Image Sharpening Using Sub-Regions Histogram Equalization

Haidi Ibrahim, *Member*, IEEE, and Nicholas Sia Pik Kong, *Student Member*, IEEE.

**Abstract — ***Histogram equalization (HE) based methods are commonly used in consumer electronics. Histogram equalization improves the contrast of an image by changing the intensity level of the pixels based on the intensity distribution of the input image. This paper presents sub-regions histogram equalization (SRHE). First, the method partitions the image based on the smoothed intensity values, which are obtained by convolving the input image with a Gaussian filter. By doing this, the transformation function used by HE is not based on the intensity of the pixels only, but the intensity values of the neighboring pixels are also taken into the consideration. Besides, this paper also presents a more robust histogram equalization transformation function. Experimental results show that the proposed method is not only can enhance the contrast, but this method also successfully sharpens the image[1].*

Index Terms — Image contrast enhancement, histogram equalization, image sharpening.

I. Introduction

Image enhancement is one of the main areas in digital image processing field. Image enhancement is a process that changes the pixel's intensity of the input image, so that the output image will look subjectively better [1]. Image enhancement can improve the interpretability or perception of information contained in the image for human viewers. Image enhancement is also can be used to provide a better input for other automated image processing systems.

One of the commonly used image enhancement methods is histogram equalization (HE). HE is popular because this method is simple to be implemented. HE remaps the gray level of an image based on the probability distribution of the input gray levels. It flattens and stretches the dynamic range of the image's histogram. As a consequence, this results in an overall contrast enhancement [2].

Unfortunately, HE is not being recommended to be used directly for the implementation in consumer electronics, such as television. This is because HE normally produces undesirable artifacts such as the saturation artifact and washed out appearance. Therefore, to overcome the problem associated with HE, in 1997, Kim [3] has suggested that the image enhancement methods used for consumer electronics should be able to maintain the original input brightness in the output image. Kim has proposed a method known as brightness preserving bi-histogram equalization (BBHE), where this method divides the image histogram into two sub-histograms based on the mean value. These sub-histograms are then equalized independently.

Work by Kim has initiates many responses from researchers. In 1999, dualistic sub-image histogram equalization (DSIHE) has been proposed by Wan et al [4]. This method is similar to BBHE, except that DSIHE separates the histogram based on the median value. This is followed by Chen and Ramli [5] with minimum mean brightness error bi-histogram equalization (MMBEBHE). MMBEBHE also divides the histogram into two, but its separating point is selected based to the value that can "optimally" maintain the mean brightness.

Separation of the histogram into two sub-histograms is still not enough to maintain the mean brightness of the input image. Thus, HE based methods that separate the histogram into more than two sub-histograms has been introduced. This work is first introduced by Wongsritong et al [6] with multi-peak histogram equalization (MPHE). Following this, in the same framework, there are recursive mean-separate histogram equalization (RMSHE) [7], recursive sub-image histogram equalization (RSIHE) [8], dynamic histogram equalization (DHE) [9], brightness preserving dynamic histogram equalization (BPDHE) [10][11], multi histogram equalization (MHE) [12], brightness preserving weight clustering histogram equalization (BPWCHE) [13], dynamic range separate histogram equalization (DRSHE) [14], and piecewise linear approximation of cumulative distribution function (PLACDF) [15]. However, most of these methods put too much constrain on keeping the mean intensity value. As a consequence, not much enhancement could be obtained from most of these methods.

Furthermore, all of the above mentioned methods do not consider the spatial relationship between pixels and their surrounding. The transformation functions they use are purely based on the intensity value distribution. Therefore, in order to consider local details and to enhance local information, local histogram equalization based methods, such as contrast limited adaptive histogram equalization (CLAHE) [16], have been proposed. Yet, these methods have relatively higher computational cost, and thus, they are not so suitable to be implemented in consumer electronics.

[1]This work is partly supported by Ministry of Science, Technology and Innovation Malaysia, under ScienceFund Grant SF-01-01-05-SF0255, and by Universiti Sains Malaysia under Research Universiti Grant No. 814012.

Haidi Ibrahim is with the School of Electrical and Electronic Engineering, Engineering Campus, Universiti Sains Malaysia, 14300 Nibong Tebal, Penang, Malaysia (e-mail: haidi_ibrahim@ieee.org).

Nicholas Sia Pik Kong is with the School of Electrical and Electronic Engineering, Engineering Campus, Universiti Sains Malaysia, 14300 Nibong Tebal, Penang, Malaysia (e-mail: pik_kong@ieee.org).

Contributed Paper
Manuscript received April 15, 2009

Thus, in this paper, we present a new methodology of image enhancement using histogram equalization. This method partitions the input image, in spatial domain, into several sub-images, based on the smoothed intensity values. By doing this, spatial relationship among the pixels is also taken into consideration for the transformation. In addition to this new method, this paper also presents a more robust transformation function for HE.

The organization of this paper is as follows. First, section II describes the alteration we introduce to HE transfer function in order to make it more robust. Section III presents the methodology of the sub-regions histogram equalization (SRHE) that we use in this work. Then, experimental results are presented in section IV. Lastly, section V presents the conclusion obtained from this work.

II. Robust HE Transformation Function

For a given image $\boldsymbol{X}$, the probability density function for intensity x, $p(x)$ is given by:

$$p(x) = \frac{n_x}{N}, \qquad \text{for } x = 0,1,\ldots,L-1 \tag{1}$$

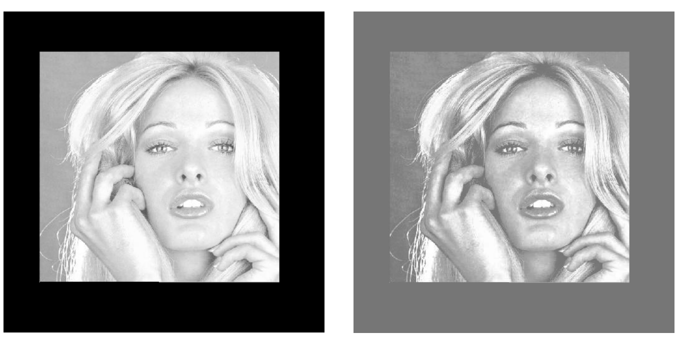
where N is the total number of pixels in the image and n_x is the number of occurrence of intensity x in the image.

In the standard implementation of HE, the transformation function $T(x)$, maps the input image into the entire dynamic range, $[X_0, X_{L-1}]$, by using the following equation.

$$T(x) = X_0 + (X_{L-1} - X_0).\sum_{k=X_0}^{x} p(k) \tag{2}$$

From here, if (i,j) are the spatial coordinates of the pixel in the image, the output image produce by HE, $\boldsymbol{Y}=\{Y(i,j)\}$, can be expressed as in equation (3).

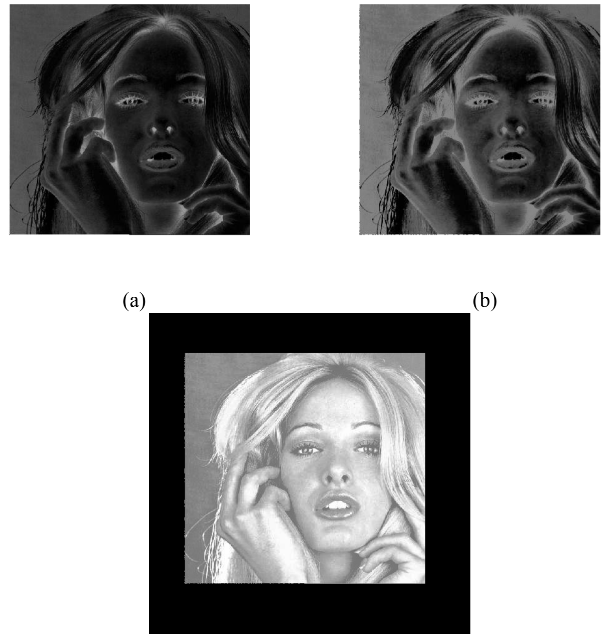
$$\boldsymbol{Y} = T(\boldsymbol{X}) = \{f(X(i,j)) \mid \forall X(i,j) \in \boldsymbol{X}\} \tag{3}$$



(a) (b)

Fig. 1. (a) The input image. (b) The corresponding output image after HE process.

An example of an image transformed by using equation (2) is shown in Fig. 1. Fig. 1(b) shows the output image from HE process. In theory, the histogram of this image has been already equalized. However, lets consider the following case. If we first inverse the intensity of the input image, equalize it, and then re-inverse the output, mostly we will not get the same output as the one without intensity inversion process. An example is shown in Fig. 2.



(a) (b) (c)

Fig. 2. (a) The negative image of Fig. 1(a). (b) The HEed version of image (a). (c) The negative image of (b).

Thus, in order to obtain the same results, we propose to take the average of these two images (e.g. the average of image shown in Fig. 1(b) and Fig. 2(c)). This is done as follows. First, consider that the transformation of the image without inversion process is T_1, as given by equation (2). Then, the transformation for the image with inversion process is T_2, and is given by equation (4).

$$T_2(x) = X_0 + (X_{L-1} - X_0).\left(1 - \sum_{k=x}^{X_{L-1}} p(k)\right) \tag{4}$$

However, the average of the output images from T_1 and T_2 is actually can be obtained by using the average of these transformation functions. This new transformation function is given as:

$$T_{new}(x) = \frac{1}{2}\left(T_1(x) + T_2(x)\right)$$

$$T_{new}(x) = \frac{1}{2}\left(\begin{array}{l} X_0 + (X_{L-1} - X_0).\left(\sum_{k=X_0}^{x} p(k)\right) + \\ \left(X_0 + (X_{L-1} - X_0).\left(1 - \sum_{k=x}^{X_{L-1}} p(k)\right)\right) \end{array}\right)$$

$$T_{new}(x) = \frac{1}{2}\left(\begin{array}{l} X_0 + (X_{L-1} - X_0).\left(\sum_{k=X_0}^{x} p(k)\right) + \\ \left(X_0 + (X_{L-1} - X_0).\left(\sum_{k=X_0}^{x-1} p(k)\right)\right) \end{array}\right)$$

$$T_{new}(x) = \frac{1}{2}\left(\begin{array}{l} X_0 + (X_{L-1} - X_0).\left(p(x) + \sum_{k=X_0}^{x-1} p(k) \right) + \\ \left(X_0 + (X_{L-1} - X_0).\left(\sum_{k=X_0}^{x-1} p(k) \right) \right) \end{array} \right)$$

$$T_{new}(x) = X_0 + (X_{L-1} - X_0).\left(0.5p(x) + \sum_{k=X_0}^{x-1} p(k) \right) \quad (5)$$

(a) (b)

Fig. 3. The HEed images obtained by using equation (5). (a) Without the inversion of the input image. (b) With the inversion of the input image.

The results obtained by using equation (5) are shown in Fig. 3. As shown by this figure, the same result will be obtained, regardless whether inversion is involved or not. This proves the robustness of the transformation function. Thus, in this work, we will use equation (5) for our transformation function, rather than equation (2).

III. Sub-Regions Histogram Equalization (SRHE)

Unlike the methods used in [3]-[15] that segments the images into several sections based on the intensity histogram, sub-regions histogram equalization (SRHE) that is proposed in this work, segments the input image into several sub-images, in spatial domain. The segmentation is carried out based on the weighted average value of the pixel with its surrounding, obtained by convolving the input image with a Gaussian filter.

Gaussian filter is used to smooth the input image through a two dimensions (2D) convolution operator. This method is used to reduce the high frequency components of the image. This is because Gaussian filter is actually a low-pass filter. Coefficients for a 2D Gaussian filter are calculated by using the following equation:

$$G(i,j) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{i^2 + j^2}{2\sigma^2} \right) \quad (6)$$

where in this equation, (i,j) are the coordinates relative to the center of the filter, and σ is the standard deviation. After all the coefficients of the Gaussian filter have been calculated, these values need to be normalized such that the sum of the coefficients must be equal to one. This step is crucial in order to maintain the signal strength in constant regions.

In order to fit the Gaussian mesh into the filter, the value of σ should be properly chosen. There is actually a relationship between σ and the size of Gaussian filter [17]. Assume that we use a square Gaussian filter of size $W \times W$. If W is an odd integer, $W=2R+1$. The relationship between σ and R is given as:

$$\sigma = \sqrt{-\frac{R^2}{2\ln(0.001)}} \quad (7)$$

Therefore, there is only one parameter need to be tuned by the user, which is the size of the filter (i.e. W or R).

In SRHE, the input image is divided into several sub-images based on the integer values obtained from the convolution with Gaussian filter. As a low-pass filter, Gaussian filter reduces the high frequency components of the image, leaving the low frequency components, which are normally the base of the objects in the image. Thus, by grouping the pixels based on this smoothed value is analogous to group the pixels into their corresponding objects. Therefore, by doing this, the intra-object contrasts could be increased. It is worth noting that if the input image has L gray levels, then the image will be divided into L sub-images.

After the image is successfully divided into sub-regions, the equalization process for each sub-group is carried out independently from each other. In SRHE, the transformation function used is based on equation (5), where X_0 and X_{L-1} in this equation present the minimum intensity value and the maximum intensity value, respectively, of the sub-region before equalization is taking place.

IV. Experimental Results

Two experiments have been carried out in this paper. The first experiment investigates the relationship between the sizes of the Gaussian filter used with the performance of SRHE. The second experiment compares the performance of SRHE with some histogram equalization based methods, subjectively. Those methods are the standard HE [1], BBHE [3], MPHE [6] and CLAHE [16]. The input images for these experiments are the commonly used images in the field of digital image processing. All of these images are with size of 512×512 pixels.

Fig. 4 shows the effect of changing the size of the Gaussian filter used in the process of creating image's sub-regions. This figure shows that as we increase the size of the Gaussian filter, more emphasize will be given by SRHE to the edges. The overall brightness of the images is almost the same for all output images, visually. However, for the output images produces from larger Gaussian filter, the enhancement obtained is not so natural. Furthermore, larger smoothing filter requires more processing time. On the other hand, the output obtained by using Gaussian filter of size 3×3 pixels is not much enhanced. Therefore, for the implementation in consumer electronics, Gaussian filter of size 5×5 pixels is recommended.

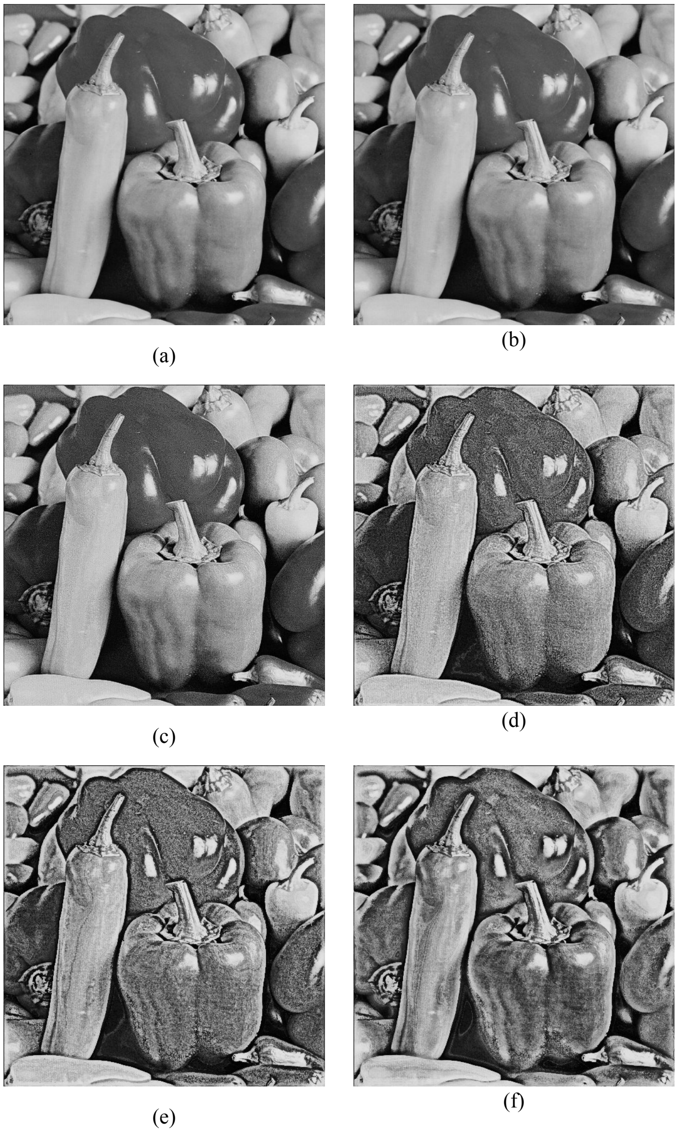


Fig. 4. (a) The input image of "*Peppers*". The corresponding SRHEed images, by using Gaussian filter of size (b) 3×3 pixels, (c) 5×5 pixels, (d) 11×11 pixels, (e) 21×21 pixels, and (f) 41×41 pixels.

Fig. 5 and Fig. 6 show our comparative experiment to evaluate SRHE method with some selected methods. For this experiment, the size of Gaussian filter used in SRHE is set to 5×5 pixels. For the implementation of CLAHE, the block size used is set to 16×16 pixels. The clipping limit for CLAHE is set to 45% from the maximum value of the input histogram.

As shown in Fig. 5 and Fig. 6, the standard HE method tends to change the intensity level abruptly, thus fails to maintain the mean brightness of the input image. CLAHE, although requires the most processing time compared to the methods used in this experiment, produces unnatural enhancement. Although the clipping limit is introduce to control the enhancement of the noise, the noise is still clearly visible on the output image of CLAHE. CLAHE has two parameters to be tuned, which are the clipping limit and the size of the block. However, it is difficult to decide the suitable values for these parameters in order to get a good result.

BBHE, MPHE, and our proposed method (i.e. SRHE), produce visually the same overall brightness, similar to the mean brightness of the input image. However, BBHE and MPHE still produce saturation artifact in their output image. For example, in Fig. 5(c) and (d), the bright saturation region is obviously visible on the right side of the image. Outputs produced from SRHE do not have this problem. Furthermore, the outputs look slightly sharper than the original image.

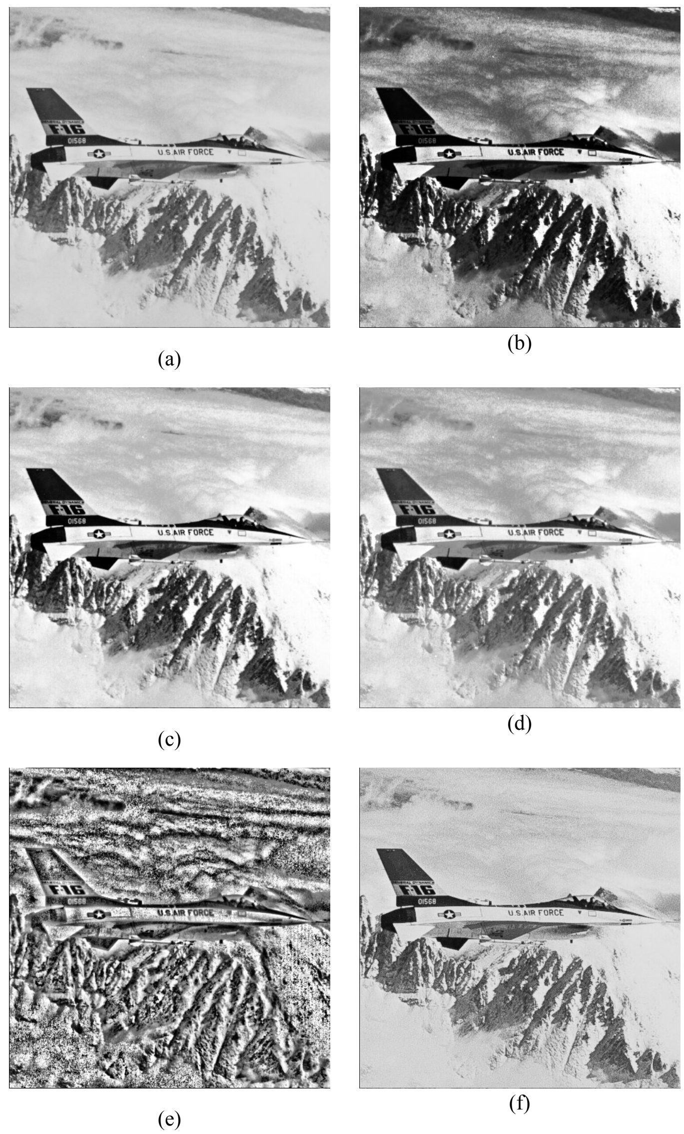


Fig. 5. (a) The input image of "*Jet*". (b) HEed image. (c) BBHEed image. (d) MPHEed image. (e) CLAHEed image. (f) SRHEed image.

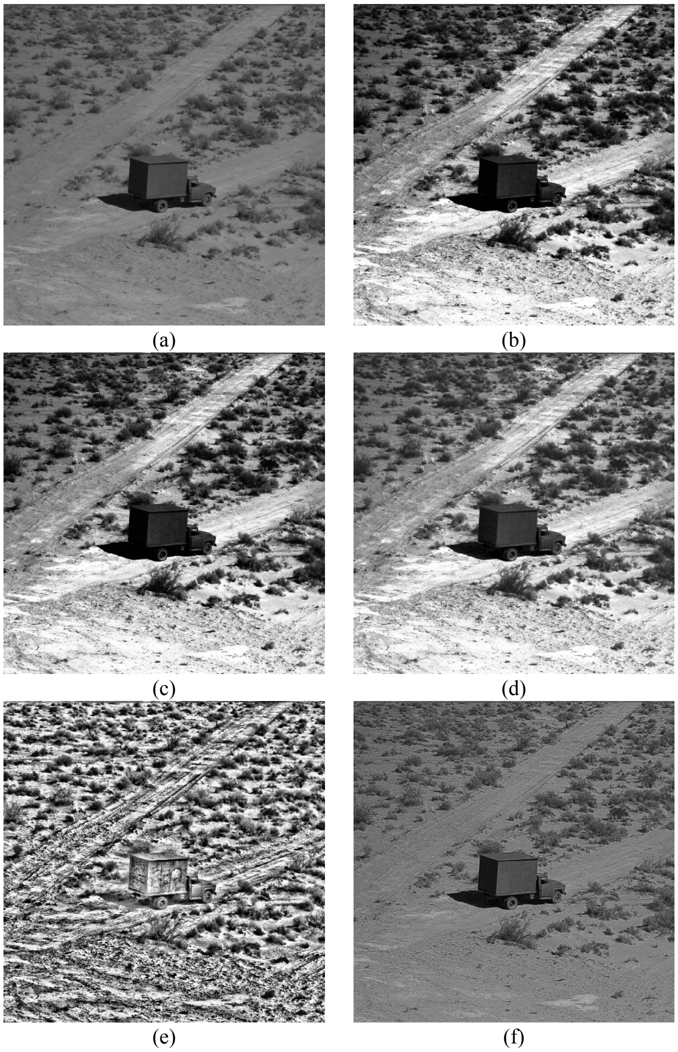


Fig. 6. (a) The input image of "*Truck*". (b) HEed image. (c) BBHEed image. (d) MPHEed image. (e) CLAHEed image. (f) SRHEed image.

I. CONCLUSION

This paper presents a new histogram enhancement based method, known as sub-regions histogram equalization (SRHE). As the image is divided into sub-images based on its weighted average value of neighboring pixels, SRHE is able to improve the contrast within the objects. Restriction of dynamic range of each sub-image enables SRHE to maintain the similar brightness intensity level as the input image. The overall transformation function which is not a monotonic function, sharpen the image. The sharpness of the output image can be controlled by using suitable Gaussian filter size. As the enhancement is done based on the histogram, SRHE is relatively has a shorter processing time compared with local histogram equalization based methods. Therefore, SRHE is suitable to be employed in consumer electronics for the purpose to sharpen or enhance the local details of the image.

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Haidi Ibrahim (M'07) was born in July, 12, 1978 in Kelantan, Malaysia. In 2000, he received the B.Eng degree in electronic engineering from Universiti Sains Malaysia, Malaysia. He received his Ph.D degree in image processing from Centre for Vision, Speech and Signal Processing (CVSSP), University of Surrey, United Kingdom in 2005. His research interest includes image enhancement, noise reduction, image segmentation, 3D visualization, and virtual reality.

Nicholas Sia Pik Kong (M'07) was born in January, 21, 1984 in Sarawak, Malaysia. He received his B.Eng degree in electronic engineering from Universiti Sains Malaysia in 2008. He is currently pursuing M.Sc degree by research mode at the same university. His research interest includes image enhancement and multidimensional signal processing.