1 shows the AMBE values for three images enhanced by various methods. The value for the proposed (FBHEM) method was lower than for the others. A smaller AMBE is better, implying that the means of the original and result images are close. This means that the FBHEM method can preserve the image brightness. As shown in Table 1, the AMBE value of FBHEM for image I was larger than those of MMBEBHE and BBHE. However, the FBHEM result looked good on visual comparison. Table 1 also shows the AMBE values of images that were first treated with the Gaussian filter and then equalized.

The proposed method is based on brightness-preserving contrast enhancement techniques and neighborhood metrics to improve local contrast, in addition to improving image quality by the image filtering process while checking neighborhood information. It is expected to not only retain the advantages of previous methods but also to improve image quality. It is possible to perform the filtering technique and then contrast enhancement sequentially. However, our method's important point to note here is that the original image information can be used for both brightness-preserving global and local contrast enhancement, and image quality improvement filtering. For example, if we first perform filtering alone, this would modify the intensities of the original image, and then neighborhood metrics would use these modified intensities of the original image. Thus, the second method uses modified information affected by the first process.

As shown in Fig. 5 and Fig. 6, the proposed method gives good results, not only preserving image brightness but also reducing the effect of noise. Although image contrast is improved on Fig. 5 (b)-(i), the noise effect is still kept in resultant images. However, our proposed method gives more

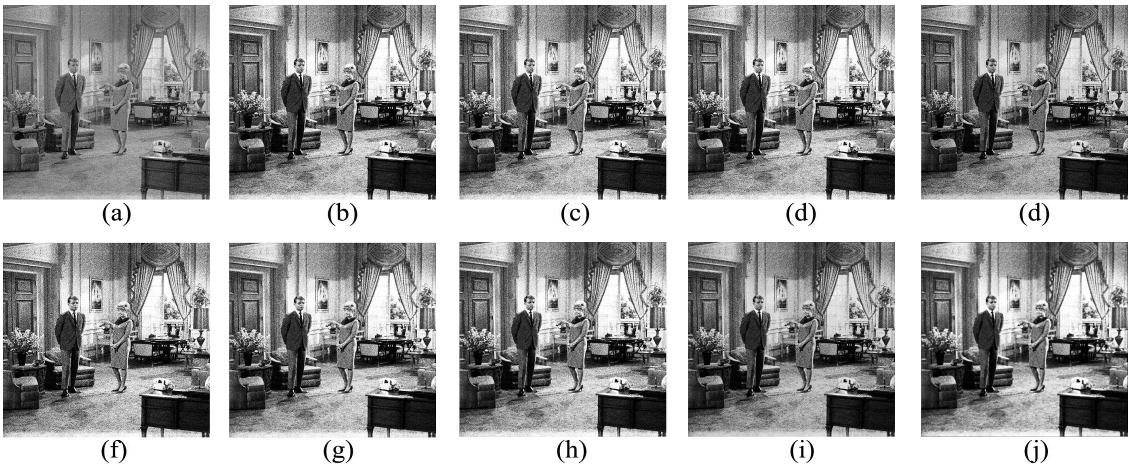


Fig. 5. Results for image II. First row; (a) original sample image II, (b) GHE image, (c) BBHE image, (d) DSIHE image, and (e) MMBEBHE image. Second row; first filtered original image then (f) GHE image, (g) BBHE image, (h) DSIHE image, (i) MMBEBHE image, and (j) proposed FBHEM image.

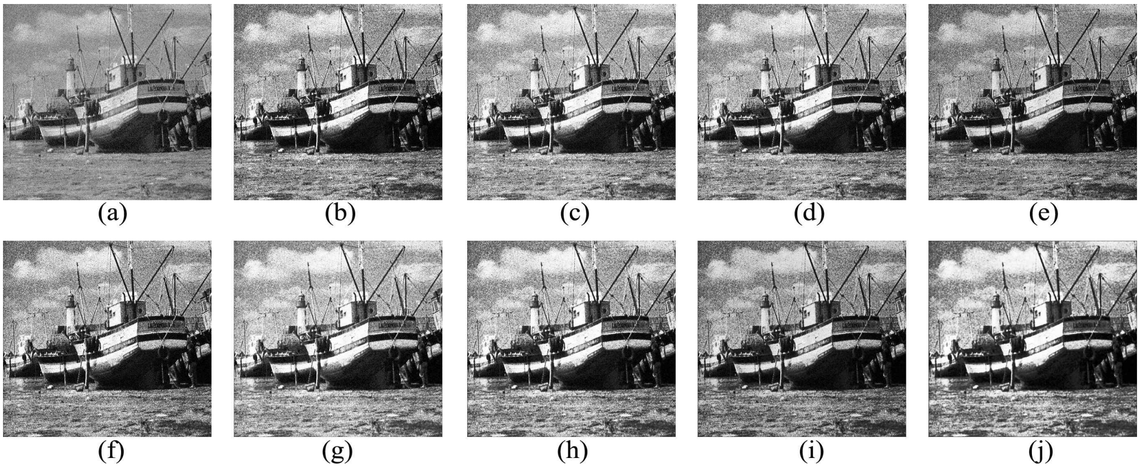


Fig. 6. Results for image III. First row; (a) original sample image III, (b) GHE image, (c) BBHE image, (d) DSIHE image, and (e) MMBEBHE image. Second row; first filtered original image then (f) GHE image, (g) BBHE image, (h) DSIHE image, (i) MMBEBHE image, and (j) proposed FBHEM image.

smoothed result which means that the effect of noise and contrast of image are simultaneously improved on Fig. 5 (j). In Figure 6, the proposed method result proves that its natural appearance is better than others. For instance, a cloud in Fig. 6 looks more natural looking on the proposed method result and the noise is removed effectively comparing to various methods.

In Table 2, the flatness value indicates that histogram equalization produces a perfectly flat histogram, which makes equal use of the entire dynamic range of image intensities and the overall contrast is improved. A smaller value of σ indicates a flatter histogram. In all samples, the flatness values for FBHEM were lower than those of the other methods.

Table 2. Histogram flatness values obtained from three sample images ($\times 10^5$)

Method	Image I	Image II	Image III
GHE	165.53	31.23	47.96
BBHE	126.90	4.17	82.09
DSIHE	165.66	3.18	24.26
MMBEBHE	599.18	126.91	90.44
FHENM	135.32	3.03	9.72

5. CONCLUSION

Our new method of histogram equalization extension, FBHEM, simultaneously improves image contrast and quality while preserving image brightness. The method uses filtering with a neighborhood metric to sort pixels of equal intensity into different sub-bins to improve image local contrast. The histogram is separated into two sub-histograms, which are equalized independently to preserve image brightness. Our experimental results indicated that FBHEM outperforms existing methods.

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