Image Enhancement Based on Bi-Histogram Equalization with Non-parametric Modified Technology

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Abstract—**This paper presents a new image enhancement method using histogram equalization called Bi-Histogram Equalization with Non-parametric Modified Technology (BHENMT). Our proposed method consists of three steps: (i) The input original histogram is divided into two parts using the Otsu method. (ii) Then the histogram modification technique is used to control over enhancement and maximize entropy. (iii) Two sub images are enhanced by the tradtional histogram equalization method using the corresponding modified histogram respectively and finally are merged into one output enhanced image. The experimental results show that BHENMT is better than other contrast enhancement methods according to subjective evaluation and various image objective evaluation measures, i.e. Entropy, AMBE and PSNR.**

Keywords: Histogram modification; Histogram equalization; Image objective evaluation measure;Brightness preserving

I. INTRODUCTION

Image enhancement is always a research hotspot of digital image processing technology. Its goal is to reduce noise and improve image contrast while maintaining the image brightness and local details as much as possible. And image enhancement technology has been extensively utilized in various applications, for example, underwater image quality improvement, medical image processing and analysis, digital photography, remote sensing, scientific visualization, and so on. Image enhancement method can be divided into two categories: transform domain enhancement method and spatial domain enhancement method. Histogram Equalization (HE) is one of spatial domain enhancement method and extensively utilized because of its simplicity, ease of implementation and effectiveness [1]. The main idea of HE is to uniformly redistribute the pixel values of the input image, so as to extend the dynamic intensity range and enhance the image contrast. However, the direct use of HE may result in large difference between the mean brightness of the original image and that of the enhanced one. Moreover, it may lead to over enhancement and produce artifacts and edge effect.

To preserve the image brightness, a lot of HE-based image enhancement approaches have been presented in recent years. These methods divide the input original histogram into two sub histograms and equalize them individually. The representative methods include BBHE [2], DSIHE [3], RMSHE [4], RSIHE [5] , MMBEBHE [6]. BBHE uses the mean intensity value to segment the input original image into two sub images. The segmentation threshold of DSIHE is the media value of the input original image. RMSHE and RSIHE are the extension of BBHE and DSIHE respectively. That is, RMSHE and RSIHE produce 2^m sub images by recursive segmentation more than once according to the mean intensity value and median value respectively. For RMSHE and RSIHE, the parameter m is both set to two. Generally, the results of RMSHE and RSIHE are better than RMSHE and RSIHE respectively due to the recursive property. However, there are two disadvantages of RMSHE and RSIHE. The first disadvantage is very difficult to find the best value of the parameter m. The second is that there is no enhancement effect when the parameter m is too large.The another improved method of BBHE is MMBEBHE, which can “optimally” preserve brightness of the image.The segmentation threshold of MMBEBHE is that would produce the least AMBE [6] value between the input original image and the output enhanced image.

Considerable progresses have also been made on the HE-based image contrast enhancement recently. These methods maximize image contrast under certain constraints. The representative methods include genetic algorithm-based image contrast enhancement [7], Gaussian mixture model-based image contrast enhancement [8], and non-parametric modified histogram equalization [9]. Among them, the last method can well preserve the shape features of original histogram, and apply to enhance images of various types. Meanwhile, it does not require parameter setting and thus has low complexity and easy implementation, which makes it highly practical.

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In this paper, we propose a novel method, namely Bi-Histogram Equalization with Non-parametric Modified Technology (BHENMT), on the basis of the above methods. Firstly, we use Otsu method [10] to segment the input histogram and obtain two sub images correspondingly. Then, we modify the histograms of these two sub-images via the non-parameter histogram modification technique. After that, we equalize the each sub image by the corresponding modified histogram, and finally merge them into a complete image. Our method takes the advantages of the histogram division and non-parameter modified histogram equalization, and can perform well in both contrast enhancement and brightness keeping. Moreover, the local details are well preserved after enhancement, which makes the output images look natural.

II. THE PROPOSED METHOD

This section will describe in detail our proposed BHENMT method. BHENMT includes three steps (see Figure 1): Histogram Segmentation and Image Division, Histogram Modification, Histogram Equalization. The following subsections will describe these three steps.

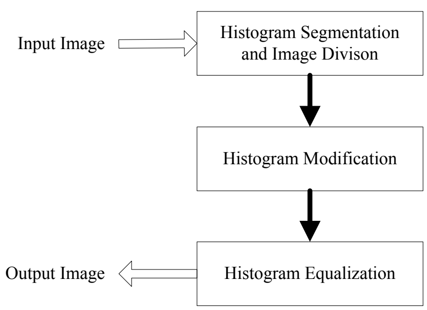


Figure 1. The flow chart of the proposed method BHENMT

A. Histogram Segmentation and Image Divsion

In this step, we use the Otsu method to segment the input original histogram into two sub histograms. From the point of view of pattern recognition, it is the best threshold to separate the object from the background and produce the best performance. Then, the object area and the background area can be enhanced by histogram equalization respectively, which can effectively improve the contrast between the object and the background. Assume that the image contains two calsses of pixels (for example, background and foreground), Otsu method is to find an optimal threshold, which can separate two classes of pixels, and minimizes their intra-class variance. The intra-class variance can be defined as a weighted sum of variances of the two classes:

$$\sigma^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{1}$$

where ω_1 and ω_2 are the weights of two classes, and t is a threshold, which is used to separate two classes of pixels. σ_1^2 and σ_2^2 are the variances of two classes, which are computed by the following equations.

$$\begin{aligned}\sigma_1^2(t) &= \sum_{k=0}^{t}\left(\left(k-\mu_1(t)\right)^2 \frac{\mathbf{h}_i(k)}{\omega_1(t)}\right)\\ \sigma_2^2(t) &= \sum_{k=t+1}^{255}\left(\left(k-\mu_2(t)\right)^2 \frac{\mathbf{h}_i(k)}{\omega_2(t)}\right)\end{aligned} \tag{2}$$

where $\mathbf{h}_i(k)$ is the normalized histogram, μ_1 and μ_2 are the class means. The following equations are the Calculating formula of the class means.

$$\begin{aligned}\mu_1(t) &= \sum_{k=0}^{t}\frac{k\times\mathbf{h}_i(k)}{\omega_1(t)}\\ \mu_2(t) &= \sum_{k=t+1}^{255}\frac{k\times\mathbf{h}_i(k)}{\omega_2(t)}\end{aligned} \tag{3}$$

The weights ω_1 and ω_2 in (1)-(3) are defined as

$$\begin{aligned}\omega_1(t) &= \sum_{k=0}^{t}\mathbf{h}_i(k)\\ \omega_2(t) &= \sum_{k=t+1}^{255}\mathbf{h}_i(k)\end{aligned} \tag{4}$$

The PDF of the input image $\mathbf{h}_i(k)$ in (2)-(4) is computed by:

$$\mathbf{h}_i(k) = \frac{\mathbf{H}(k)}{N} \tag{5}$$

where $\mathbf{H}(k)$ is the total number of pixels whose gray value equals to k, and $N = \sum_{k=1}^{255}\mathbf{H}(k)$.

Otsu method uses exhaustive method to find optimal threshold. Thus the threshold I_t can be defined as

$$I_t = \arg\min_t\left\{\sigma^2(t), t = 0,1,2,...,255\right\} \tag{6}$$

Then, according to the threshold I_t, the image $\mathbf{I}$ is segmented into two sub images $\mathbf{I}_{low}$ and $\mathbf{I}_{up}$, which are given in (7) to (8).

$$\mathbf{I} = \mathbf{I}_{low} \cup \mathbf{I}_{up} \tag{7}$$

where

$$\begin{aligned}\mathbf{I}_{low} &= \left\{\mathbf{I}(i,j)\,\middle|\,\mathbf{I}(i,j) \le I_t, \forall\mathbf{I}(i,j)\in\mathbf{I}\right\}\\ \mathbf{I}_{up} &= \left\{\mathbf{I}(i,j)\,\middle|\,\mathbf{I}(i,j) > I_t, \forall\mathbf{I}(i,j)\in\mathbf{I}\right\}\end{aligned} \tag{8}$$

Please note that $\mathbf{I}_{low}$ is made up of $\{I_0, I_1, ..., I_t\}$, and $\mathbf{I}_{up}$ is made up of $\{I_{t+1}, I_{t+2}, ..., I_{255}\}$.

B. Histogram Modification

The traditional HE often yields over enhanced image Because HE technique tries to create a uniform distribution histogram. For overcome this disadvantage, we can modify the input original histogram. Then, we use the modified histogram to create the mapping function of HE. Here, the modification process can be viewed as a double standard problem optimization process. The objective is to look for a modified histogram that approaches the uniform distribution histogram ($\mathbf{u}$) as required, and makes the remainder $\mathbf{h}_i$ - $\mathbf{u}$ little [11]. A solution to this optimization can be written as

$$\tilde{\mathbf{h}} = (1-w)\cdot\mathbf{h}_i + w\cdot\mathbf{u} \tag{9}$$

where $\tilde{\mathbf{h}}$ is the modified histogram, w is a weighting factor whose range is 0 to 1.

For computing $\mathbf{h}_i$, Arici et al. [11] proposed a simple and intuitive method that only adopts those pixels which have dissimilarity with their neighbors. Specifically, the modified histogram is gained by using only those pixels that have a two-lagged horizontal diversity larger than a threshold value given in (10):

$$\mathbf{h}_i^{'}(k) = p\left[k|C\right] \tag{10}$$

where $p\left[k|C\right]$ is the probability of occurrence of the given event C, and C represents a horizontal contrast strength. Like [9], C is set to six empirically in our experiments. According to the threshold I_t, we can segment the modified histogram into two sub histograms. And then two sub modified histogram are normalized to keep the value in between 0 and 1, and denoted as $\mathbf{h}_{i,low}^{'}(k)$ and $\mathbf{h}_{i,up}^{'}(k)$.

The next task is to compute the weight factor w in (9), which is used to balance $\mathbf{h}_i$ and $\mathbf{u}$. Because there are two sub images $\mathbf{I}_{low}$ and $\mathbf{I}_{up}$, we have to compute two weighting factors w_{low} and w_{up} respectively. Firstly, according to the threshold I_t, we obtain two uniform PDFs $\mathbf{u}_{low}$ and $\mathbf{u}_{up}$ as given in (11).

$$\begin{aligned} \mathbf{u}_{low} &= \text{ones}\left(I_t+1,1\right)/\left(I_t+1\right) \\ \mathbf{u}_{up} &= \text{ones}\left(255-I_t,1\right)/\left(255-I_t\right) \end{aligned} \tag{11}$$

Two sub-histograms are obtained from $\mathbf{h}_i$ by the following two equations respectively

$$\begin{aligned} \mathbf{h}_{i,low}(k) &= \lambda_{low}\mathbf{h}_i(k), k=0,1,...,I_t \\ \mathbf{h}_{i,up}(k) &= \lambda_{up}\mathbf{h}_i(k), k=I_t+1,...,255 \end{aligned} \tag{12}$$

where $\lambda_{low} = 1\Big/\sum_{k=0}^{I_m}\mathbf{h}_i(k)$ and $\lambda_{up} = 1\Big/\sum_{k=I_m+1}^{L-1}\mathbf{h}_i(k)$.

Then two sub-histograms are given as

$$\begin{aligned} \mathbf{h}_{low}^{c} &= \min\left(\mathbf{h}_{i,low}(k), \mathbf{u}_{low}(k)\right), k=0,1,...,I_t \\ \mathbf{h}_{up}^{c} &= \min\left(\mathbf{h}_{i,up}(k), \mathbf{u}_{up}(k)\right), k=I_t+1,...,255 \end{aligned} \tag{13}$$

Two weighting factors w_{low} and w_{up} are now calculated by the following two equations respectively

$$\begin{aligned} w_{low} &= sum\left(\mathbf{u}_{low} - \mathbf{h}_{low}^{c}\right) \\ w_{up} &= sum\left(\mathbf{u}_{up} - \mathbf{h}_{up}^{c}\right) \end{aligned} \tag{14}$$

The respective PDF of two sub-images $\mathbf{I}_{low}$ and $\mathbf{I}_{up}$ are computed by

$$\begin{aligned} \mathbf{h}_{low}^{m}(k) &= \left(1-w_{low}\right)\mathbf{h}_i^{'}(k) + w_{low}\mathbf{u}_{low}(k), k=0,1,...,I_t \\ \mathbf{h}_{up}^{m}(k) &= \left(1-w_{up}\right)\mathbf{h}_i^{'}(k) + w_{up}\mathbf{u}_{up}(k), k=I_t+1,...,255 \end{aligned} \tag{15}$$

C. Histogram Equalization

The respective CDF two sub-images $\mathbf{I}_{low}$ and $\mathbf{I}_{up}$ are defined as

$$\begin{aligned} C_{low}(k) &= \sum_{q=0}^{k}\mathbf{h}_{low}^{m}(q), k=0,1,...,I_t \\ C_{up}(k) &= \sum_{q=I_t+1}^{k}\mathbf{h}_{up}^{m}(q), k=I_t+1,...,255 \end{aligned} \tag{16}$$

The transformation functions for histogram equalization based on (16) can be defined as

$$\begin{aligned} f_{low}(k) &= I_t \cdot C_{low}(k), k=0,1,...,I_t \\ f_{up}(k) &= I_t+1+\left(254-I_t\right)\cdot C_{up}(k), k=I_t+1,...,255 \end{aligned} \tag{17}$$

Then, these two transformation functions are used to equalize the divided sub-images independently. In the end, the enhanced image of BHENMT, $\mathbf{E}$, is described by (18) - (19)

$$\mathbf{E} = \mathbf{E}_{low} \cup \mathbf{E}_{up} \tag{18}$$

where

$$\begin{aligned} \mathbf{E}_{low} &= f_{low}\left(\mathbf{I}_{low}\right) = \left\{f_{low}\left(\mathbf{I}(i,j)\right) \middle| \forall \mathbf{I}(i,j) \in \mathbf{I}_{low}\right\} \\ \mathbf{E}_{up} &= f_{up}\left(\mathbf{I}_{up}\right) = \left\{f_{up}\left(\mathbf{I}(i,j)\right) \middle| \forall \mathbf{I}(i,j) \in \mathbf{I}_{up}\right\} \end{aligned} \tag{19}$$

III. EXPERIMENTAL RESULTS

This section will give the experimental comparison between our BHENMT method and other image enhancement methods, such as BBHE, NMHE, DSIHE, RSIHE and RMSHE. For RMSHE and RSIHE, the recursion level is set to two. In our experiments, four test images: *Field*, *Tank*, *U2*, *Landscape*, are used. In order to test the performance of BHENMT, we use three image objective evaluation measures, i.e. Entropy, AMBE, PSNR.

A. Quantitative Comparison

Tables I-III show the matrices of all three objective evaluation measures for four sample images, where the columns represent the test images and the rows represent various image enhancement methods. The values indicated in bold type are the best values for each comparison. The matrix shown in Table I is the AMBE values of all the images for all methods. BHENMT is better than all other methods because BHENMT has the least average AMBE value. Further, the average of the proposed method is 4.015, which is markedly smaller than the values of the other methods. Table II shows PSNR for all images using various methods. BHENMT provides best results because it has least PSNR value for all test images, which indicates that the proposed method hardly amplifies the noise during the process of image enhancement. The results for the entropy measure are shown in Table III. BHENMT produces the highest entropy value for four test images, which indicates that the proposed method is very suitable to bring out average information content of the image. Moreover, the mean of entropy values obtained by BHENMT is 5.952 that is almost equal to the mean (6.000) of entropy values for all original images.

TABLE I. AMBE MEASURE OBTAINED FROM FOUR SAMPLE IMAGES

	Field	Tank	U2	Landscape	Average
HE	21.040	4.812	94.998	3.471	31.080
BBHE	14.705	21.252	14.759	11.281	15.499
DSIHE	13.638	5.343	41.699	6.879	16.890
RMSHE	8.282	13.520	**4.319**	9.503	8.906
RSIHE	7.506	6.728	17.313	**2.253**	8.450
NMHE	17.441	30.506	42.489	28.166	29.651
BHENMT	**0.159**	**4.799**	5.011	6.091	**4.015**

TABLE II. PSNR MEASURE OBTAINED FROM FOUR SAMPLE IMAGES

	Field	Tank	U2	Landscape	Average
HE	14.913	13.778	7.157	14.303	12.538
BBHE	15.328	13.893	15.633	14.432	14.821
DSIHE	15.410	13.758	10.942	14.308	13.604
RMSHE	19.915	17.336	22.407	17.396	19.263
RSIHE	19.358	17.432	15.680	18.111	17.645
NMHE	18.447	17.155	13.938	17.334	16.718
BHENMT	**23.248**	**25.748**	**26.961**	**21.178**	**24.284**

TABLE III. ENTROPY MEASURE OBTAINED FROM FOUR SAMPLE IMAGES

	Field	Tank	U2	Landscape	Average
Original	6.563	5.496	5.641	6.299	6.000
HE	5.956	4.966	5.044	5.463	5.357
BBHE	6.465	5.430	5.545	6.227	5.917
DSIHE	6.470	5.395	5.503	6.215	5.896
RMSHE	6.497	5.471	5.455	6.126	5.887
RSIHE	**6.516**	5.453	5.427	6.159	5.889
NMHE	6.345	5.258	5.332	5.924	5.715
BHENMT	6.472	**5.485**	**5.576**	**6.276**	**5.952**

B. *Qualitative Comparison*

The analysis of subjective evaluation from Figure 2-5 shows the superiority of BPNMBHE over the other image enhancement methods in all test images according to contrast enhancement, enhancement rate control and natural appearance. From Figure 2 of *Field* image, we can see that the results of the HE, BBHE and DSIHE methods are over enhanced. Although the result of BHENMT is visually comparable to RMSHE, RSIHE and NMHE, BHENMT is the best in terms of image objective evaluation measure. Figure 3 gives the original image of *Tank* image and the enhanced images for all methods. From Figure 3(a), the contrast of the original image is low. The outputs of NMHE, DSIHE, HE and BBHE cannot produce a clear visual effect of the concerned target. However, BPNMBHE produces a contrast enhanced image, and the output of the proposed method has natural appearance. The results in Figure 4 of *U*2 image clearly show the supremacy of BHENMT. Especially, the noise of the enhanced images of HE, DSIHE and NMHE is severely amplified. In contrast, the enhanced image of the proposed method provides good contrast enhancement and the noise is suppressed. Figure 5 shows the enhanced images of *Landscape* image for all methods. It can be observed that HE, BBHE, DSIHE, RMSHE and RSIHE produce a very bad enhanced image. The mountain covered with ice and the load became too bright, and the tree becomes too dark as shown in Figure 5(b)-(f). However, images enhanced by NMHE and BHENMT show noticeable improvement and have a better natural appearance. Further, BHENMT produces the highest PSNR and entropy values.

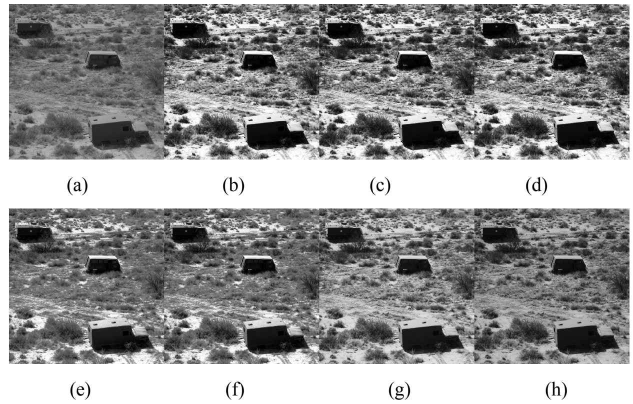


Figure 2. Enhancement results of *Field* image: (a) Original, (b) HE, (c) BBHE, (d) DSIHE, (e) RMSHE, (f) RSIHE, (g) NMHE, (h) BHENMT

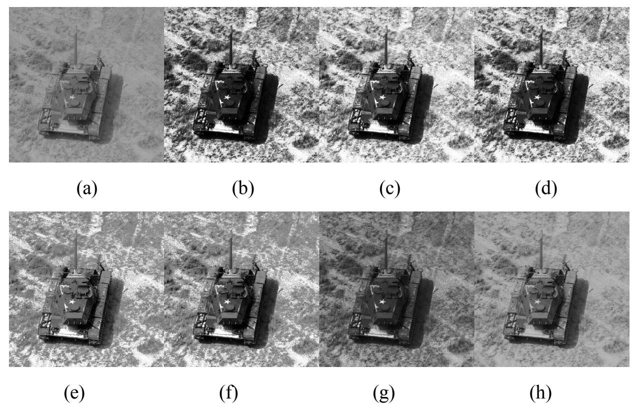


Figure 3. Enhancement results of *Tank* image: (a) Original, (b) HE, (c) BBHE, (d) DSIHE, (e) RMSHE, (f) RSIHE, (g) NMHE, (h) BHENMT

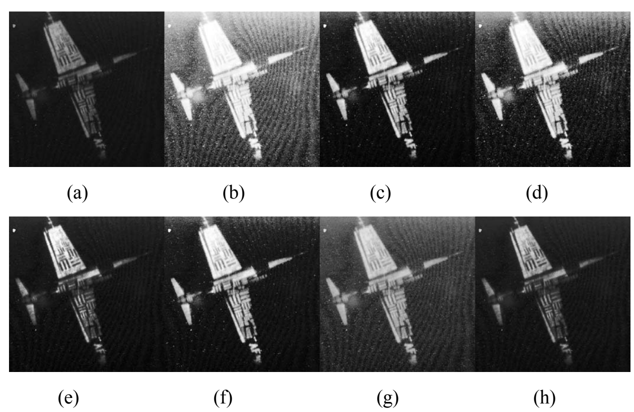
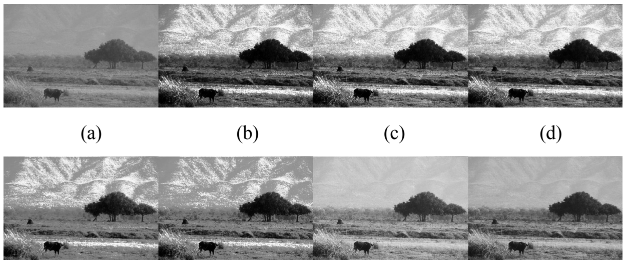


Figure 4. Enhancement results of *U2* image: (a) Original, (b) HE, (c) BBHE, (d) DSIHE, (e) RMSHE, (f) RSIHE, (g) NMHE, (h) BHENMT



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

(e) (f) (g) (h)

Figure 5. Enhancement results of *Landscape* image: (a) Original, (b) HE, (c) BBHE, (d) DSIHE, (e) RMSHE, (f) RSIHE, (g) NMHE, (h) BHENMT

C. *Summary of evaluation*

According to quantitative and qualitative comparison result, we can get the following conclusions: (i) BHENMT is better than other image enhancement methods for brightness preservation. (ii) BHENMT is the best method among other image enhancement methods in terms of three image objective evaluation measures. (iii) BHENMT yields enhanced images that have natural appearance and a good contrast enhancement. This paper has three objectives: (i) to maximize entropy, (ii) to preserve original brightness, (iii) to control the over enhancement. In order to compete these objectives, two techniques are used. The first technique is segmentation. Specifically, we use Otsu method to divide the input image into two sub images, which is conducive to preserve brightness. The second technique is histogram modificaton approach, which is conducive to maximize entropy and controll enhancement rate.

IV. CONCLUSIONS

The paper presents a novel image enhancement method called BHENMT. In our method, the histogram modificaton approach is used to control over enhancement and maximize entropy in the histogram equalization process. Experimental results obviously show that BHENMT outperforms other contrast enhancement methods based on four image objective evaluation measures. Subjective evaluation results also demonstrate the superiority of BHENMT over other image enhancement methods according to natural appearance.

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