Opt Rev (2015) 22:246–255
DOI 10.1007/s10043-015-0073-x

REGULAR PAPER

Range limited double-threshold multi-histogram equalization for image contrast enhancement

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Received: 13 August 2014 / Accepted: 30 December 2014 / Published online: 27 March 2015

Abstract Thresholding segmentation method is the commonly applied technique for extracting objects from the background of the image. If the single object in the image is clearly distinguishable from the background, the histogram of the image would be bimodal and the threshold can be easily chosen at the bottom of the histogram valley. However, histograms are not always bimodal. Thus, new methods are required to solve this problem. This paper raises a novel contrast enhancement method called range limited double-threshold multi-histogram equalization (RLDTMHE). First, we deduce the Otsu's double-thresholds method, and divide the image into three parts with the double thresholds. In order to preserve the brightness, range of the equalized image is calculated to yield minimum absolute mean brightness error (AMBE) between the output image and the original one. Finally, each sub-image is equalized independently using the new range. Experiment results show that our algorithm obtains more clear details, while keeping the brightness of the original image very well.

Keywords Image contrast enhancement · Histogram equalization · Brightness preserving enhancement · Range limit · Double thresholds

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1 Introduction

Since histogram equalization (HE) is computationally fast and simple to implement, HE is widely used to enhance the global contrast of images, especially when the contrast of the effective information of the image is quite close to each other. Based on utilizing the cumulative density function (CDF) of image for transformation of the gray levels of original image to the levels of enhanced image, global histogram equalization (GHE) technique tends to homogenize the distribution of pixels in the image, expand the dynamic range of the original image, improve the specific high contrast of the image, and make it more suitable for the naked eye observation or machine analysis [1]. As is known to all, global histogram equalization is based on the distribution of the brightness of the whole image. However, it will also lead to over-enhancement, increasing the contrast of background noise, loss in image details, and thus reducing the contrast of useful signals [2]. Especially in the consumer electronics such as digital cameras, it is particularly important to keep the brightness of the original image.

Therefore, in recent years, many scholars proposed various effective global histogram equalization methods. Kim first presented brightness preserving bi-histogram equalization (BBHE) [3]. BBHE divides the histogram into two parts based on the input mean brightness and equalizes the two sub histograms independently. Then, equal area dualistic sub-image histogram equalization (DSIHE) claimed that it is better than BBHE in terms of preservation of brightness and average information content of an image [4]. Chen introduced minimum mean brightness error bi-histogram equalization (MMBEBHE) for preserving the mean brightness "optimally" [5]. Sim presented recursive mean-separate histogram equalization (RSIHE) [6]. This algorithm performs the division of histogram based on median value of brightness instead of mean brightness. Zuo presented range limited bi-histogram equalization (RLBHE) [7], etc. RLBHE divides the input image histogram into two parts based on the Otsu's method. However, these above discussed algorithms do not provide mechanism for adjusting the level of enhancement. In RLBHE, when using Otsu's method to acquire the single threshold, the most basic requirement is that the image gray histogram has obvious bimodal characteristics [8]. The RLBHE algorithm cannot perform well when dealing with the complex scene, because the image gray histogram frequently presents the characteristics of three peaks or more. Especially for the multi-objective or complex background image, using RLBHE methods to segment image with the single threshold is no longer perfect.

Inspired by Zuo, we put forward a new double-threshold histogram equalization algorithm, called range limited double-threshold multi-histogram equalization (RLDTMHE). First of all, extended Otsu's double-threshold method is used to obtain two thresholds of the image. Then, we ensure that the mean brightness of the output image is almost consistent with the mean brightness of the input image by limiting the range of the image. In this paper, GHE and RLBHE histogram equalization method and their mathematical formula are reviewed in Sects. 2 and 3. The RLDTMHE method is shown in Sect. 4. Section 5 lists a few experimental results to illustrate the performance of RLDTMHE. Section 6 shows the conclusion of this paper.

2 Global histogram equalization

Let us suppose that $f(i, j) = I = \{I(i, j)\}$ stands for a digital image, where $I(i, j)$ stands for the gray level of the pixel at (i, j). N denotes the total number of the image pixels, and the image intensity is digitized and divided into L levels as $\{I_0, I_1, I_2,\ldots, I_{L-1}\}$. So it is obvious that $\forall I(i, j) \in \{I_0, I_1, I_2,\ldots, I_{L-1}\}$. Suppose n_k stands for the total number of pixels with the gray level of I_k in the image, then the probability density function (PDF) $p(I_k)$ can be written as follows:

$$p(I_k) = \frac{n_k}{N}, (k = 0, 1, 2, \ldots, L-1) \tag{1}$$

Based on the image's PDF, its cumulative distribution function (CDF) is defined as

$$c(I_k) = \sum_{i=0}^{k} p(I_i) = \sum_{i=0}^{k} \frac{n_k}{N}, (k = 0, 1, 2, \ldots, L-1) \tag{2}$$

It is easy to know that $c(I_{L-1}) = 1$. The transform function $T(I)$ can be defined as follows based on the CDF:

$$T(I) = I_0 + (I_{L-1} - I_0)c(I) \tag{3}$$

Then the output image of the GHE, $O = \{O(i, j)\}$ can be written as follows:

$$O = T(I) = \{T(I(i, j)|\{I_0, I_1, I_2, \ldots, I_{L-1}\})\} \tag{4}$$

Suppose that I is a continuous random variable, i.e., $L = \infty$, then the output image O is also regarded as a continuous random. It is obvious that the PDF of the output gray level of O follows a uniform distribution because $T(I)$ is a linear function, i.e., the density function of the output image would be distributed over the whole range. The mean brightness of the output image can be expressed as

$$E(O) = \frac{X_0 + X_{L-1}}{2}, \tag{5}$$

where $E(\bullet)$ stands for a statistical expectation. X_0 and X_{L-1} stand for the image intensity of the gray level 0 and $L - 1$, respectively. Since $E(O)$ is a constant that has nothing to do with the brightness of the input image, the GHE algorithm does not take the mean brightness of the input image into consideration. The GHE algorithm cannot be immigrated into the electronics such as the digital camera due to the change of the brightness of the input image.

3 Range limited bi-histogram equalization

RLBHE algorithm is formally defined by the following procedures:

3.1 Choosing a proper threshold using Otsu's method for histogram separation

Otsu's method is used to automatically separate the image into two parts, the target region and the background. The algorithm assumes that the image to be thresholded contains two classes of pixels (e.g., foreground and background); then the optimum threshold is calculated to separate those two classes so that their intra-class variance is maximum.

$$\sigma^2(X_T) = W_L(E(X_L) - E(X))^2 + W_U(E(X_U) - E(X))^2, \tag{6}$$

where $E(X_L)$ and $E(X_U)$ stand for the mean brightness of the two sub-images thresholded by X_T. $E(X)$ is the mean brightness of the whole image. W_L and W_U stand for the numbers of two classes of pixels of the whole.

$$W_L = \frac{n_L}{N} \tag{7}$$

and

$$W_U = \frac{n_U}{N} \tag{8}$$

3.2 Determine the upper and the lower bounds for histogram equalization

The mean brightness of the output image of bi-histogram equalization using X_T is as follows:

$$E(Y) = E(Y|X \leq X_T)p(X \leq X_T) + E(Y|X > X_T)p(X > X_T) \tag{9}$$

The output image should keep the mean brightness of the original image as much as possible:

$$E(Y) \approx E(X) = X_m \tag{10}$$

To make Eq. (10) hold, the range of equalized image is modified. Two variables X'_{L-1} and X'_0 are used to replace the upper bound X_{L-1} and the lower bound X_0, where X'_{L-1} and X'_0 are chosen to yield minimum AMBE between the equalized image and the original image.

3.3 Equalize each partition independently

Then what to do is to equalize each sub-histogram independently. It is same with all bi-histogram equalization methods except for the mapping range. That is, the output image of RLBHE, Y, is finally expressed as

$$Y = \{Y(i,j)\} = Y_L \cup Y_U \tag{11}$$

4 Range limited double-threshold multi-histogram equalization

Referring to the RLBHE algorithm, the RLDTMHE algorithm can be mainly divided into the following steps:

1. Choosing double thresholds to separate the input image
2. Determining the upper and the lower bounds for histogram equalization
3. Equalizing each partition independently

Then in the following subsection, the details of each step will be discussed.

4.1 Choosing double thresholds to separate the input image

In RLBHE algorithm, using Otsu's method to choose a single threshold for histogram separation, requests that the density histogram of image have obvious bimodal characteristics. But in fact, the density histogram of image always has more than two peaks, i.e., three or more. When dealing with such multi-objective or complex background image, the RLBHE algorithm cannot separate the image well with only a single threshold. For example, from Fig. 1a, it is easy to find that the figure contains tree, house, and sky. And the histogram of Fig. 1a has an obvious three-peak characteristic. In this condition, double thresholds are required to divide the image into three parts, of course, the foreground, the background, and the target region. Otherwise, it is also available to divide the image into more parts, and the result will be more effective. But there is no doubt that it will increase the amount of calculation, which means the working efficiency of the algorithm will be reduced a lot. And we also find that double-threshold is the lowest limit to obtain better enhancement.

Assumed that $f(i, j) = I = \{I(i, j)\}$ stands for a digital image, where $I(i, j)$ stands for the gray level of the pixel at (i, j). N denotes the total number of the image pixels, and the image intensity is digitized and divided into L levels as $\{I_0, I_1, I_2,\ldots, I_{L-1}\}$. So it is obvious that $\forall I(i, j) \in \{I_0, I_1, I_2,\ldots, I_{L-1}\}$. Using T_1 and T_2, obviously, T_1, T_2 - $\{I_0, I_1, I_2,\ldots, I_{L-1}\}$, the input image I can be decomposed into three sub-images I_L, I_U, and I_V as

$$I = I_L \cup I_U \cup I_V \tag{12}$$

where

$$I_L = \{I(i,j)|I(i,j) \leq I_{T_1}, \forall I(i,j) \in I\} \tag{13}$$

$$I_U = \{I(i,j)|I_{T_1} < I(i,j) \leq I_{T_2}, \forall I(i,j) \in I\} \tag{14}$$

and

$$I_V = \{I(i,j)|I(i,j) > I_{T_2}, \forall I(i,j) \in I\} \tag{15}$$

Then, the PDF of the sub-images I_L, I_U and I_V can be written as follows:

$$p_L(I_k) = \frac{n_k}{N}, (k = 0, 1, 2, \ldots, T_1) \tag{16}$$

$$p_U(I_k) = \frac{n_k}{N}, (k = T_1 + 1, T_1 + 2, \ldots, T_2) \tag{17}$$

$$p_V(I_k) = \frac{n_k}{N}, (k = T_2 + 1, T_2 + 2, \ldots, L - 1), \tag{18}$$

where n_k stands for the total number of pixels with the gray level of I_k in I_L, I_U, and I_V, N is the total number of pixels in I. Then the CDF for I_L, I_U, and I_V can be defined as

$$c_L(I_k) = \sum_{j=0}^{k} p_L(I_j), (k = 0, 1, 2, \ldots, T_1) \tag{19}$$

$$c_U(I_k) = \sum_{j=T_1+1}^{k} p_U(I_j), (k = T_1 + 1, T_1 + 2, \ldots, T_2) \tag{20}$$

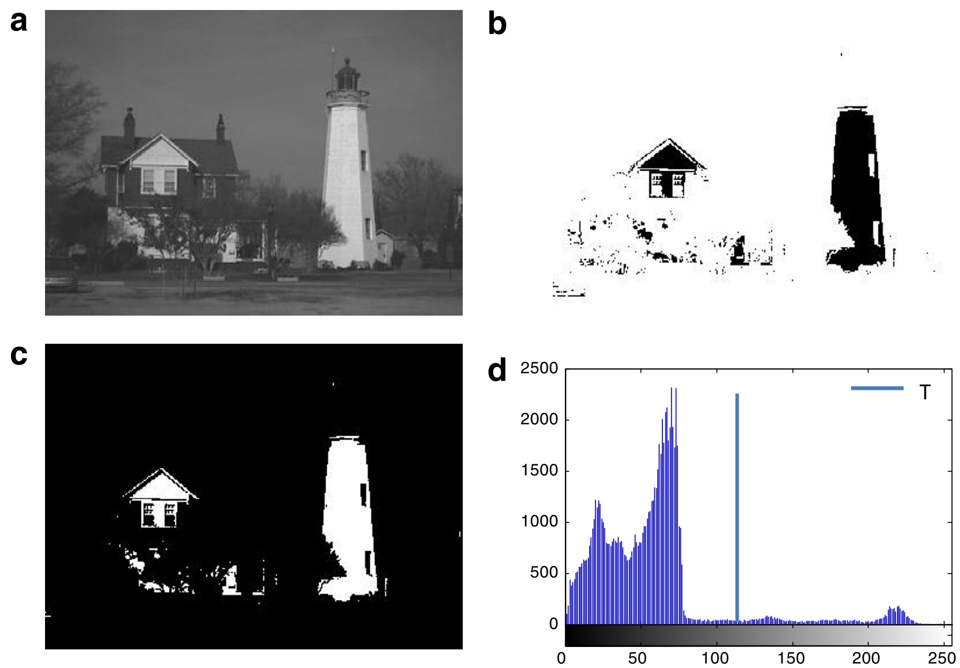

Fig. 1 **a** Original image of House. **b** Separation result using the single threshold Otsu's method. **c** Separation result using the single threshold Otsu's method. **d** The location of threshold using the single threshold Otsu's method (Color online)

$$c_V(I_k) = \sum_{j=T_2+1}^{k} p_V(I_j), (k = T_2+1, T_2+2, \ldots, L-1) \tag{21}$$

Thus, the transform function can be defined as

$$f_L(I_k) = I_0 + (T_1 - I_0)c_L(I_k), (k = 0, 1, 2, \ldots, T_1) \tag{22}$$

$$f_U(I_k) = T_1 + 1 + (T_2 - (T_1+1))c_U(I_k), \\ (k = T_1+1, T_1+2, \ldots, T_2) \tag{23}$$

$$f_V(I_k) = T_2 + 1 + (I_{L-1} - (T_2+1))c_V(I_k), \\ (k = T_2+1, T_2+2, \ldots, L-1) \tag{24}$$

Inspired by the single threshold Otsu's method, we deduced the double-threshold Otsu's method and then divided the image into three parts with the double-thresholds T_1 and T_2. The algorithm assumes that the image to be thresholded contains three classes of pixels (e.g., the foreground, the background, and the target region) and then calculates the adaptive thresholds dividing those three classes so that their inter-class variance is maximum:

$$g(T_1, T_2) = \underset{0<T_1<T_2<L-1}{\mathrm{ArgMax}} \Big\{ p_L(E(I_L) - E(I))^2 + p_U(E(I_U) - E(I))^2 \\ + p_V(E(I_V) - E(I))^2 \Big\}, \tag{25}$$

where T_1 and T_2 are the double thresholds, p_L, $p_{U,}$ and p_V stand for the PDF of the sub-images I_L, $I_{U,}$ and I_V. $E(I_L)$, $E(I_U)$ and $E(I_V)$ are defined as the mean brightness of the three sub-images divided by T_1 and T_2. $E(I)$ is the mean brightness of the whole image.

In order to acquire the best segmentation, Otsu's method requests that the mean of the sub-images be divided by the thresholds should be far away from the center of the image. And the gray mean of the image is used to represent the target and the background. In this paper, the average variance is used instead of the mean of the image because the average variance reflects the uniformity of the image gray scale distribution. The image gray scale distribution within the target and the background area is homogeneous, but the gray scale of the boundary and the surrounding pixels changes heavily. Thus, the average variance can be regarded as a reflection of the gray mutation between the boundary and the surrounding pixels. If the average variance of one certain sub-image is close to that of the whole image, likely to divide the whole boundary and the surrounding pixels into this part, it shows the wrong segmentation. According to the analysis above, it is reasonable to use the average variance instead of the mean of the image in Otsu's method. Thus Eq. (25) can be written as

$$g(T_1, T_2) = \underset{0<T_1<T_2<L-1}{\mathrm{Arg\ Max}} \Big\{ p_L(\sigma_L^2 - \sigma^2)^2 + p_U(\sigma_U^2 - \sigma^2)^2 \\ + p_V(\sigma_V^2 - \sigma^2)^2 \Big\}, \tag{26}$$

where

$$\sigma_L^2 = \frac{1}{c_L(I_k)} \sum_{j=0}^{T_1} (j - E(I))^2 p_L(I_j) \tag{27}$$

$$\sigma_U^2 = \frac{1}{c_U(I_k)} \sum_{j=T_1+1}^{T_2} (j - E(I))^2 p_U(I_j) \tag{28}$$

$$\sigma_V^2 = \frac{1}{c_V(I_k)} \sum_{j=T_2+1}^{L-1} (j - E(I))^2 p_V(I_j) \tag{29}$$

$$\sigma^2 = \sum_{j=0}^{L-1} (j - E(I))^2 p(I_j) \tag{30}$$

$$p(I_k) = \frac{n_k}{N}, (k = 0, 1, 2, \ldots, L - 1) \tag{31}$$

According to Eq. (26), the algorithm exhaustively searches for the thresholds that maximize the inter-class variance.

Figure 1b and c shows the separation result of Fig. 1a using the single threshold Otsu's method. And the location of T is shown in Fig. 1d.

Figure 2a–c shows the separation result of Fig. 1a using the double-threshold Otsu's method. And the location of T_1 and T_2 is shown in Fig. 2d. It can be seen that the multi-threshold Otsu's method yields a more reasonable result than the single threshold Otsu's method and the target region is totally separated from the foreground and the background.

4.2 Determine the upper and the lower bounds for histogram equalization

In the application such as the mobile camera, the preservation of the mean brightness is always of high requirement. Even though the thresholds searched by the double-threshold Otsu's method can divide the input image effectively, the mean brightness cannot be kept intact. Thus, the new upper and the lower bounds for histogram equalization should be determined to improve the defect as much as possible. The mean brightness of the output image of multi-histogram equalization using T_1 and T_2 is as follows:

$$\begin{aligned} E(O) &= E(O|I_0 \le I \le T_1)p(I_0 \le I \le T_1) \\ &\quad + E(O|T_1 + 1 \le I \le T_2)p(T_1 + 1 \le I \le T_2) \\ &\quad + E(O|T_2 + 1 \le I \le L - 1)p(T_2 + 1 \le I \le L - 1) \\ &= \frac{I_0 + T_1}{2}\left(\sum_{j=0}^{T_1} p(I_j)\right) + \frac{T_1 + 1 + T_2}{2}\left(\sum_{j=T_1+1}^{T_2} p(I_j)\right) \\ &\quad + \frac{T_2 + 1 + I_{L-1}}{2}\left(\sum_{j=T_2+1}^{L-1} p(I_j)\right) \end{aligned} \tag{32}$$

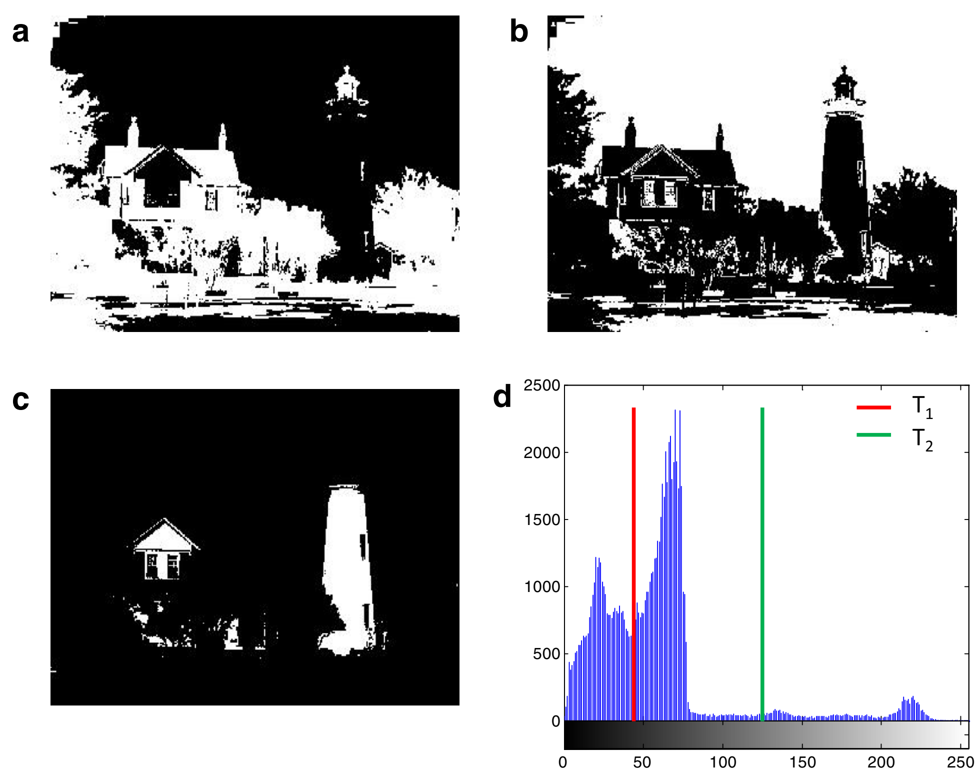

Fig. 2 **a** The foreground of the image. **b** The background of the image. **c** The target region of the image. **d** The location of thresholds using the double-threshold Otsu's method ($T_1 = 45$ and $T_2 = 125$) (Color online)

In order to keep the mean brightness of the original image as much as possible, the mean of the output image should meet the following equation:

$$E(O) \approx E(I) = I_m = \sum_{j=0}^{L-1} I_j p(I_j), \tag{33}$$

where I and O denote the input and output image, and I_m stands for the mean of the input image.Here, let us define

$$a = \sum_{j=0}^{T_1} p(I_j) \tag{34}$$

$$b = \sum_{j=T_1+1}^{T_2} p(I_j) \tag{35}$$

Thus, it is obvious that

$$\sum_{j=T_2+1}^{I_{L-1}} p(I_j) = 1 - a - b \tag{36}$$

By substituting Eqs. (32), (34), (35), and (36) into Eq. (33), we get

$$\frac{I_0 + T_1}{2} a + \frac{T_1 + 1 + T_2}{2} b + \frac{T_2 + 1 + I_{L-1}}{2} (1 - a - b) \approx I_m \tag{37}$$

As can be seen from Eq. (37), T_1 and T_2 can be got by the double-threshold Otsu's method, and $a = \sum_{j=0}^{T_1} p(I_j)$, $b = \sum_{j=T_1+1}^{T_2} p(I_j)$ and I_m can be easily got from the input image because they have nothing to do with the output image, but related to the input image only. Thus, the new lower bound I'_0 and the upper bound I'_{L-1} are needed to substitute for the I_0 and I_{L-1} to make Eq. (37) hold. Here we define that $0 \le I'_0 \le T_1$ and $T_2 \le I'_{L-1} \le L-1$. I'_0 and I'_{L-1} should ensure that the AMBE is minimum between the output image and the input image:

$$\begin{aligned}
\left(I'_{L-1}, I'_0\right) &= \text{Arg Min}\{|E(O) - E(I)|\} \\
&= \text{Arg Min}\left|\frac{1}{2}\left[(I'_0 + T_1)a + (T_1 + 1 + T_2)b + (T_2 + 1 + I'_{L-1})(1 - a - b) - 2I_m\right]\right| \\
&= \text{Arg Min}\left|\frac{1}{2}\left[aI'_0 + (1 - a - b)I'_{L-1} - [2I_m - (a + b)T_1 - (1 - a)T_2 - (1 - a)]\right]\right|
\end{aligned} \tag{38}$$

In Eq. (38), since a, b, T_1, T_2, and I_m can be calculated beforehand, define that

$$c = 1 - a - b \tag{39}$$

$$d = 2I_m - (a + b)T_1 - (1 - a)T_2 - (1 - a) \tag{40}$$

Thus Eq. (38) can be written as

$$\left(I'_{L-1}, I'_0\right) = \text{Arg Min}\left[\left(aI'_0 + cI'_{L-1} - d\right)^2\right], s.t. \begin{cases} 0 \le I'_0 \le T_1 \\ T_2 \le I'_{L-1} \le L - 1 \end{cases} \tag{41}$$

As can be seen from Eq. (41), it is a simple quadric optimization problem with a unique solution. Thus, the solutions I'_0 and I'_{L-1} ensure that the AMBE is minimum between the output image and the input image so that the brightness of the input image can be kept as much as possible.

4.3 Equalize each partition independently

The final step in RLDTMHE is to equalize each sub-image independently. It is all the same with any bi-histogram equalization methods except for the new range I'_0 and I'_{L-1}. The transform functions Eqs. (22), (23), and (24) using I'_0 and I'_{L-1} instead of I_0 and I_{L-1} can be expressed as follows:

$$f_L(I_k) = I'_0 + (T_1 - I'_0)c_L(I_k), (k = 0, 1, 2, \ldots, T_1) \tag{42}$$

$$f_U(I_k) = T_1 + 1 + (T_2 - (T_1 + 1))c_U(I_k), (k = T_1 + 1, T_1 + 2, \ldots, T_2) \tag{43}$$

$$f_V(I_k) = T_2 + 1 + \left(I'_{L-1} - (T_2 + 1)\right)c_V(I_k), (k = T_2 + 1, T_2 + 2, \ldots, L - 1) \tag{44}$$

Based on the above three transform functions, we equalized the sub-images independently and finally the output image of RLDTMHE is composed of the results of the equalized sub-imagesThus, the output image O is as follows:

$$O = O_L \cup O_U \cup O_V, \tag{45}$$

where

$$O_L = f_L(I_k) = \{f(I(i,j))|I(i,j) \le I_{T_1}, \forall I(i,j) \in I\} \quad (46)$$

$$O_U = f_U(I_k) = \{f(I(i,j))|I_{T_1} < I(i,j) \le I_{T_2}, \forall I(i,j) \in I\}, \quad (47)$$

and

$$O_V = f_V(I_k) = \{f(I(i,j))|I(i,j) > I_{T_2}, \forall I(i,j) \in I\} \quad (48)$$

Table 1 The resulting AMBE for GHE, RLBHE, and RLDTMHE

	GHE	RLBHE	RLDTMHE
House	70.0088	7.1166	4.9416
F16	51.6538	0.7945	0.5404
Villa	69.2612	6.7452	0.3769

5 Results and discussion

Besides the RLDTMHE, this paper also realized the GHE and RLBHE algorithms as references. Table 1 shows the AMBE for the three algorithms mentioned above.

Wide varieties of standard images ranging from under exposed to over exposed, low contrast to high contrast, dark background to bright background, are chosen to test the robustness and versatility of the RLDTMHE method. Here we present an analysis of three images: House, F16 And Villa. The results from Figs. 3, 4, 5 shows the superiority of RLDTMHE in all the images in terms of contrast enhancement and control on over enhancement.

The concrete results in terms of contrast enhancement can be clearly observed in Fig. 3 of House image. It is easy to see that the tower and the sky are over enhanced by GHE. The windows of the house and the tower are obscured by RLBHE. However, RLDTMHE provides control

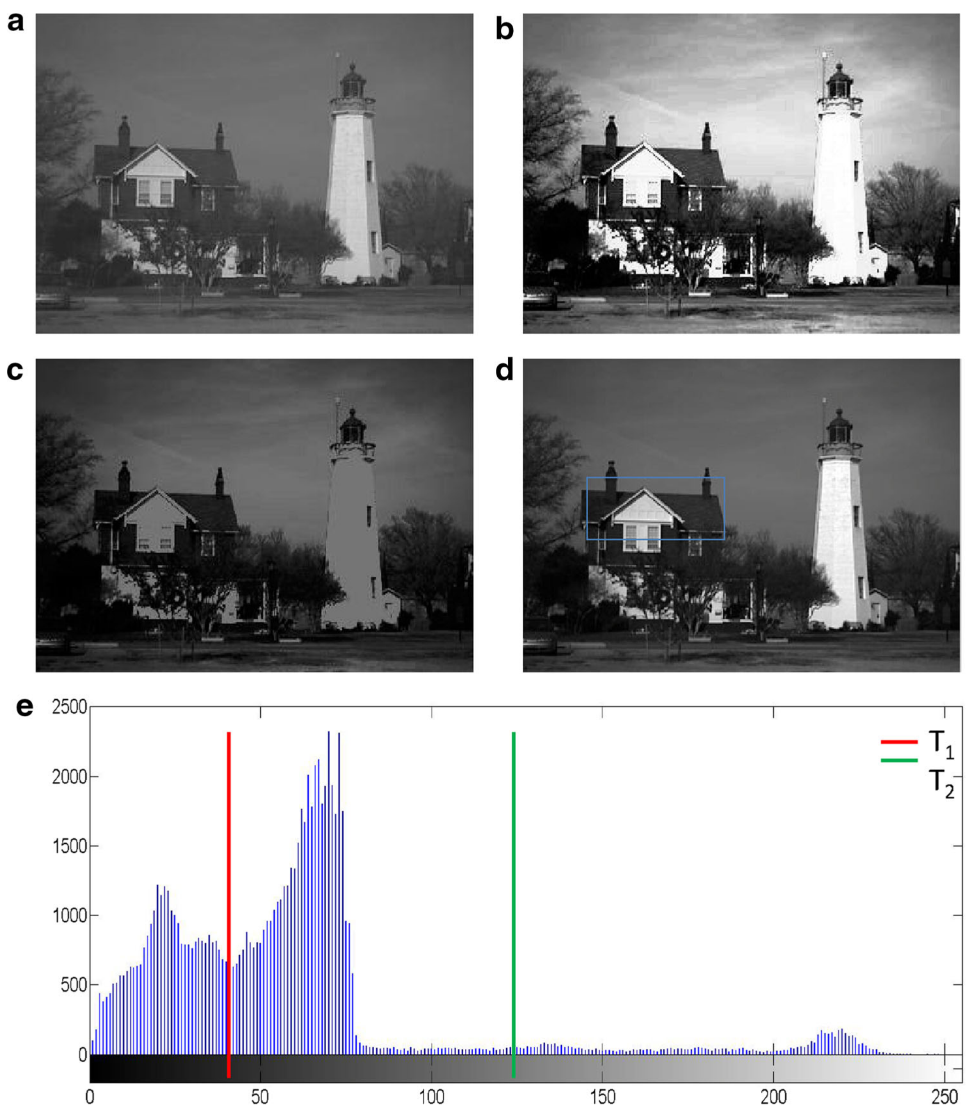

Fig. 3 **a** Original image of House. **b** Result of GHE. **c** Result of RLBHE. **d** Result of RLDTMHE. **e** The location of thresholds using the double-threshold Otsu's method ($T_1 = 45$ and $T_2 = 125$) (Color online)

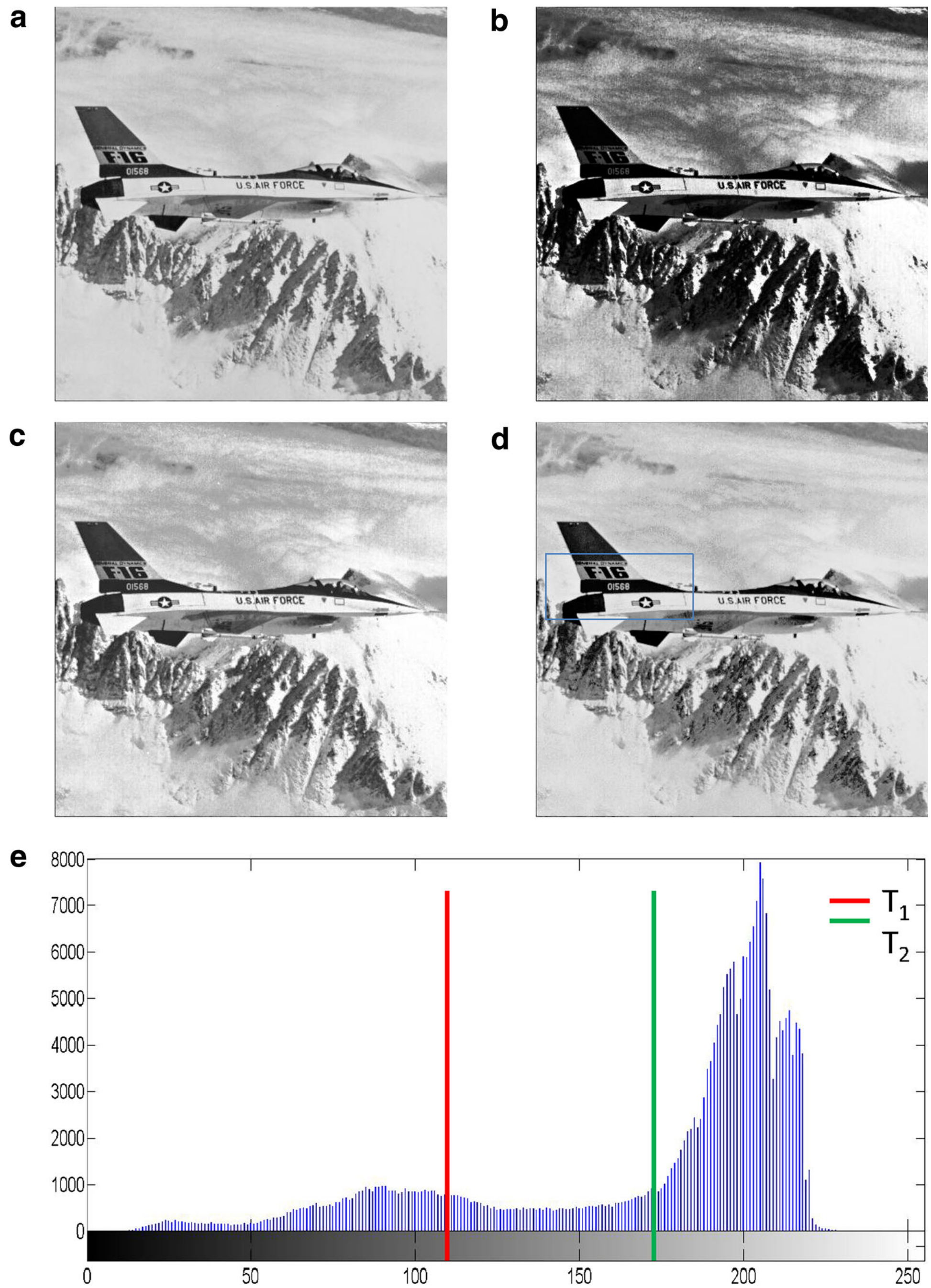

Fig. 4 **a** Original image of F16. **b** Result of GHE. **c** Result of RLBHE. **d** Result of RLDTMHE. **e** The location of thresholds using the double-threshold Otsu's method ($T_1 = 107$ and $T_2 = 168$) (Color online)

on over enhancement leading to good contrast enhancement. Observe the house and the tower in the image; we can perceive contrast enhancement. The front edge of the tower and the squares of the house shown in the blue rectangle can be seen clearly. By observing the processed images, it is noticeable that our proposed method is the only one among the other methods that can produce natural-looking images.

The test image F16 (Fig. 4) is chosen as the representative of images with high mean brightness (bright background). It shows that the output of GHE changes the brightness (darker) a lot, while the result of RLDTMHE shows more details and the contrast of F16 is significantly improved than that of RLBHE. The RLDTMHE method generates better enhancement around the letters "F16" than the RLBHE method.

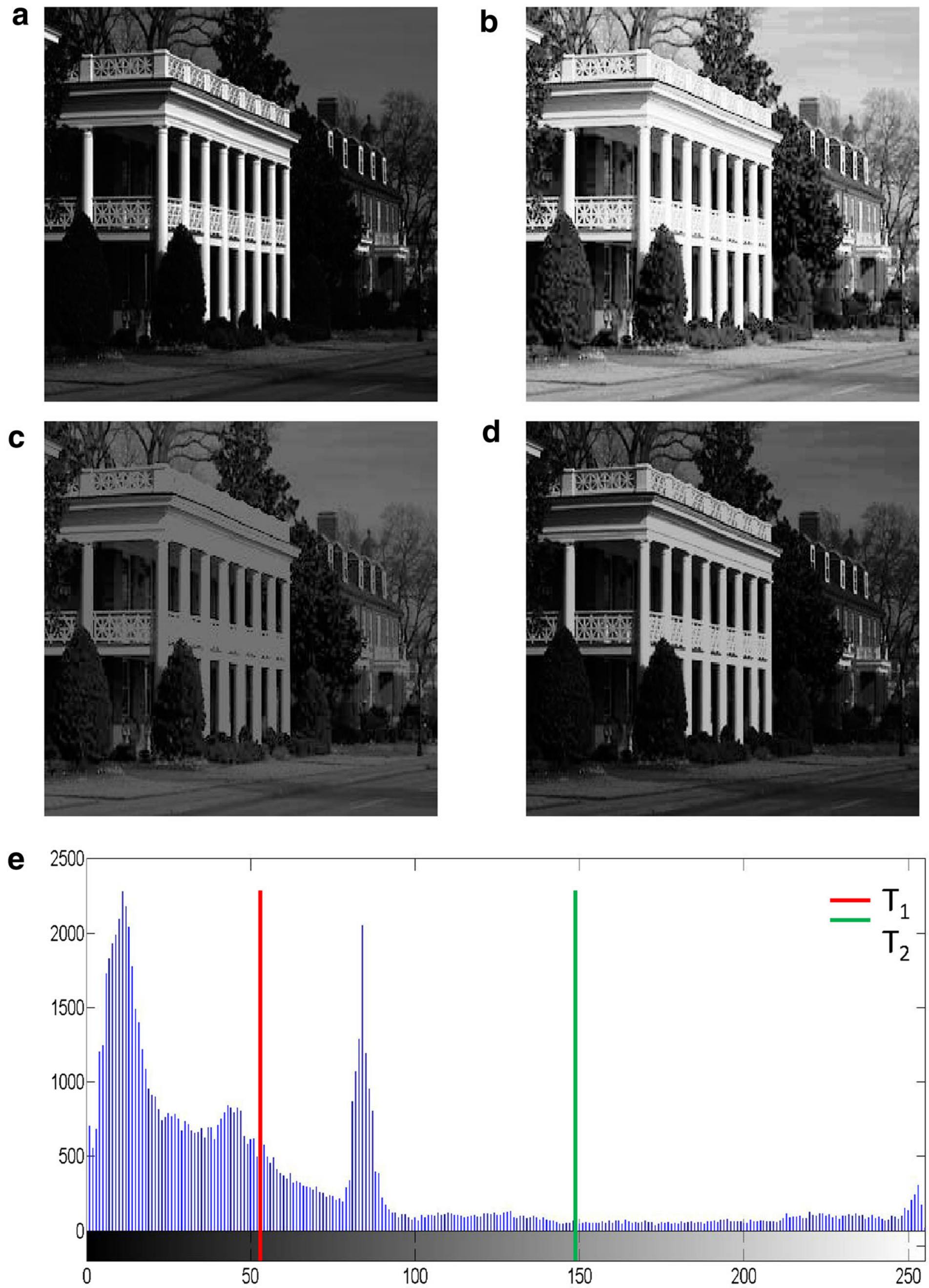

Fig. 5 **a** Original image of Villa. **b** Result of GHE. **c** Result of RLBHE. **d** Result of RLDTMHE. **e** The location of thresholds using the double-threshold Otsu's method ($T_1 = 53$ and $T_2 = 148$) (Color online)

It is obvious that the result of GHE in the test image Villa (Fig. 5) is much brighter when compared to the original image. RLBHE loses many details of the house and the brightness is not kept well. The result of RLDTMHE shows that the mean brightness is preserved well and the details of the house, the tree, and the sky are also well enhanced.

After visually observing some processed images, we can conclude that (1) the RLDTMHE method produces images with better quality than the other methods and that (2) it also presents satisfactory brightness preserving and natural looking images.

6 Conclusion

In this paper, we put forward a new contrast enhancement method, called range limited multi-histogram equalization. Primarily, RLDTMHE divides the histogram using double-threshold Otsu's method. Afterwards, RLDTMHE limits the range of the equalized image to preserve the input mean intensity. As can be seen from Figs. 3, 4, and 5, the results of the double-threshold method are better than that of single threshold method anyhow. The RLDTMHE algorithm can obtain obviously satisfactory result of the input image while keeping the input brightness. In addition, the RLDTMHE can be easily transplanted into the real-time processing because of its simplicity and effectiveness. We are satisfied with the results of our method by dividing the histogram using double-threshold Otsu's method. Nevertheless, we will discuss how to determine the number of the thresholds of the histogram adaptively in the later research.

Acknowledgments This work was supported by Jiangsu Natural Science Foundation (Grand No. BK2011698); Specialized Research Fund for the Doctoral Program of Higher Education of China (Grand No. 20113219120017); The 12th five-year plan research of general armament department (Grand No. 40405030103).

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