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Minimum Mean Brightness Error Bi-Histogram Equalization in Contrast Enhancement

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Abstract — *Histogram equalization (HE) is widely used for contrast enhancement. However, it tends to change the brightness of an image and hence, not suitable for consumer electronic products, where preserving the original brightness is essential to avoid annoying artifacts. Bi-histogram equalization (BBHE) has been proposed and analyzed mathematically that it can preserve the original brightness to a certain extends. However, there are still cases that are not handled well by BBHE, as they require higher degree of preservation. This paper proposes a novel extension of BBHE referred to as Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) to provide maximum brightness preservation. BBHE separates the input image's histogram into two based on input mean before equalizing them independently. This paper proposes to perform the separation based on the threshold level, which would yield minimum Absolute Mean Brightness Error (AMBE - the absolute difference between input and output mean). An efficient recursive integer-based computation for AMBE has been formulated to facilitate real time implementation. Simulation results using sample image which represent images with very low, very high and medium mean brightness show that the cases which are not handled well by HE, BBHE and Dualistic Sub Image Histogram Equalization (DSIHE), can be properly enhanced by MMBEBHE. Besides, MMBEBHE also demonstrate comparable performance with BBHE and DSIHE when come to use the sample images shown in [2] and [3]*[1].

Index Terms — Bi-histogram equalization, dualistic sub-image, histogram equalization, minimum mean brightness error.

I. INTRODUCTION

Histogram equalization (HE) is a very popular technique for enhancing the contrast of an image [1]. Its basic idea lies on mapping the gray levels based on the probability distribution of the input gray levels. It flattens and stretches the dynamics range of the image's histogram and resulting in overall contrast improvement. HE has been applied in various fields such as medical image processing and radar image processing [2].

Nevertheless, HE is not commonly used in consumer electronics such as TV because it may significantly change the brightness of an input image and cause undesirable artifacts. In theory, it can be shown that the mean brightness of the histogram-equalized image is always the middle gray level regardless of the input mean. This is not a desirable property in some applications where brightness preservation is necessary.

Mean preserving Bi-histogram equalization (BBHE) has been proposed then, to overcome the aforementioned problems. BBHE firstly separate the input image's histogram into two based on its mean; one having range from minimum gray level to mean and the other ranges from mean to the maximum gray level. Next, it equalizes the two histograms independently. It has been analyzed both mathematically and experimentally that this technique is capable to preserve the original brightness to a certain extends [2]. Later, Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE) has been proposed and claimed to outperform BBHE both in term of brightness and also image content (entropy) preservation. Both BBHE and DSIHE is similar except that DSIHE choose to separate the histogram based on gray level with cumulative probability density equal to 0.5 instead of the mean as in BBHE. The theory behind is that this would yield maximum entropy for the output image [3].

Nevertheless, there are still cases that are not handled well by both the BBHE and DSIHE. These images require higher degree of brightness preservation to avoid annoying artifacts. This paper proposes to separate the histogram using the threshold level that would yield minimum Absolute Mean Brightness Error (AMBE – the absolute difference between input and output mean). An efficient recursive, integer-based computation of AMBE has been formulated to facilitate real time implementation. Simulation results using sample image which represent images with very low, very high and medium mean brightness show that the cases which are not handled well by HE, BBHE and Dualistic Sub Image Histogram Equalization (DSIHE), can be properly enhanced by MMBEBHE. Besides, MMBEBHE also demostrate comparable performance with BBHE and DSIHE when come to use the sample images shown in [2] and [3].

In what follows, HE and BBHE for digital input image is reviewed together with their mathematical formulation in Section 2. The extension of BBHE, namely – Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) will be presented in section 3 together with the formulation of the recursive integer-based computation of AMBE. Section 4 lists a few experimental results to illustrate the performance of MMEBHE. Section 5 serves as the conclusion of this paper.

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II. Histogram Equalization

This section covers the details regarding HE and BBHE as well as their mathematical analysis in brightness preservation. It is basically a reprint of [2] and [4]

A. Typical Histogram Equalization

For a given image **X**, the probability density function $p(X_k)$ is defined as

$$p(X_k) = \frac{n^k}{n} \tag{1}$$

For $k = 0, 1, \ldots, L-1$, where n^k represents the number of times that the level X_k appears in the input image **X** and n is the total number of samples in the input image. Note that $p(X_k)$ is associated with the histogram of the input image which represents the number of pixels that have a specific intensity X_k. In fact, a plot of n^k vs. X_k is known histogram of **X**. Based on the probability density function, the cumulative density function is defined as

$$c(x) = \sum_{j=0}^{k} p(X_j) \tag{2}$$

where $X_k = x$, for $k = 0, 1, \ldots, L-1$. Note that $c(X_{L-1}) = 1$ by definition. HE is a scheme that maps the input image into the entire dynamic range, (X_0, X_{L-1}), by using the cumulative density function as a transform function. Let's define a transform function $f(x)$ based on the cumulative density function as

$$f(x) = X_0 + (X_{L-1} - X_0)c(x) \tag{3}$$

Then the output image of the HE, $\mathbf{Y} = \{Y(i, j)\}$, can be expressed as

$$\mathbf{Y} = f(\mathbf{X}) \tag{4}$$
$$= \{f(X(i,j)) \mid \forall X(i,j) \in \mathbf{X}\} \tag{5}$$

The high performance of the HE in enhancing the contrast of an image as a consequence of the dynamic range expansion, Besides, HE also flattens a histogram. Base on information theory, entropy of message source will get the maximum value when the message has uniform distribution property [3].

As addressed previously, HE can introduce a significant change in brightness of an image, which hesitates the direct application of HE scheme in consumer electronics. For instance, Fig. 1 and Fig. 2 shows original image *arctic hare* and the resultant image of the HE that are composed of 256 gray levels. Observe that here the equalized image is much darker than the input image. Observe also the unnatural enhancement in most part of the image. This is a direct consequence of the excessive change in brightness by HE when image has a high density over high gray levels. Note that the HE maps its input gray to a gray level, which is proportional to cumulative density up to the input gray level regardless of the input gray level. Fig. 3 is a given original image *U2* and the fig. 4 is the result of HE. Observe that image becomes much brighter. There are annoying artifacts in the background and the contrast of the plane's body has also decreased. The fundamental reason behind such limitation of the HE is that HE does not take the mean brightness of an image into account.

Fig. 1. Original image of *arctic hare*

Fig. 2. Result of HE of image *arctic hare*

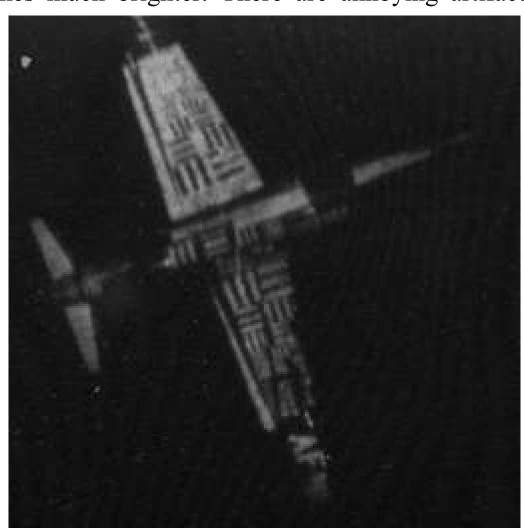

Fig. 3. Original image of *U2*

Fig. 4. Result of HE of image *U2*

B. Brightness Preserving Bi-Histogram Equalization

Denote by X_m the mean of the image $\mathbf{X}$ and assume that $X_m \in \{X_0, X_1, \ldots, X_{L-1}\}$. Based on the mean, the input image is decomposed into two sub-images $\mathbf{X}_L$ and $\mathbf{X}_U$ as

$$\mathbf{X} = \mathbf{X}_L \cup \mathbf{X}_U \tag{6}$$

where

$$\mathbf{X}_L = \{X(i, j) | X(i, j) \le X_m, \forall X(i, j) \in \mathbf{X}\} \tag{7}$$

and

$$\mathbf{X}_U = \{X(i, j) | X(i, j) > X_m, \forall X(i, j) \in \mathbf{X}\} \tag{8}$$

Note that the sub-image $\mathbf{X}_L$ is composed of $\{X_0, X_1, \ldots, X_m\}$ and the other image $\mathbf{X}_U$ is composed of $\{X_{m+1}, X_{m+2}, \ldots, X_{L-1}\}$.

Next, define the respective probability density functions of the sub-images $\mathbf{X}_L$ and $\mathbf{X}_U$ as

$$p_L(X_k) = \frac{n_L^k}{n_L} \tag{9}$$

where $k = 0, 1, \ldots, m$, and

$$p_U(X_k) = \frac{n_U^k}{n_U} \tag{10}$$

where $k = m+1, m+2, \ldots, L-1$, in which n_L^k and n_U^k represent the respective numbers of X_k in $\mathbf{X}_L$ and $\mathbf{X}_U$, and n_L and n_U are the total number of samples in $\mathbf{X}_L$ and $\mathbf{X}_U$, respectively. Note that $n_L = \sum_{k=0}^{m} n_L^k$, $n_U = \sum_{k=m+1}^{L-1} n_U^k$ and $n = n_L + n_U$. The respective cumulative density functions for $\mathbf{X}_L$ and $\mathbf{X}_U$ are then defined as

$$c_L(x) = \sum_{j=0}^{k} p_L(X_j) \tag{11}$$

and

$$c_U(x) = \sum_{j=m+1}^{k} p_U(X_j) \tag{12}$$

where $X_k = x$. Note that $c_L(X_m) = 1$ and $c_U(X_{L-1}) = 1$ by definition.

Similar to the case of HE where a cumulative density function is used as a transform function, let's define the following transform functions exploiting the cumulative density functions

$$f_L(x) = X_0 + (X_m - X_0)\, c_L(x) \tag{13}$$

and

$$f_U(x) = X_{m+1} + (X_{L+1} - X_{m+1})\, c_U(x) \tag{14}$$

Based on these transform functions, the decomposed sub-images are equalized independently and the composition of the resulting equalized sub-images constitute the output of BBHE. That is, the output image of BBHE, $\mathbf{Y}$, is finally expressed as

$$\mathbf{Y} = \{Y(i, j)\} \tag{15}$$

$$= f_L(\mathbf{X}_L) \cup f_U(\mathbf{X}_U), \tag{16}$$

where

$$f_L(\mathbf{X}_L) = \{ f_L(X(i, j)) | \forall X(i, j) \in \mathbf{X}_L \} \tag{17}$$

and

$$f_U(\mathbf{X}_U) = \{ f_U(X(i, j)) | \forall X(i, j) \in \mathbf{X}_U \} \tag{18}$$

If one note that $0 \le c_L(x), c_U(x) \le 1$, it is easy to see that $f_L(\mathbf{X}_L)$ equalizes the sub-image $\mathbf{X}_L$ over the range (X_0, X_m) whereas $f_U(\mathbf{X}_U)$equalizes the sub-image $\mathbf{X}_U$ over the range (X_{m+1}, X_{L-1}). As a consequence, the input image $\mathbf{X}$ is equalized over the entire dynamic range (X_0, X_{L-1}) with the constraint that the sample less than the input mean are mapped to (X_0, X_m) and the samples greater than the mean are mapped to (X_{m+1}, X_{L-1}).

C. Analysis On The Brightness Change By the BBHE [2]

Suppose that $\mathbf{X}$ is a continuous random variable, i.e., $L = \infty$, then the output of the HE, $\mathbf{Y}$ is also regarded as a random variable. It is well known that the HE produces an image, whose gray levels have a uniform density, i.e.,

$$p(x) = 1 / (X_{L-1} + X_0) \tag{19}$$

for $X_0 \le x \le X_{L-1}$. Thus, it is easy to show that the mean brightness of the output image of the HE is the middle gray level since

$$E(Y) = \sum_{X_0}^{X_{L-1}} xp(x)dx \tag{20}$$

$$= \sum_{X_0}^{X_{L-1}} \frac{x}{X_{L-1} - X_0} dx \tag{21}$$

$$= \frac{X_{L-1} + X_0}{2} \tag{22}$$

where $E(.)$ denotes a statistical expectation. It should be emphasized here that the output mean of the HE has nothing to do with the input image. That is, it is always the middle gray level no matter how much the input image is bright/dark. Clearly, this property is not desirable in many applications.

Turning the attention to the man change by the BBHE, suppose that $\mathbf{X}$ is a random variable, which has symmetric distribution around its mean, X_m. When the sub-images are equalized independently, the mean brightness of the output of the BBHE can be expressed as

$$\begin{aligned} E(\mathbf{Y}) &= E(\mathbf{Y} \mid \mathbf{X} \le X_m) Pr(\mathbf{X} \le X_m) \\ &+ E(\mathbf{Y} \mid \mathbf{X} > X_m) Pr(\mathbf{X} > X_m) \\ &= ½ \{E(\mathbf{Y} \mid \mathbf{X} \le X_m) + E(\mathbf{Y} \mid \mathbf{X} > X_m)\} \end{aligned} \tag{23}$$

where $Pr(\mathbf{X} \le X_m) = Pr(\mathbf{X} > X_m) = ½$ is used since $\mathbf{X}$ is assumed to have a symmetric distribution around X_m. With similar discussion used to obtain (22), it can easily shown that

$$E(\mathbf{Y} \mid X \le X_m) = (X_0 + X_m) / 2 \tag{24}$$

and

$$E(\mathbf{Y} \mid X > X_m) = (X_m + X_{L-1}) / 2 \tag{25}$$

The use of (24) and (25) in (23) results in

$$E(\mathbf{Y}) = (X_m + X_G) / 2 \tag{26}$$

where

$$X_G = (X_0 + X_{L-1}) / 2 \tag{27}$$

is the middle gray level, which implies that the mean brightness of the equalized image by BBHE locates in the middle of the input mean and the middle gray level. Note that the output mean of the BBHE is a function of the input mean brightness X_m. This fact clearly indicates that the BBHE preserves the brightness compared to the case of typical HE where output mean is always the middle gray level.

However, using input mean as the threshold level to separate the histogram does not guarantee maximum brightness preservation. The brightness preservation described here is based on an objective measurement referred as Absolute Mean Brightness Error (AMBE). It is defined as the absolute difference between the input and the output mean as follow:

$$AMBE = | E(\mathbf{X}) - E(\mathbf{Y}) | \tag{28}$$

Lower AMBE implies better brightness preservation. BBHE that set the threshold level, X_T as input mean does not guarantee minimum AMBE. This fact is clearly shown in table 1 which contains the AMBE for images *U2*, *Arctic hare, Copter, F16 and Hand* after being enhanced by HE, BBHE, DSIHE and MMBEBHE respectively. Notice that the BBHE that use the input mean as the threshold level do not yield minimum AMBE. Image *F16* has been used in [2] to demonstrate the success of BBHE. Notice that in this particular case, the threshold used by BBHE and MMBEBHE is very close to each other. The AMBE for both BBHE and MMBEBHE are also close to zero. In other words, the threshold level should be chosen base on the resulting AMBE and not fixed to the input mean.

III. Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)

Based on the above discussion, MMBEBHE is formally defined by the following procedures:

1. Calculate the AMBE for each of the threshold level.
2. Find the threshold level, X_T that yield minimum MBE,
3. Separate the input histogram into two based on the X_T found in step 2 and equalized them independently as in BBHE

Step 2 and 3 are straightforward process. Step 1 would require considerable amount of computation if one full BBHE process is required to calculate the AMBE for each of the possible threshold level, especially when the number of gray level is large. This could become a major drawback of MMBEBHE in real time implementation.

Fortunately, the value of AMBE could be closely approximated because the output mean, E(Y) could be approximated based on (23). Let's denote E_T(Y) as the output mean of BBHE with threshold level set as X_T. Since X_T is not limited to the input mean, X_m only, $\mathbf{X}$ cannot be assumed to have symmetry distribution around X_T as in (23). Then it follows that:

$$\begin{aligned} E_T(Y) &= \left(\frac{X_0 + X_T}{2}\right)\left(\sum_{i=0}^{T} P(X_i)\right) + \left(\frac{X_{T+1} + X_{L-1}}{2}\right)\left(\sum_{i=T+1}^{L-1} P(X_i)\right) \\ &= \frac{1}{2}\left[(X_0 + X_T)\left(\sum_{i=0}^{T} P(X_i)\right) + (X_T + 1 + X_{L-1})\left(1 - \sum_{i=0}^{T} P(X_i)\right)\right] \end{aligned} \tag{29}$$

Assuming that $X_0 = 0$ (this assumption will be corrected automatically in the later part of the calculation), then $1 + X_{L-1} = L$ and it follows that:

$$E_T(Y) = \frac{1}{2}\left[X_T\left(\sum_{i=0}^{T}P(X_i)\right) + (X_T + L)\left(1 - \sum_{i=0}^{T}P(X_i)\right)\right] \quad (30)$$
$$= \frac{1}{2}\left[X_T + L\left(1 - \sum_{i=0}^{T}P(X_i)\right)\right]$$

Then, the output mean with threshold level set as $X_T + 1$:

$$\begin{aligned} E_{T+1}(Y) &= \frac{1}{2}\left[X_T + 1 + L\left(1 - \sum_{i=0}^{T+1}P(X_i)\right)\right] \\ &= \frac{1}{2}\left[X_T + 1 + L\left(1 - \sum_{i=0}^{T}P(X_i) - P(X_{T+1})\right)\right] \\ &= \frac{1}{2}\left[X_T + L\left(1 - \sum_{i=0}^{T}P(X_i)\right)\right] + \frac{1}{2}\left[1 - LP(X_{T+1})\right] \\ &= E_T(Y) + \frac{1}{2}\left[1 - LP(X_{T+1})\right] \end{aligned} \quad (31)$$

From (31), it is clear that the output mean has a recursive solution that requires less operations and memory. The calculation is started with the simplest solution where $X_T = X_0 = 0$. Then, it follows that:

$$\begin{aligned} E_0(Y) &= \frac{1}{2}\left[L(1 - P(X_0))\right] \\ E_1(Y) &= E_0(Y) + \frac{1}{2}\left[1 - LP(X_1)\right] \\ &\ldots \\ E_T(Y) &= E_{T-1}(Y) + \frac{1}{2}\left[1 - LP(X_T)\right] \end{aligned} \quad (32)$$

In order to calculate Mean Brightness Error (MBE), one need to calculate the input mean $E(\mathbf{X})$ with similar assumption that $X_0 = 0$, as in the calculation of output mean $E(\mathbf{Y})$ shown earlier. It follows that:

$$E(X) = \sum_{i=0}^{L-1} iP(X_i) \quad (33)$$

Note that when the assumption that $X_0 = 0$ does not hold, the only correction required is to add the actual X_0 to both $E(\mathbf{X})$ and $E(\mathbf{Y})$. Then it follows that these two terms shall cancel off each other in the calculation of MBE as shown below:

$$MBE = (E(Y) + X_0) - (E(X) + X_0) = E(Y) - E(X) \quad (34)$$

Hence, MBE for each threshold level can be expressed as follows:

$$\begin{aligned} MBE_0 &= E_0(Y) - E(X) = \frac{1}{2}\left[L(1 - P(X_0))\right] - E(X) \\ MBE_1 &= E_1(Y) - E(X) \\ &= E_0(Y) + \frac{1}{2}\left[1 - LP(X_1)\right] - E(X) \\ &= MBE_0 + \frac{1}{2}\left[1 - LP(X_1)\right] \\ &\ldots \\ MBE_T &= MBE_{T-1} + \frac{1}{2}\left[1 - LP(X_T)\right] \end{aligned} \quad (35)$$

Observe that the above calculation of MBE involves $P(X)$ which are floating point numbers. Since the application requires only finding the threshold level with minimum AMBE, the scaled MBE would be sufficient. Scaled MBE involves only integer numbers. Let's denote $F(X_i)$ as the number of pixel for gray level X_i and N as the total number of pixel. Then it follows that:

$$\begin{aligned} MBE_0 &= \frac{1}{2}\left[L\left(1 - \frac{F(X_0)}{N}\right)\right] - \sum_{i=0}^{L-1}\frac{iF(X_i)}{N} \\ &= \frac{1}{2N}\left[L(N - F(X_0)) - 2\sum_{i=0}^{L-1}iF(X_i)\right] \end{aligned} \quad (36)$$

Hence, the scale factor to remove the divider is $2N$. Let's denote the scaled MBE as SMBE defined as follows

$$SMBE = (2N)MBE \quad (37)$$

Then, it follows that:

$$\begin{aligned} SMBE_0 &= (2N)MBE_0 \\ &= L(N - F(X_0)) - 2\sum_{i=0}^{L-1}iF(X_i) \\ SMBE_1 &= (2N)MBE_1 \\ &= 2N\left[MBE_0 + \frac{1}{2}\left[1 - LP(X_1)\right]\right] \\ &= 2N\left[MBE_0 + \frac{1}{2N}\left[N - LF(X_1)\right]\right] \\ &= (2N)MBE_0 + \left[N - LF(X_1)\right] \\ &= SMBE_0 + \left[N - LF(X_1)\right] \\ &\ldots. \\ SMBE_T &= SMBE_{T-1} + \left[N - LF(X_T)\right] \end{aligned} \quad (38)$$

The number gray levels are often of base 2. In such cases, the multiplication with L could be replaced with basic shift operation. Suppose $L = 2^l$, it follows that,

$$
\begin{aligned}
SMBE_0 &= [(N - F(X_0)) << l] - \left(\sum_{i=0}^{L-1} iF(X_i) \right) << 1 \\
SMBE_1 &= SMBE_0 + [N - (F(X_1) << l)] \\
&\ldots \\
SMBE_T &= SMBE_{T-1} + [N - (F(X_T) << l)]
\end{aligned} \tag{39}
$$

In order to find the absolute value of SMBE, a comparator is required. Check each SMBE and if it is negative, negate the value as shown below:

IF (SMBE<0) THEN
ASMBE = - SMBE
ELSE ASMBE = SMBE

IV. Results and Discussions

In order to demonstrate the performance of the proposed algorithm, simulation results of HE, BBHE, DISHE and also MMBEBHE for images *arctic hare*, *U2*, *copter*, *F16* and *hands* are presented. Table 1 lists the selected threshold level and the resulting AMBE for each of the above algorithms

Table 1

	HE	BBHE		DSIHE		MMBEBHE	
	AMBE	X_T	AMBE	X_T	AMBE	X_T	AMBE
Arctic hare	90.5	239	24.2	244	37.9	224	13.5
U2	96.7	31	13.3	23	41.5	40	6.24
Copter	63.4	148	18.1	155	28.0	142	3.5
F16	48.7	176	0.35	197	14.6	173	0.02
Hands	99.5	27	17.5	0	18.3	9	15.4

List of the selected threshold level, X_T and the resulting AMBE for HE, BBHE, DSIHE and MMBEBHE

Image *arctic hare* is chosen as the representative of images with high mean brightness (bright background). Observe that resulting images of HE (fig. 2), BBHE (fig. 5) and DSIHE (fig. 6) have mean brightness much darker compared to the original image and hence, results in unnatural contrast enhancement. Result from MMBEBHE (fig. 7) clearly shows that the proposed algorithm has increased the brightness preservation (brighter mean brightness) and yielded a more natural enhancement.

Fig. 5. Result of BBHE of image *arctic hare*

Fig. 6. Result of DSIHE of image *arctic hare*

Fig. 7. Result of MMBEBHE of image *arctic hare*

Image *U2* is chosen as the representative of images with low mean brightness (dark background). Notice that unpleasant artifacts (noise in white color) due to excessive increment in brightness in the image from HE (fig. 4), BBHE (fig. 8), and DSIHE (fig. 9) is not seen at all in the results of MMBEBHE (fig. 10).

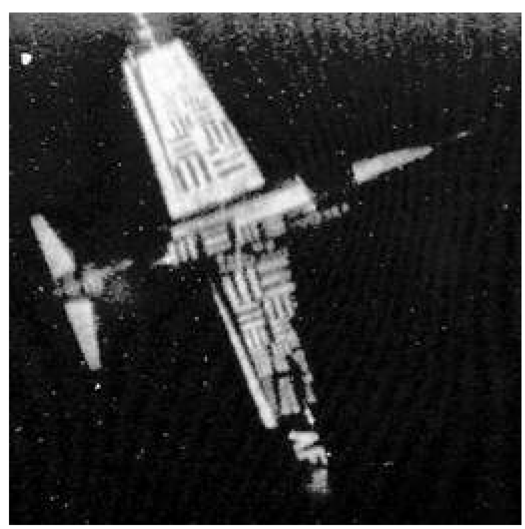

Fig. 8. Result of BBHE of image *U2*

Fig. 9. Result of DSIHE of image *U2*

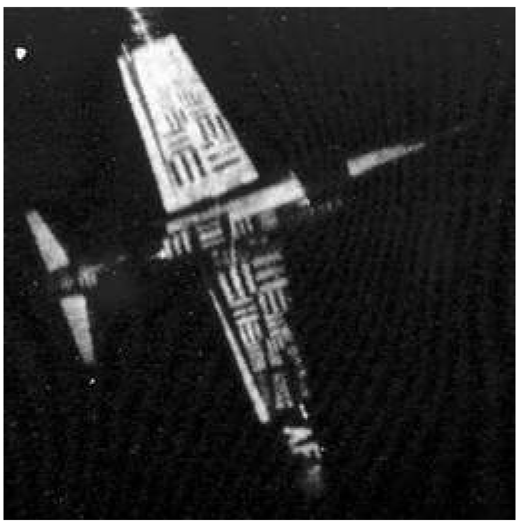

Fig. 10. Result of MMBEBHE

Image *Copter* (fig. 11) is chosen as the representative of images with medium mean brightness (gray background).

Fig. 11. Original image of *Copter*

Notice that the result of HE (fig. 12), BBHE (fig. 13) and DSIHE (fig. 14) have experienced excessive change in brightness and result in unnatural enhancement and contrast decrement in the main object (copter). The result of MMBEBHE (fig. 15) shows the proposed algorithm has not only preserved the brightness up to the required level, but also gives natural enhancement in most part of the image.

Fig. 12. Result of HE of image *copter*

Fig. 13. Result of BBHE of image *copter*

Fig. 14. Result of DSIHE of image *copter*

Fig. 15. Result of MMBEBHE of image *copter*

Image *F16* (fig. 16) has been used in [2] to demonstrate the success of BBHE.

Fig. 16. Original image of *F16*

Fig. 17. Result of BBHE of image of *F16*

Note that the output of BBHE (fig. 17) and MMBEBHE (fig. 18) is very similar while the result of HE (fig. 19) and DSIHE (fig. 20) shows obvious change in brightness (darker) and decrease of contrast around the letters “F16”.

Fig. 18. Result of MMBEBHE of image *F16*

Fig. 19. Result of HE of image *F16*

Fig. 20. Result of DSIHE of image *F16*

Fig. 21. Original image of *Hands*

Fig. 22. Result of MMBEBHE of image *Hands*

Fig. 23. Result of DSIHE of image *Hands*

Fig. 24. Result of BBHE of image *Hands*

Image *Hands* (fig. 21) has been used in both [2] and [3] to demonstrate the success of BBHE and DSIHE. Notice that the result of MMBEBHE (fig. 22) is very similar to DSIHE (fig. 23) and is better compared to BBHE (fig. 24) in term of background color preservation. Observe also that there are annoying artifacts (white spots) along the edges in the result of DSIHE, which are not seen at all in the result of MMBEBHE.

V. CONCLUSION

In this paper, a new contrast enhancement algorithm referred as the Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) with better brightness preservation is proposed. The MMBEBHE is a novel extension of BBHE. The main idea lies on separating the histogram using the threshold level that would yield minimum Absolute Mean Brightness Error (AMBE). The ultimate goal behind the MMBEBHE is to allows maximum level of brightness preservation in Bi-Histogram Equalization to avoid unplesant artifacts and unnatural enhancement due to excessive equalization while enhancing the constrast of a given image as much as possible. This paper has also formulated an efficient, recursive and integer-based solution to approximate the output mean as function of threshold level. Simulation results using sample image which represent images with very low, very high and medium mean brightness have demonstrated that the cases which are not handled well by HE, BBHE and DSIHE, can be properly enhanced by MMBEBHE. Besides, MMBEBHE also demostrate comparable performance with BBHE and DSIHE when come to use the sample images shown in [2] and [3].

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