

LETTER

Image Contrast Enhancement Using Adaptive Slope

Hwa-Soo WOO[†], *Nonmember* and Jong-Wha CHONG^{†a)}, *Member*

SUMMARY In this paper, we propose an algorithm for contrast enhancement based on Adaptive Histogram Equalization (AHE) to improve image quality. Most histogram-based contrast enhancement methods have problems with excessive or low image contrast enhancement. This results in unnatural output images and the loss of visual information. The proposed method manipulates the slope of the input of the Probability Density Function (PDF) histogram. We also propose a pixel redistribution method using convolution to compensate for excess pixels after the slope modification procedure. Our method adaptively enhances the contrast of the input image and shows good simulation results compared with conventional methods.

key words: adaptive contrast enhancement, first derivative, convolution redistribution scheme

1. Introduction

Most scenery capture devices have some limitations ranging from ISO sensor sensitivity to saturation in the image sensor. These kinds of problems can produce low contrast images. Because of the limits of human vision, low contrast images appear unclear. To overcome this phenomenon, histogram modification-based contrast enhancement methods have been proposed.

Histogram modification methods are divided into two large groups: Global Histogram Equalization (GHE) and Local Histogram Equalization (LHE). GHE techniques use a single histogram mapping function from a whole image [1]–[3]. However, GHE methods have a structural problem that may cause exaggerated contrast enhancement and limits improvement in contrast in local image areas where the pixel values are similar or equal. To suppress this drawback, LHE based methods have been suggested [4]–[6]. The CLAHE method [6] divides the whole image into a group of small partial images and redefines pixels with clipping-limit which regulates the maximum slope of the mapping function to avoid excessive contrast enhancement. After that, clipped pixels are redistributed to all grayscale levels uniformly to compensate for the total pixel number. Then bilinear interpolation is performed. Although CLAHE can effectively limit excessive contrast enhancement, it cannot deal with under-enhancement and counteract it adaptively because of the fixed value of the clipping-limit parameter. Q.Y. Tian et al. [9] insist that their algorithm adaptively enhances each sub-image based on the characteristics of local

information. Though their method is relatively simple, its output result is limited to Histogram Equalization (HE) and Contrast Stretching. Other LHE techniques are described in [7], [8].

In this paper, we will propose a new contrast enhancement algorithm by regulating the slope of the PDF input histogram based on LHE. Also we propose a new approach to the pixel redistribution method to supplement the total number of pixels and extend the dynamic range. This paper is organized as follows. In Sect. 2, we present our method for contrast enhancement. Simulation results are shown in Sect. 3 and the conclusion in Sect. 4.

2. Proposed Algorithm

2.1 Concept of Algorithm

As previously mentioned, CLAHE enhances image contrast by implementing a clipping-limit to avoid excessive contrast enhancement caused by an unduly concentrated pixel population. However, clipped pixels have the same enhancement rate, and relatively small pixel population graylevels will become clearly distinguishable after the mapping function procedure. Finally, undesirable spot noise will appear in the enhanced image. Thus, grayscale levels of different pixel populations should be treated differently based on the number of pixels in the histogram; relatively large pixel population levels have to be enhanced more than comparatively low pixel number grayscale levels because the low contrast results from a lot of similar pixels in the input image. We therefore conserve the shape of the input histogram for noise suppression by modifying the slope of the input PDF histogram.

A method of modifying a slope is illustrated in Fig. 1. When a part of the input histogram is as shown Fig. 1 (a), the pixel population of the $x + 1_{th}$ bin should be larger than that of the x_{th} bin to preserving input histogram after histogram modification. Then, the absolute difference between the pixel populations of the two bins creates a slope which is equal to the first derivative at this point and is proportional to the volume of contrast between two bins. If excessive contrast enhancement occurred between the x_{th} and $x + 1_{th}$ bins in the Fig. 1 (a), the pixel population of the $x + 1_{th}$ bin should be decreased as in Fig. 1 (b). On the other way, if under-enhancement takes place in Fig. 1 (c), the input histogram has to be modified to increase the slope between the two bins by increasing the pixel population of the $x + 1_{th}$

Manuscript received October 31, 2013.

Manuscript revised December 28, 2013.

[†]The authors are with the Department of Electronics and Computer Engineering, Hanyang University, Korea.

a) E-mail: jchong@hanyang.ac.kr (Corresponding author)

DOI: 10.1587/transinf.E97.D.1382

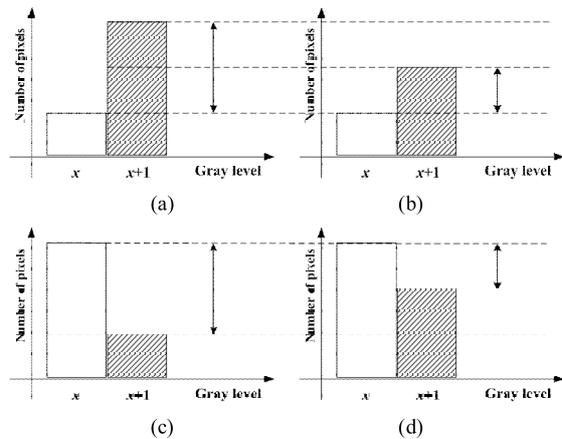


Fig. 1 Examples of first derivative modification. First row (Left to right): over contrast enhancement in histogram bins and its solution. Second row (Left to right): under enhancement of histogram bins and its solution.

bin as in Fig. 1 (d) because the volume of the contrast is inversely proportional to the absolute difference between two bins. We will define this slope modification process as First Derivative modification and the slope in the PDF histogram as the First Derivative (FD).

In the following sections, we will discuss three FD modification weight functions for adaptively adjusting the FD depending on the characteristics of the input histogram. Moreover, we will propose a new approach to redistribute clipped pixels, which are clipped by an FD modification procedure, by using convolution.

2.2 FD Modifying Weight Functions

To reform the FD, we will generate weights in accordance with the characteristics of input histograms. The weights to regulate each bin are decided by three functions: luminance, pixel concentration, and pixel population. The equation is as follows:

$$w(x) = w_{lum}(x) \cdot w_{con}(x) \cdot w_{pop}(x) \quad (1)$$

where the $w(x)$ is weight for FD modification; the $w_{lum}(x)$ is weight function about luminance; the $w_{con}(x)$ is weight function regarding the pixel concentration; the $w_{pop}(x)$ is weight function related to pixel population; and the g is the number of grayscale levels.

Each generated $g-1$ element of $w(x)$ is multiplied by FD to regulate over- and under-enhancement in the image.

Commonly, the saturation phenomenon of the image sensor appears in the brighter region. Z. Hameed [8] claimed that the intensity of image data signals is decreased when the image of an area is in saturation. In the image regions suffering from this saturation phenomenon, intensity levels of pixels only have small differences from each other. Therefore, histograms in this region are more likely to have peak-shaped features because their pixel intensity levels are concentrated. To overcome this defect, brighter regions of images have to be enhanced to become clear with obvious

features. The equation of the weight function related to luminance is expressed as:

$$w_{lum}(x) = \exp\{\gamma_{lum} \cdot (x - 255)\} \quad (2)$$

where the γ_{lum} is parameter which controls weight function $w_{lum}(x)$ and x is pixel intensity of input histogram.

Another weight function is related to the pixel concentration. A histogram represents the probability distribution of the pixel intensities from an image. If an image contains similar brightness value pixels, ranging from flat wall to skin, the peak pixel distribution will appear in its histogram. This concentrated peak-shaped histogram remains in a shifted formation after an equalization process [8]. Its shape results in a steep slope of the CDF mapping function, resulting in excessive contrast enhancement. Therefore it is important to determine the peak for rearranging the FD of the input histogram.

As in previous studies [9], we utilize the coefficient of variation with a mean deviation method to detect highly concentrated areas in the image histogram. The FD controlling weight regarding concentration in the PDF histogram is then obtained by:

$$w_{con}(x) = \exp[\gamma_{con} \cdot \{(M.D_x/m_x) - 1\}] \quad (3)$$

$$M.D_x = \frac{1}{bins} \sum_{i=x-\text{floor}(bins/2)}^{x+\text{floor}(bins/2)} |h(i) - m_x| \quad (4)$$

where $w_{con}(x)$ is weight function regarding histogram concentration, γ_{con} is the controlling parameter, $M.D_x$ is the mean deviation, $bins$ is the number of histogram bins used, floor is the round toward negative infinity function, m_x is the mean pixel population value in the histogram bins used, $h(i)$ is the pixel population at the i th gray-level.

The third weight function is related to pixel population. As discussed earlier, contrast enhancement is directly proportional to the amount of pixel population in the histogram. Thus, our proposed method regulates the population of each bin by manipulating the FD with a weight function in contrast with CLAHE method which simply cuts over-populated pixels at all grayscale levels in the histogram uniformly. Based on the average pixel population of the histogram, as the pixel number increases, the FD should be slight rather than precipitous. This weight function $w_{pop}(x)$ is expressed as:

$$w_{pop}(x) = \exp\{-\gamma_{pop} \cdot p(x)\} \quad (5)$$

where γ_{pop} is the controlling constant parameter and $p(x)$ denotes the difference between the mean pixel population and the number of pixels at the x th grayscale level.

If the input PDF histogram has a uniform mean pixel population distribution over all graylevels, its CDF will have a linear function feature and histogram matching will not work for pixel transformation. However, if the pixel population in the input histogram is greater than the mean pixel number, the slopes in the CDF will be changed to the values of the input image pixels. Thus, the function $p(x)$ has conditionally different computations. This function is computed

as:

$$p(x) = \begin{cases} \frac{h(x)-(s_{hist}/g)}{s_{hist}}, & h(x) > (s_{hist}/g) \\ 0, & \text{Otherwise} \end{cases} \quad (6)$$

where $h(x)$ is the pixel population at the x th gray level, s_{hist} indicates number of pixels in the histogram and g refers to the number of gray levels.

2.3 Convolution Redistribution Scheme

In the previous sub chapter, we discussed three weight functions for modifying the FD of the input histogram, which may cause over and under contrast enhancement. After the FD modification process using three weight functions, most FD remain constant or decrease because the generated weights have values of 1 and 0 to preserve the original shape of the input histogram. Therefore, there is a need for compensating pixels that are clipped from the original histogram.

To the end, we suggest a new method of pixel redistribution, which performs with convolution, and we call it as the Convolution Redistribution Scheme. The purpose of using convolution is to prevent undue pixel count and brightness changes. When convolution is performed on the input histogram, the resultant histogram will be symmetrical and the mean brightness in the histogram will not be different from that of the original histogram. Using this method, the number of pixels in the output histogram will become the same as the original sub-image and dramatic changes in brightness will be prevented. The equation we propose is calculated as:

$$h_{out}(x) = h_{mod}(x) + E \cdot \frac{w_{conv}(x)}{\sum_{i=1}^g w_{conv}(i)} \quad (7)$$

where $h_{out}(x)$ represents one of the pixel complemented histograms of the sub-images, $h_{mod}(x)$ is an FD modified histogram, E is the number of clipped pixels, g is the number of gray levels and $w_{conv}(x)$ is the convolution processed weight for pixel redistribution.

The $w_{conv}(x)$ is composed of the convolution between the Gaussian distribution mask and the FD modified histogram. In this process, we should carefully select the parameters of the Gaussian distribution mask because if the mask has a sharp peak shape, the redistributed histogram may return to the shape of the original input histogram. It will cause excessive or low contrast enhancement. Inversely, if the mask has gradual slope, the resulting histogram would be almost uniformly reallocated and be unable to enhance the contrasting image. The equation convolution processed weight $w_{conv}(x)$ is as follows:

$$w_{conv}(x) = h_{mod}(x) * g(x) = \sum_{\tau=1}^g h_{mod}(\tau) \cdot g(x - \tau) \quad (8)$$

$$g(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left\{ -\frac{(x - m)^2}{2\sigma^2} \right\} \quad (9)$$

where $g(x)$ is the Gaussian distribution mask, m is the mean

or expectation of the distribution, σ is the standard deviation and σ^2 is the variance.

3. Simulation Result

As discussed in the procedure in Sect.3, our proposed method has been simulated to evaluate contrast enhancement. The contrast enhancement is intuitive and subjective. Therefore, to give an accurate assessment, we compare two widely used global and local approach methods, the HE and the CLAHE. In our experiment, all the methods are implemented in MATLAB. Most of the simulation results in this paper are realized by setting parameters γ_{lum} to 0.01, γ_{con} to 0.01, γ_{pop} to 60, $bins$ to 21, σ to 50, the length of convolution mask to 101 bins, and bilinear interpolation is performed to eliminate the blocking effect.

Figure 2 represents simulation results from three different methods and two conventional algorithms are performed with default parameters. The results of HE demonstrate that local contrast is too low and there is too low and there is excessive enhancement in the hair and skin in the Tiffany image, on the surface of the peppers in the Pepper image, and in the shaded area in the Pentagon image. Also, CLAHE shows that noise enhancement and washout appear in the right eye and dark region of the left hand in the Tiffany image, on the surface of the peppers and in the dark area be-

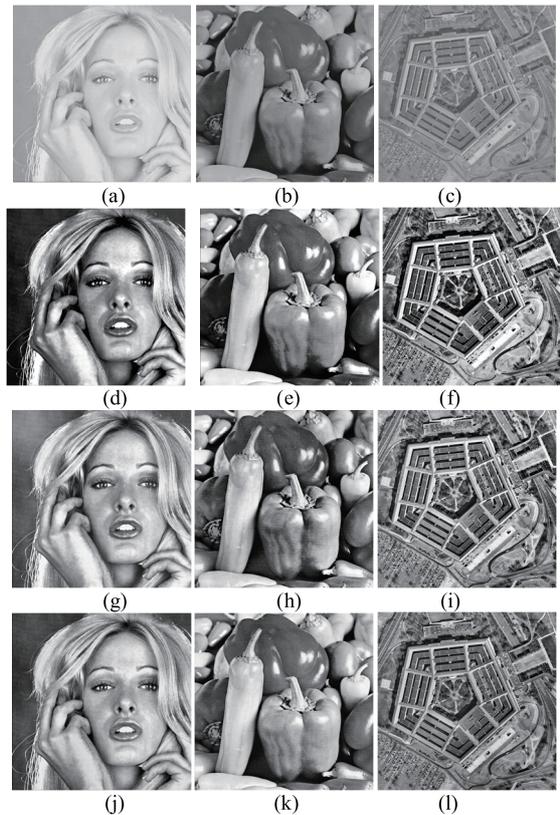


Fig.2 Simulation result images from different contrast enhancement techniques. From left to right column: Tiffany, Peppers, and Pentagon images. From top to bottom: original, HE, CLAHE, proposed algorithm.

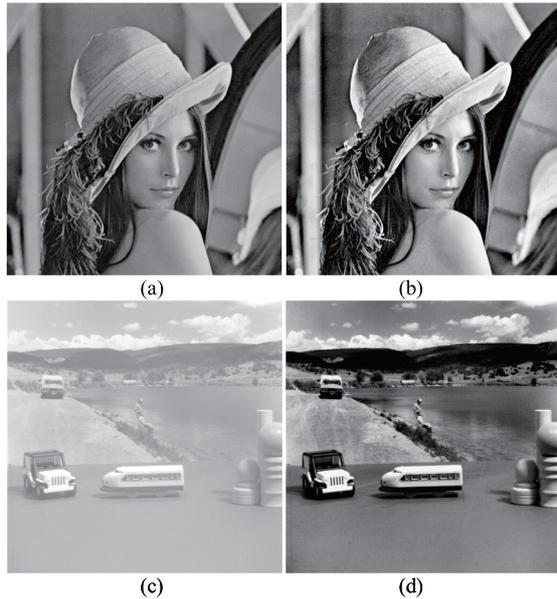


Fig. 3 Simulation results from our algorithm. Left and right column: original image, proposed algorithm, respectively.

tween the two peppers in the peppers image, and at the heli-stop on the right side of the Pentagon in the Pentagon image. Comparing two conventional algorithms, our method indicates a more natural visual look, more detailed information and more noise suppression ability. Original images and contrast-enhanced images obtained using our proposed method are shown in Fig. 3. Compared to the original image shown in Fig. 3 (a), pleats on the hat were more recognizable and the area at the hat brush was clearer without noise amplification of the black surface of the right curved background after in our method. Also, while Fig. 3 (c) shows an unclear and undistinguishable image, clouds in the sky, automobile tracks on the road, and toys on the downside of the display without intensifying noise on the downside of the flat region can be seen in the image enhanced by our proposed algorithm, as shown in Fig. 3 (d).

4. Conclusion

In this paper, we have introduced a novel method of contrast enhancement. Our proposed method is based on AHE and each sub-image is separately enhanced by modifying the FD

of the corresponding histograms. All the FD are regulated by three weight functions which depend on the characteristics of the histogram. Also, clipped pixels are supplemented by a convolution redistribution scheme. Our contrast enhancement method prevents noise enhancement in dark regions and increases the contrast in bright regions, resulting in more detailed information.

Acknowledgments

This research was supported by the MSIP (Ministry of Science, ICT & Future Planning), Korea, under the ITRC (Information Technology Research Center) support program supervised by the NIPA (National IT Industry Promotion Agency) (NIPA-2013-H0301-13-1011). The IDEC provide research facilities for this study.

References

- [1] R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, Prentice-Hall, New Jersey, 2001.
- [2] Y.T. Kim, "Enhancement using brightness preserving bi-histogram equalization," *IEEE Trans. Consum. Electron.*, vol.43, no.1, pp.1–8, Feb. 1997.
- [3] S.-D. Chen and A.R. Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement", *IEEE Trans. Consum. Electron.*, vol.49, no.4, pp.1310–1319, Nov. 2003.
- [4] R. Hummel, "Image enhancement by histogram transformation," *Comp. Graph. Image Process.*, vol.6, pp.184–195, 1977.
- [5] S.M. Pizer, E.P. Amburn, J.D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B.H. Romeny, J.B. Zimmerman, and K. Zuiderveld, "Adaptive histogram equalization and its variations," *Computer Vision, Graphics, and Image Processing*, vol.39, pp.355–368, 1987.
- [6] S.M. Pizer, R.E. Johnston, J.P. Ericksen, B.C. Yankaskas, and K.E. Muller, "Contrast-limited adaptive histogram equalization: speed and effectiveness," *Visualization in Biomedical Computing, 1990, Proc. First Conference on*, pp.337–345, 22–25 May 1990.
- [7] C.S. Josephus and S. Remya, "Multilayered contrast limited adaptive histogram equalization using frost filter," *IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 2011, pp.638–641, 22–24 Sept. 2011.
- [8] Z. Hameed and C.Y. Wang, "Contrast enhancement by adaptive mapping function with local information," *2011 IEEE 54th International Midwest Symposium on Circuits and Systems (MWSCAS)*, pp.1–4, Aug. 2011.
- [9] Q.Y. Tian and J. Duan, "Local histogram modification based contrast enhancement," *2012 International Conference on Audio, Language and Image Processing (ICALIP)*, pp.1–6, July 2012.