Brightness Preserving Image Contrast Enhancement using Spatially Weighted Histogram Equalization

Chao Zuo, Qian Chen, Xiubao Sui, and Jianle Ren
Department of Optoelectronic Technology, Nanjing University of Science and Technology, China

Abstract: *This paper presents a simple and effective method for image contrast enhancement called spatially weighted histogram equalization. Spatially weighted histogram not only considers the times of each grey value appears in a certain image, but also takes the local characteristics of each pixel into account. In the homogeneous region of an image, the spatial weights of pixels tend to zero, whereas at the edges of the image, this weights are very large. In order to maintain the mean brightness of the original image, the grey level transformation function calculated by spatial weighted histogram equalization is modified, and the final result is given by mapping the original image through this modified grey level transformation function. The experimental results show that the proposed method has better performance than the existing methods, and preserve the original brightness quite well, so that it is possible to be utilized in consumer electronic products.*

Keywords: *Image contrast enhancement, histogram equalization, brightness preserving enhancement, spatially weighted histogram.*

Received July 14, 2011; accepted December 30, 2011; published online January 29, 2013

1. Introduction

Global Histogram Equalization (GHE) is one of the most commonly used methods for image contrast enhancement because it has high efficiency and simplicity. It is achieved by normalizing the intensity distribution using its cumulative distribution function so that the result image may have a uniform distribution of intensity [8].

It is known, however, since GHE is basically using the intensity distribution of the whole image, it may suffers from the some drawbacks such as over enhancement, increase in the noise level, lost in details, and washed-out effect in some almost homogeneous area [10, 11]. So, in consumer electronics such as TV, GHE is rarely employed because it may significantly change the brightness of an input image and cause undesirable artefacts.

In the recently years, many researchers proposed many useful algorithms to solve these problems involved in GHE technique [1, 2, 5, 6, 8, 9, 11]. These methods includes Brightness preserving Bi-Histogram Equalization (BBHE) [6], equal area Dualistic Sub-Image Histogram Equalization (DSIHE) [9], Recursive Mean Separate HE (RMSHE) [2], and Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) [1] etc., BBHE divides the input image histogram into two parts based on the mean of the input image and then each part is equalized independently. It has been analysed both mathematically and experimentally that this technique is capable to preserve the original brightness to a certain extents. The DSIHE method is similar to BBHE except that it separates the histogram based on the median value. MMBEBHE is another extension of BBHE that provides maximal brightness preservation by using the threshold level, which would yield minimum difference between input and output mean. Though these methods can perform good contrast enhancement, they also cause more annoying side effects depending on the variation of grey level distribution in the histogram. RMSHE uses the BBHE iteratively to further preserve the brightness. It is difficult to guarantee the both good contrast enhancement and brightness preservation. Since when the iteration level grows larger, the output mean converges to the input mean, and thus yields good brightness preservation. However, the output histogram is exactly the input histogram, and the input image will be output without any enhancement at all.

In this paper, a novel enhancement method is proposed which can yield the appropriate contrast enhancement while preserve the mean brightness very well, called Spatially Weighted Histogram Equalization (SWHE). The organization of this paper is as follows: Section 2 will briefly explain global histogram equalization, and a thorough analysis of side effects in GHE is undertaken. Section 3 will present our methodology. The experimental results will be shown in section 4. Finally, section 5 presents our conclusions.

2. Global Histogram Equitation and Its Problems

Let's suppose that $X=\{X(i,j)\}$ denotes a digital image, where $X(i,j)$ denotes the grey level of the pixel at (i,j) place. The total number of the image pixels is N, and the image intensity is digitized into L levels that are $\{X_0, X_1, X_2, \ldots, X_{L-1}\}$. So, it is obvious that $\forall X(i,j) \in \{X_0, X_1, X_2, \ldots, X_{L-1}\}$. Suppose N_k denotes the total number of pixels with grey level of X_k in the image, then the probability density of X_k will be:

$$P_X(X_k) = \frac{N_k}{N},\ k = 0,1,\ldots L-1 \tag{1}$$

The relationship between $P_X(X_k)$ and X_k is defined as the Probability Density Function (PDF), and the graphical appearance of PDF is known as the histogram. Based on the image's PDF, its cumulative distribution function is defined as:

$$c(X_k) = \sum_{j=0}^{L-1} P_X(X_j) = \sum_{j=0}^{L-1} \frac{N_k}{N} \tag{2}$$

where $k=0,1,\ldots,L-1$, and it is obvious that $c(X_{L-1})=1$. This cumulative distribution function is used as the gray level transform function of GHE:

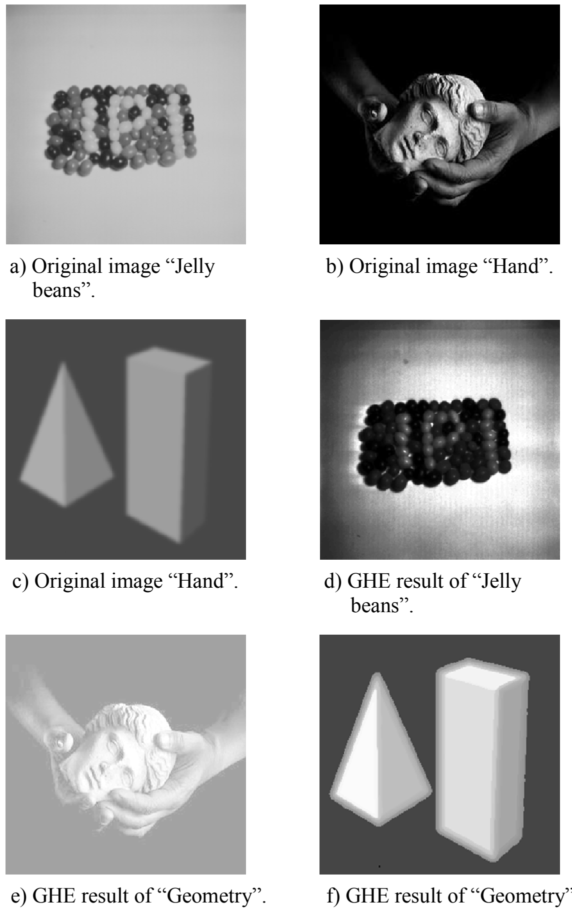
$$T_{GHE}(X_k) = c(X_k) \tag{3}$$

Suppose $Y=\{Y(i,j)\}$ is defined as the equalized image, then:

$$Y(i,j) = X_0 + (X_{L-1} - X_0) T_{GHE}(X(i,j)) \tag{4}$$

It is not difficult to find out that the PDF of the output grey level Y follows a uniform distribution ranging from zero to one. Since Y should has a histogram with a uniform distribution, i.e., the output image should have a density function equally distributed over the entire range, it get the maximum entropy. However, due to the discreteness nature of histogram, the image's histogram after GHE is not necessarily flat. Besides, it can be known from equation 2 that GHE relate the degree of enhancement for a specific ranges of grey level with their area (occurrence times). Therefore, the more frequent the grey values occur in an image, the more they will be enhanced, whereas the grey levels with smaller area will be compressed, or even be merged together. So, when an image is consisted of those areas having similar brightness, then GHE may generate deteriorated result image having poor quality.

Figure 1 gives three examples where some objects are located on simple backgrounds. By emphasizing the global difference between the brightness and darkness the background, noise is amplified excessively in Figure 1-d. A washed-out effect also appears in Figure 1-e since GHE changes the mean brightness of input image to the middle level. In Figure 1-c, the area for the grey values at the blurred edges of objects is very small. After GHE, these grey levels are merged together, so that false contours appear around the objects in Figure 1-f.



a) Original image "Jelly beans". b) Original image "Hand".

c) Original image "Hand". d) GHE result of "Jelly beans".

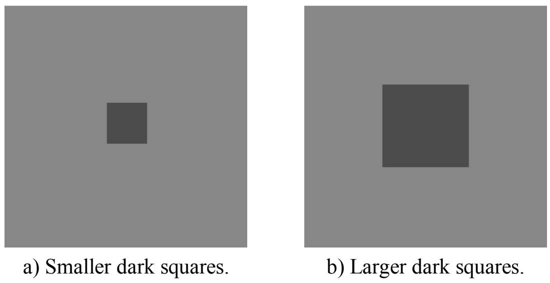
e) GHE result of "Geometry". f) GHE result of "Geometry".

Figure 1. Example images acquired by applying the global equalization.

3. Spatially Weighted Histogram Equalization

3.1. Spatially Weighted Histogram

Contrast is the difference in visual properties that makes an object (or its representation in an image) distinguishable from other objects and the background. This means that the contrast is make sense only between two or more scenes or objects.



a) Smaller dark squares. b) Larger dark squares.

Figure 2. Example images with dark squares located in gray backgrounds.

Consider the two example images shown in Figure 2. Two dark squares with different sizes are located at the center of gray background respectively. The histograms of two images are clearly different, so the enhanced images through GHE are also different. But we can find that the Figure 2-b can be viewed as a magnified version of the central part of Figure 2-a. Similarly, Figure 2-a can be got by expanding the background of Figure 2-b. Therefore, the backgrounds and objects in the two images are actually identical. The contrast between the square and the background should be related to their difference in gray-level rather than their sizes. When the two images are enhanced by one contrast enhancement method, the gray-values of the two corresponding areas in the two processed images should be equal.

To satisfy this, the contrast enhancement method must make use of some characteristics shared by both images. Although, the area of the squares and backgrounds of the two images are obviously different, it is not difficult to find out that the ratio between the contiguous areas of the squares and the backgrounds are both equal to one in the two example images since the object and the background share a same border.This seems quite natural but yet to confirm what is mentioned above: the contrast is make sense only between two or more scenes or objects. The contrast enhancement should be determined by contact area while not concerned with homogeneous region.

From the above discussion, we know that the gray-scale transform function of GHE depends only on the probability density function of the image, regardless of pixels' local features, which is obviously unreasonable. Therefore, we expect to obtain a new gray-scale transformation function, which depends on the contact area for each gray-scale. In another word, we need to form another kind of histogram which should take the pixels' local characteristics into account. Here, we modified the traditional histogram by spatial weighting and this modified histogram called spatially weighted histogram is defined as:

$$P_{SW\,X}(X_k) = \frac{p_{SW}(X_k)}{\sum_{j=0}^{L-1} p_{SW}(X_j)} \tag{5}$$

where

$$p_{SW}(X_k) = \sum_{i,j} f(c(i,j))\delta(X(i,j), X_k) \tag{6}$$

here $k=0,\ 1,\ \ldots,\ L\text{-}1$, $\delta(s,\ l)$ represents the Kronecker delta function, which equals 1 if $k=1$ and equals 0 otherwise. $f(\bullet)$ is the weight function, and $c(i,\ j)$ is the contrast factor [7] which is the average of difference values between the reference pixel $(i,\ j)$ and its neighbouring pixels as explained in equation 7:

$$\begin{aligned} c(i,j) = \frac{1}{4}(&|X(i,j) - X(i+1,j)| + |X(i,j) - X(i-1,j)| \\ &+ |X(i,j) - X(i,j+1)| + |X(i,j) - X(i,j-1)|) \end{aligned} \tag{7}$$

The spatially weighted histogram should contain only the information of contact area of each region (region boundaries), and ignore the interior of homogeneity region. However, note that the contact area as used above has not been formally defined. We mean here the perceptual subjective notion of an edge as a region boundary. Obviously the larger $c(i,\ j)$ is, the pixel is more likely at the region boundaries. So, $f(\bullet)$ has to be a nonnegative monotonically increasing function with $f(0)=0$ and $\lim_{c\to+\infty} f(c) = 1$ as shown in Figure 3. Since the choice of weight function is not unique, here we give two forms of $f(\bullet)$ as follows:

$$f(c) = 1 - exp\left(-\left(\frac{c}{K}\right)\right)^2 \tag{8}$$

$$f(c) = \frac{\left(\frac{c}{K}\right)^2}{1 + \left(\frac{c}{K}\right)^2} \tag{9}$$

Compare equations 8 and 9, it is clear that the value of two weight function both tends to one with the increases of c, but equation 9 increase slower than equation 8. So, equation 8 privileges high-contrast boundaries over low-contrast ones, equation 9 privileges wide regions over smaller ones. The constant K is a threshold to determine whether a pixel is located at the region boundaries. If $K=0$ i.e., the weight function equals one for every pixel in the image, equation 5 is reduced to equation 1. Therefore, the conventional histogram can be regarded as the special case of the spatially weighted histogram. The constant K can be fixed either by hand at some fixed value by experience, or using the "noise estimator" described by Canny [3]: a histogram of the absolute values of the gradient throughout the image was computed, and K was set equal to the 95%～99% value of its integral.

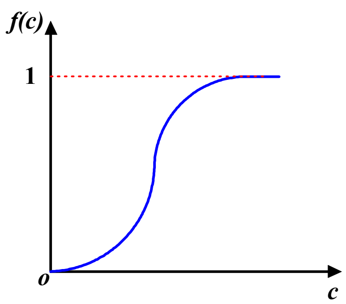


Figure 3. The qualitative shape of the weight function $f(\bullet)$.

Take Figure 1-c for an example, the value of K estimated through canny noise estimator is 2.1875. The spatial weights for Figure 1-c calculated by equation 8 are illustrated in Figure 4. It is shown that the background of the image has the same gray-level, thus the weights of these area are zero. Similarly, the weights of the interior surfaces of the triangular pyramid and four-prism are close to zero too. The largest weights locate at the region boundaries. Since the edges of objects in the image are blurred, there exists some transitional region of the weight function at the region boundaries.

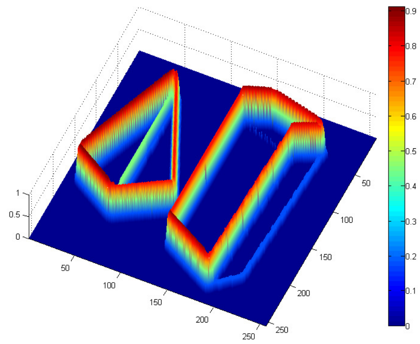
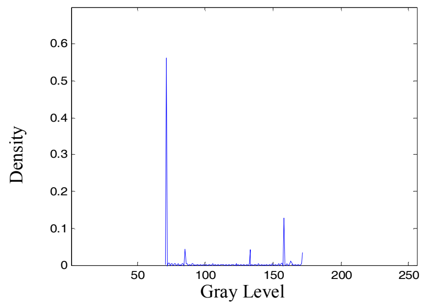


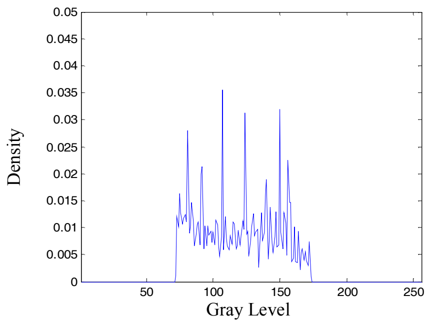
Figure 4. Spatial weights of Figure 1-c.

Figure 5 shows the conventional histogram Figure 5-a and spatially weighted histogram Figure 5-b. From Figure 5-a, we can see that about 60% pixels in the image have same gray-value. The other peaks of the histogram stands for the gray-levels of the surfaces of the objects. The gray-scale for the transitional boundaries can be ignored in the histogram compared to these peaks. In the spatially weighted histogram, the peak of background gray-level has been suppressed a lot, and it is no longer the highest one. The locations and heights of the other peaks are changed and their widths have expanded.

Besides the peaks which stand for the large uniform regions, several new peaks appear. These peaks are corresponding to the gray levels of the transition area (blurred edges) which are almost negligible in the conventional histogram.



a) Conventional histogram of Figure 1-c.



b) Spatially weighted histogram of Figure 1-c.

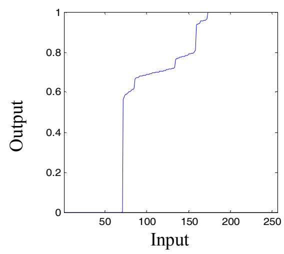
Figure 5. Comparison of conventional histogram and spatially weighted histogram.

3.2. Histogram Equalization

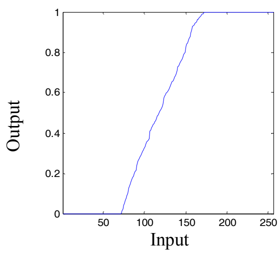
As SWHE is a histogram equalization based method, cumulative density functions are used as the gray scale transform functions to assign the new intensity values to the input image. The transform function for SWHE is defined as:

$$T(X_k) = \sum_{j=0}^{L-1} P_{SW\,X}(X_j),\ k = 0, 1, \ldots L-1 \tag{10}$$

The transform functions obtained by the histograms shown in Figures 5-a and 5-b are illustrated in Figures 6-a and 6-b. Figure 6-c is the enhanced version by mapping each pixel through the transform function of Figure 6-b. The transform function of GHE does not fully utilize the display range. Most pixels' gray-scale is concentrated on less than half of the output dynamic range, i.e. from 0.6 to 1, thus leading to a washed-out effect. In addition, the transform function changes abruptly at several specific gray-levels, which also results in some pseudo-edges in Figure 1-f. The transform function of SWHE fully uses the display ranges and the curve is rather smooth. The processed image Figure 6-c shows great contrast improvement and the transitional regions are preserved very well.



a) Gray level transform function of GHE.



b) Gray level transform function of SWHE.

c) SWHE result of Figure1-c.

Figure 6. Gray level transform function curves and SWHE result of Figure 1-c.

3.3. Maintaining the Image Brightness

The preservation of the mean brightness is of high demands in consumer electronics. Although, spatially weighted histogram equalization can effectively avoid the washed-out effect, the mean brightness may not be strictly constrained. Additional measures must be taken to maintain the origin image brightness. Some modifications are adopted on the grey scale transform function:

$$T_{SWHE}(X_k) = \frac{M_i}{M_o} T(X_k) \tag{11}$$

where M_i is the mean brightness of the original image, and M_o is the mean brightness of the output obtained after the equalization process. T_{SWHE} is the final grey scale transform function, and $T(X_k)$ is the grey scale transform function got by equation (10). This method works well when $M_o > M_i$, but if $M_o < M_i$, some pixels with high gray scale may saturate, affecting the image quality. So, in the case of $M_o > M_i$, we adopt another nonlinear brightness mapping function:

$$T_{SWHE}(X_k) = \frac{T(X_k)}{1+T(X_k)^{\frac{M_i}{M_o}}}\left(1+T(X_k)\right) \tag{12}$$

Since the human visual system has a weaker response to low brightness, so we stretch the lower grey levels while limiting the high grey scales to increase the average brightness of the image. Using the two brightness mapping functions, the mean output brightness can be almost modified to the mean input brightness.

4. Results and Discussions

In addition to SWHE, we also implement four other methods, which are GHE, BBHE, DSIHE, and RMSHE to demonstrate the performance of the proposed method. For the implementation of RMSHE, we set the recursion level to be equal to two. With this parameter setting, it will divide the input histogram into four sub-histograms. In SWHE, we adopt equation 6 as the weight function and K is set as the 99% of the cumulative histogram of the contrast factor. Simulation results using four test images are presented in Figures 8-11, respectively.

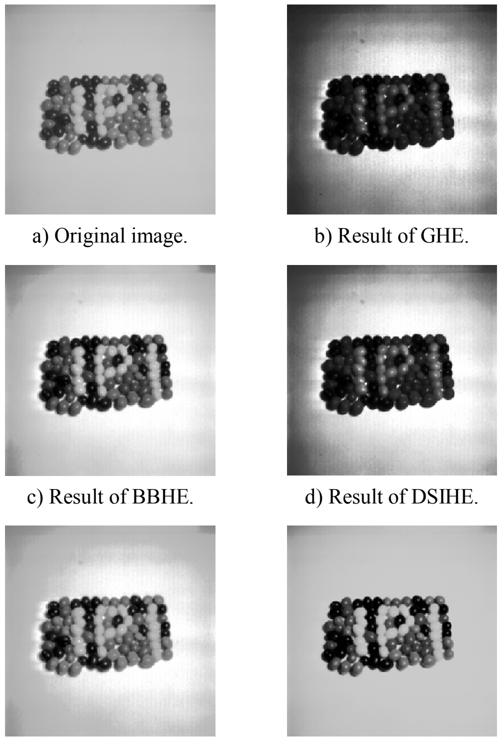
The brightness preservation described here is based on an objective measurement referred as Absolute Mean Brightness Error (AMBE). It is defined as the absolute difference between the input and the output mean as follow:

$$AMBE = \left|E(X) - E(Y)\right| \tag{13}$$

X and Y denote the input and output image respectively. Lower AMBE indicates that the brightness is better preserved. Table 1 lists the resulting AMBE for each of the above algorithms.

Table 1. The resulting AMBE for HE, BBHE, DSIHE, RMSHE and SWHE.

Image	GHE	BBHE	DSIHE	RMSHE	SWHE
Jelly Beans	46.042	13.721	17.335	11.166	0.025
Hand	151.393	25.493	18.183	4.391	0.216
Bottle	48.743	15.264	18.436	2.580	3.603
Aircraft	47.478	1.553	23.886	9.929	0.129
Castle	1.586	3.719	4.489	0.894	0.118

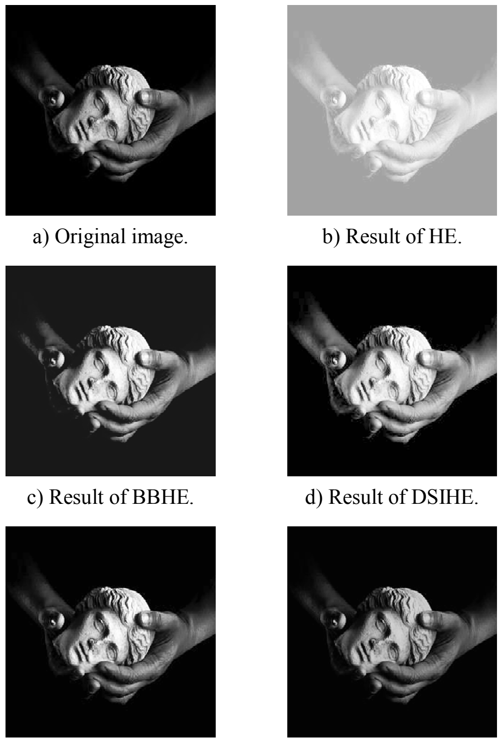


a) Original image. b) Result of GHE.

c) Result of BBHE. d) Result of DSIHE.

e) Result of RMSHE. f) Result of SWHE.

Figure 7. Results of all methods tested in this work using “Jelly beans”.



a) Original image. b) Result of HE.

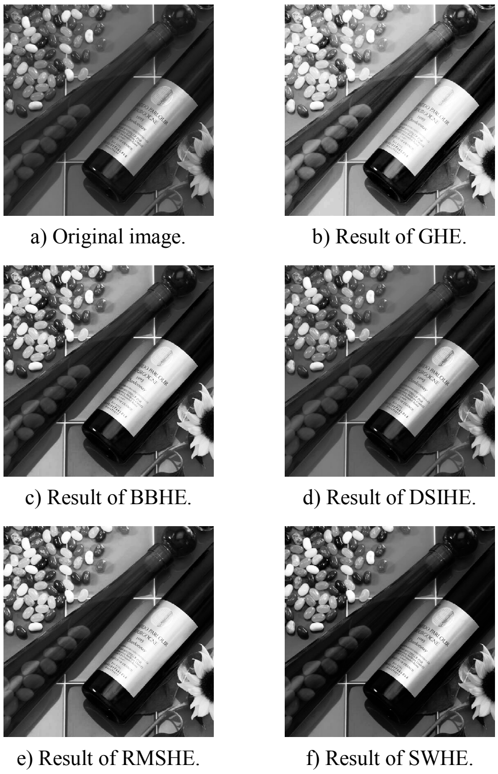
c) Result of BBHE. d) Result of DSIHE.

e) Result of RMSHE. f) Result of SWHE.

Figure 8. Results of all methods tested in this work using “Hand”.

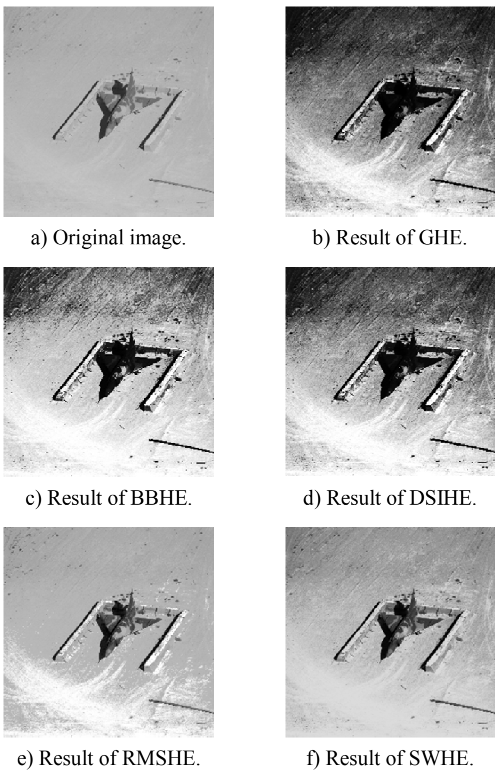
The test image jelly beans shown in Figure 7 is chosen as the representative of images with high mean brightness (bright background). Observe that resulting images of HE, BBHE, DSIHE, and RMSHE have mean brightness much darker compared to the original image and hence, results in unpleasant artifacts in the over-equalized background. Also, the beans region's contrast is reduced. These artifacts are not seen with

SWHE.SWHE has preserved the brightness very well and yielded a more natural enhancement.



a) Original image. b) Result of GHE.
c) Result of BBHE. d) Result of DSIHE.
e) Result of RMSHE. f) Result of SWHE.

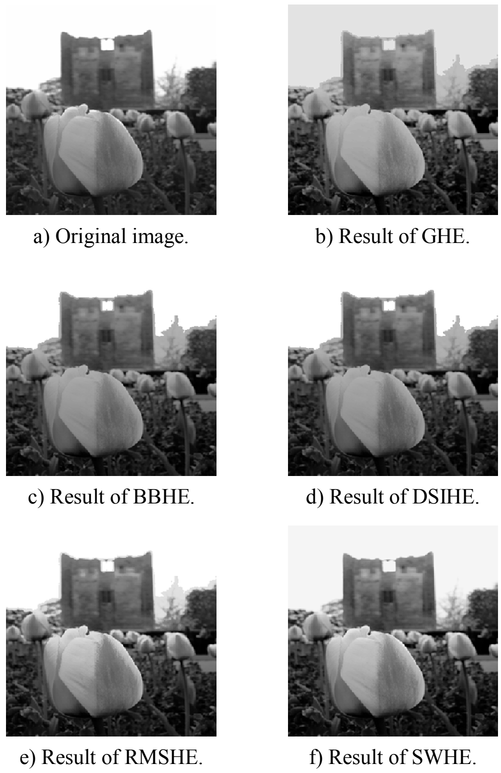
Figure 9. Results of all methods tested in this work using “Bottle”.



a) Original image. b) Result of GHE.
c) Result of BBHE. d) Result of DSIHE.
e) Result of RMSHE. f) Result of SWHE.

Figure 10. Results of all methods tested in this work using “Aircraft”.

The second test image is hand shown in Figure 8, although it has low mean brightness (dark background), actually, the input image is already has a good contrast. SWHE does not change the original image so much while the resultant images of GHE, BBHE, DSIHE, and RMSHE have experienced excessive changes in brightness.



a) Original image. b) Result of GHE.
c) Result of BBHE. d) Result of DSIHE.
e) Result of RMSHE. f) Result of SWHE.

Figure 11. Results of all methods tested in this work using “Castle”.

From the results of test image bottle shown in Figure 9, we can see that the results based on GHE, BBHE, and DSIHE seem to have larger global contrast than the ones based on RMSHE and SWHE. However, the mean brightness of GHE, BBHE, and DSIHE deviate very much from that of the original image. RMSHE and SWHE preserve the mean brightness very well. But SWHE shows better results in terms of visual perception and the characters on the label of the bottle are clearest to recognize.

It can be seen from the test image aircraft shown in Figure 10 that the object of interest, which is the aircraft, occupies only a small portion of the image and has almost the same intensity with its background. GHE, BBHE, and DSIHE, tend to enhance the take-off trail of the aircraft, while changing the pattern on the aircraft body. RMSHE enhances the target’s contrast well, while ignoring the details of the background. Result from SWHE indicates that, not only the details of the trail are enhanced but also the contrast of the aircraft is significantly improved.

Results of all methods using test image castle are shown in Figure 11. In this case, the focus on the input image is the flower, which is located at the front. As the objects behind is defocus, they appear blurred. The sky on the input image is presented by only one grey value. Some false contours appear near the transition between ground and sky in the resultant images of GHE, BBHE, DSIHE, and RMSHE, which are not seen at all in the result of SWHE. Using SWHE, the image's original brightness is well preserved and the enhancement yielded is more natural.

5. Conclusions

In this paper, we have proposed a novel contrast enhancement method using the spatially weighted histogram equalization. To reduce undesired artefacts associated with the conventional histogram, a weight function according to each pixel's spatial activity is introduced to make the contrast enhancement appropriate to the human observers. Then the grey scale transform function is calculated by accumulating this spatially weighted histogram. Finally, the transform function is modified to make sure that the mean output intensity will be almost equal to the mean input intensity. Therefore, the proposed method can achieve visually more pleasing contrast enhancement while maintaining the input brightness. More importantly, the amount of calculation and storage involved in this algorithm is rather low which makes it more competitive in real-time processing.

Acknowledgments

This work was supported by the Research and Innovation Plan for Graduate Students of Jiangsu Higher Education Institutions, China (Grant Number CXZZ11_0237). The authors would like to thank Xiaoxue Zhang (Nanjing University) for several useful discussions and suggestions.

References

[1] Chen D. and Ramli R., "Minimum Mean Brightness Error Bi-Histogram Equalization in Contrast Enhancement," *IEEE Transaction Consumer Electronics*, vol. 49, no. 4, pp. 1310-1319, 2003.

[2] Chen D. and Ramli R., "Contrast Enhancement using Recursive Mean-Separate Histogram Equalization for Scalable Brightness Preservation," *IEEE Transaction Consumer Electronics*, vol. 49, no. 4, pp. 1301-1309, 2003.

[3] Canny J., "A Computational Approach to Edge Detection," *IEEE Transaction Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679-698, 1986.

[4] Gonzalez C. and Woods E., *Digital Image Processing*, Prentice Hall, 2002.

[5] Kabir H., Al-Wadud A., and Chae O., "Brightness Preserving Image Contrast Enhancement using Weighted Mixture of Global and Local Transformation Functions," *International Arab Journal of Information Technology*, vol. 7, no. 4, pp. 403-410, 2010.

[6] Kim Y., "Contrast Enhancement using Brightness Preserving Bi-Histogram Equalization," *IEEE Transaction Consumer Electronics*, vol. 43, no. 1, pp. 1-8, 1997.

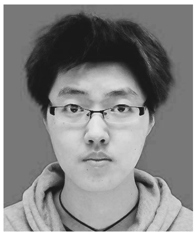
[7] Matkovic K., Neumann L., Neumann A., Psik T., and Purgathofer W., "Global Contrast Factor-a New Approach to Image Contrast," *in Proceedings of Computational Aesthetics in Graphics, Visualization and Imaging*, pp.159-168, 2005.

[8] Umbaugh E., *Computer Vision and Image Processing*, Prentice Hall, New Jersey, 1998.

[9] Wan Y., Chen Q., and Zhang B., "Image Enhancement Based on Equal Area Dualistic Sub-Image Histogram Equalization Method," *IEEE Transaction Consumer Electronics*, vol. 45, no. 1, pp. 68-75, 1999.

[10] Zuo C., Chen Q., Liu N., Ren J., and Sui X., "Display and Detail Enhancement for High-Dynamic-Range Infrared Images," *Optical Engineering*, vol. 50, no. 12, pp. 127401-127409, 2011.

[11] Zuo C., Chen Q., and Sui X., "Range Limited Bi-Histogram Equalization for Image Contrast Enhancement," *Optik-International Journal for Light and Electron Optics*, vol. 124, no. 5, pp. 425-431, 2013.



Chao Zuo received his BS degree from Nanjing University of Science and Technology, P.R. China, in 2009. He is currently pursuing his PhD degree in the School of Electronic Engineering and Optoelectronic Techniques, Nanjing University of Science and Technology, P.R. China. His research interests include signal and image processing, algorithms for infrared spectral sensors and imagers, digital holography and 3-D shape measurement. He is student member of OSA and SPIE.

Qian Chen received his BS, MS, and PhD degree from the School of Electronic Engineering and Optoelectronic Techniques, Nanjing University of Science and Technology. He is currently a professor and the dean of the Department of Optoelectronic Technology, Nanjing University of Science and Technology. He has led many research projects and authored more than 100 journal papers. His works have covered different topics, such as real-time digital image processing, optoelectronic imaging, electro-optical displaying technology, optoelectronic signal processing and transmission. He is member of SPIE and SID.

Xiubao Sui received his PhD degree in optical engineering from the School of Electronic Engineering and Optoelectronic Techniques, Nanjing University of Science and Technology. Now his research interests include the driver of infrared focal plane arrays and the theory research of infrared detectors.

Jianle Ren received his BS degree from Nanjing University of Science and Technology, in 2009. He is a PhD candidate in optical engineering from the School of Electronic Engineering and Optoelectronic Techniques, Nanjing University of Science and Technology. He is interested in infrared image processing and image fusion.