Adaptive Contrast Enhancement Using Gain-Controllable Clipped Histogram Equalization

Taekyung Kim and Joonki Paik, *Member*, IEEE

Abstract — *Histogram equalization is a simple and effective method for contrast enhancement as it can automatically define the intensity transformation function based on statistical characteristics of the image. However, it tends to alter the brightness of the entire image, which it is not suitable for consumer electronic products, where preservation of the original brightness is essential to avoid annoying artifacts. This paper presents a new contrast enhancement method for generalization of the existing bi-histogram equalization (BHE) and recursive mean-separate histogram equalization (RMSHE) methods.*

The proposed method is referred to gain-controllable clipped histogram equalization (GC-CHE) to provide both histogram equalization and brightness preservation. More specifically adaptive contrast enhancement is realized by using clipped histogram equalization with controllable gain. The clipping rate is determined based on the mean brightness, and the clipping threshold is determined based on the clipping rate. The clipping rate is adaptively controlled to enhance the contrast with preserving the mean brightness. It is mathematically proven that the mean brightness of the output image converges to that of the input image with adaptive controlled. Simulation results show that the proposed GC-CHE method outperforms existing histogram-based methods, such as HE, BHE, and RMSHE, in various situations[1].

Index Terms — Contrast enhancement, Clipped histogram equalizaion.

I. Introduction

Histogram equalization (HE) has been widely used for contrast enhancement of images by uniformly distributing the probability of intensity values. As a result, it flattens and stretches the dynamic range of the original, which improves overall contrast of the image [1]. Applications of histogram equalization (HE) are found in many application areas such as medical image processing, texture synthesis, and speech recognition, to name a few. Recently, its application area has extended to video enhancement for digital broadcasting and internet-based streaming.

In spite of its fundamental advantage, HE has a significant drawback of changing the brightness globally, which results in either under-saturation or over-saturation of important regions. From this reason, for the implementation of contrast enhancement in consumer electronics, it is advised that the lost intensity values by the histogram processing should be minimized in the output image [2]. The first challenge of modified histogram has been proposed by using bi-histogram equalization (BHE) [2]. In this method, based on the mean value the histogram is divided into two groups, which are independently equalization. It has been analyzed both mathematically and experimentally that this technique can better preserve the original brightness to a certain extent.

An alternative approach, referred as dualistic sub-image histogram equalization (DSHE), has been proposed by Wan et al [3]. DSHE is similar to BHE, except that histogram separation is based on median value instead of the mean value. The threshold of the separation is chosen such that two histograms have the equal number of pixels. It is claimed that DSHE is better than BHE in terms of preserving both brightness and entropy of the input image. Each histogram with cumulative probability density of 0.5 guarantees the maximum entropy in the output image. In spite of evenly distributed histograms BHE and DSHE cannot meet the higher degree of brightness preservation to avoid undesired artifacts.

Chen and Ramli have proposed an improved contrast enhancement scheme referred as recursive mean-separate histogram equalization (RMSHE) [4]. This technique iteratively performs the BHE, where the mean of each sub-histograms is calculated, and sub-histograms are then further divided into two parts based on this mean values. This process is repeats for a prespecified number of n times. Thus, this technique will produce separately equalized 2^n sub-histogram. It is claimed that RMSHE has good brightness preservation technique when the number of iterations is large, because the output mean converges to the input mean. However, too many number of iterations result in null processing, where this condition, the output image is exactly the copy of the input image.

In addition to drawbacks of individual methods, the common challenge to histogram-based methods is the amplification of noise along with the enhanced contrast of the image. Noise amplification results in significant degradation of image quality. Accordingly, without a priori information of noise behavior, the performance of contrast enhancement is limited to a certain degree.

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Taekyung Kim is with the Department of Image Engineering, Chung-Ang University, Seoul, Korea. (e-mail: kimktk@wm.cau.ac.kr).

Joonki Paik is with the Department of Image Engineering, Chung-Ang University, Seoul, Korea. (e-mail: paikj@cau.ac.kr).

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As a solution for controlling noise amplification as well as preserving the original brightness the clipped histogram equalization (CHE) method has been proposed [5]. The CHE algorithm controls maximum value of histogram by clipping histograms higher than the prespecified threshold. Although CHE can best preserve the original intensity distribution, its contrast enhancement is weaker than HE methods. In this paper we present the gain controllable CHE (GC-CHE) method for solving above mentioned problems in contrast enhancement.

This paper is organized as follows. Section II summarizes fundamental theory of HE, and describes several related methods using the unified terminologies. Section III describes the proposed GC-CHE method its major applications. Section IV gives experimental results, and section V concludes the paper.

II. FUNDAMENTALS OF HISTOGRAM EQUALIZATION

This section summarizes fundamental background of standard histogram equalization (SHE), and compares several important variants of SHE.

A. Standard Histogram Equalization

Let $r_k \in [0, L-1]$ be the $k-th$ intensity level, and then the probability density function (PDF) r_k is defined as

$$r_k = \frac{n_k}{n}, \quad for \quad k = 0,1,\cdots,L-1, \tag{1}$$

where n_k represents the number of occurrences of r_k, and n the total number of samples in the input image. Note that $P(r_k)$ is called the histogram of the input image. Based on the theory of probability, the cumulative density function (CDF) is defined as

$$c(r_k) = \sum_{j=0}^{k} p(r_j), \quad for \quad k = 0,1,\cdots,L-1. \tag{2}$$

Note that $c(r_{L-1}) = 1$ by definition. HE is a scheme that maps the input image into another image that has a uniform histogram by using CDF as the intensity transformation function defined as

$$T(r) = r_0 + r_{L-1} - r_0 \bullet C(r). \tag{3}$$

then the result of HE can be expressed as

$$g(x,y) = T(f(x,y)), \tag{4}$$

where f and g respectively represents the input and output images of HE, and (x,y) the $2D$ coordinate of images.

B. Bi-Histogram Equalization

Let m denote mean intensity image $f(x,y)$, where $m \in \{r_0, r_1, \cdots, r_{L-1}\}$. Based on the mean, $f(x,y)$ is decomposed into two sub-images f_L and f_U as

$$\begin{aligned} & f = f_L \cup f_U \quad and\ f_L \cap f_U = \emptyset, \\ & f(x,y) = f_L(x,y) + f_U(x,y), \quad and\ f_L(x,y) \bullet f_U(x,y) = 0, \quad for \quad all\ (x,y) \end{aligned} \tag{5}$$

where

$$f_L(x,y) \in \{0,1,\cdots,m-1\}, \tag{6}$$

and

$$f_U(x,y) \in \{m, m+1, \cdots, L-1\}, \tag{7}$$

We can compute two histograms corresponding to the sub-images f_L and f_U as

$$f_L(r_k) = \frac{n_k^L}{n^L}, \quad for \quad k = 0,1,\cdots,m-1, \tag{8}$$

and

$$f_U(r_k) = \frac{n_k^U}{n^U}, \quad for \quad k = m, m+1, \cdots, L-1, \tag{9}$$

where n_k^L and n_k^U respectively the number of occurrences of r_k in f_L and f_U, and n^L and n^U respectively the total number of samples in f_L and f_U.

Note that $n^L = \sum_{k=0}^{m-1} n_k^L$, $n^U = \sum_{k=m+1}^{L-1} n_k^U$ and $n = n^L + n^U$. Corresponding CDFs of for f_L and f_U are respectively defined as

$$c_L(r_k) = \sum_{j=0}^{k} P_L(r_j), and \quad c_U(r_k) = \sum_{j=m}^{k} P_U(r_j) \tag{10}$$

Note that $c_L(r_{m-1}) = 1$ and $c_U(r_{L-1}) = 1$ by definition.

Similar to the case of HE, two intensity transformation functions of BHE are defined as

$$T_L(r) = r_0 + (r_{m-1} - r_0) c_L(r), \tag{11}$$

and

$$T_U(r) = r_m + (r_{L-1} - r_m) c_U(r) \tag{12}$$

Based on these transform functions, the decomposed sub-images are independently equalized and the equalized sub-images are combined to produce the output of BHE, which is expressed as

$$g(x,y) = T_L(f_L(x,y)) + T_U(f_U(x,y)). \tag{13}$$

If one notes that $0 \le c_L(r), c_U(r) \le 1$, it is easy to see that $T_L(f_L)$ equalizes the sub-images f_L over the range $[0, m-1]$ whereas $T_U(f_U)$ equalizes the sub-image f_U over the range $[m, L-1]$.

As a consequence, the input image f is equalized over the entire dynamic range $[0, L-1]$ such that a sample less than the input mean is mapped to $[0, m-1]$ and another samples greater than the mean is mapped to $[m, L-1]$.

C. Recursive Mean-Separate Histogram Equalization

Decomposition of image by the mean value before HE, which is referred to mean-separation, can preserve a certain level of brightness. This is indicated by Equation (14) where input mean, m has equal weight as the middle gray level, that is the output mean denoted by m_g. In fact, RMSHE is equivalent to BHE with recursion level 1. In order to achieve higher brightness preservation, that multiple, recursive mean separations are needed.

Supposed that $f(x,y)$ is twice separated into four portions based on the means of the two sub-histograms, m_L and m_U. Defined as

$$m_L = \frac{\int_0^m rp(r)dr}{\int_{X_0}^{X_m} p(r)dr} = 2\int_0^m rp(r)dr \tag{14}$$

and

$$m_U = \frac{\int_m^{L-1} rp(r)dr}{\int_m^{L-1} p(r)dr} = 2\int_m^{L-1} rp(r)dr, \tag{15}$$

where

$$\int_0^m p(r)dr = \int_m^{L-1} p(r)dr = 1/2 \tag{16}$$

Because $f(x,y)$ is assumed to have two identical distributions around m [2].

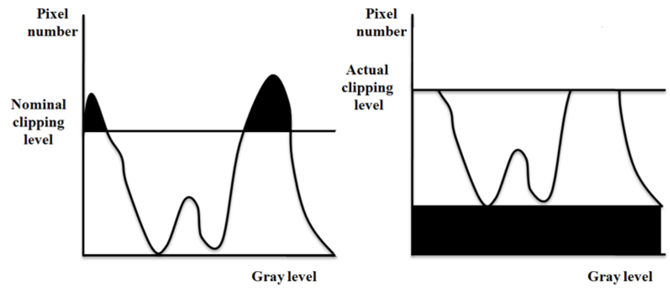
The result of RMSHE with recursion level 2, for example, can be formulated as

$$g(x,y) = T_{LL}(f_{LL}(x,y)) + T_{LU}(f_{LU}(x,y)) + T_{UL}(f_{UL}(x,y)) + T_{UU}(f_{UU}(x,y)) \tag{17}$$

where T_{PQ} and f_{PQ}, for $P,Q \in \{L,U\}$, respectively represents one of four intensity transformation functions and one of four decomposed images.

D. Clipped Histogram Equalization

Clipped histogram equalization (CHE) is far more effective for contrast enhancement than the existing HE-based methods [4]. Given a pre-specified upper limit, CHE re-distributes a part of histogram over the limit to the entire dynamic range as shown in Fig. 1.



(a) (b)

Fig. 1. Histograms (a) before and (b) after CHE.

III. Gain Control for Clipped Histogram Equalization

Most contrast enhancement techniques cannot avoid noise amplification during the contrast extension process. Noise amplification in the pre-processing stage results in serious degradation of image and/or video quality of a general image processing system.

The proposed method is devised to overcome limit of the existing CHE method in that it sacrifices the amount of contrast for controlling noise and for preserving the original intensity level.

A. Clipped Level Control

The proposed GC-CHE method can dynamically control the clipping level, and appropriately re-distribute dynamic range by locally regulating the clipping gain. By computing the PDF and the CDF using Equations (18) and (19), respectively, contrast enhancement is accomplished using Equation (20) with a proper clipping level C.

$$pdf[k] = \frac{1}{MN} \| \{i,j\} \mid f(i,j) = k \|, \tag{18}$$

$$cdf[k] = \sum_{t=1}^{k} pdf[t], \tag{19}$$

and

$$g(i,j) = C \cdot cdf[f(i,j)]. \tag{20}$$

In order to solve the noise amplification problem in enhancing the contrast of a low light-level image, we adjust the contrast elevation ratio according to the input image and compensate contrast using the gain control method given in Equations (21) and (22).

$$B_{cr} = \{\, k,\ if\ \ cdf[k] = 0.5\}, \tag{21}$$

and

$$CR = 100 - B_{cr} \times 0.4. \tag{22}$$

where B_{cr} represents mean brightness, CR represents the clipped-rate, whose value is in the range of [0-100]. Fig. 2 illustrates the proposed histogram re-distribution method, where T_{cr} represents 50% intensity of the histogram. In the dark region, the clipping ratio increases, and the slope of the CDF becomes linear so that the output is the same to the input intensity. The low and high local gains represent clipping levels of black (dark) and white (bright) regions, respectively. After fixing the global gain, we adaptively control the global gain rate in the range [0-100]. In case the rate is 100%, histogram equalization is applied on the global image without adjusting the local gain. With the given global gain, contrast enhancement is performed by controlling the local gain.

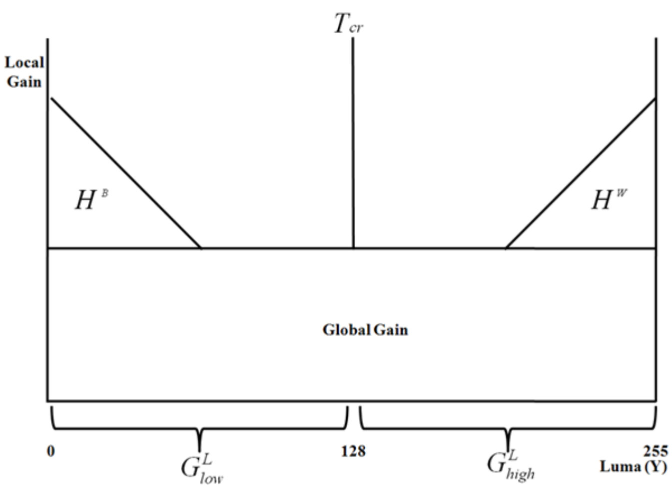


Fig. 2. Histogram redistribution using controllable high and low clipping levels.

B. Local Gain Control

The first region, that is the black level region, and the second region, that is the white level region, can be determined in the clipped histogram, so that contrast correction in the black level region is different from that of the white level region over the entire image. Accordingly, the local gain may be divided into the first local gain low, the second local gain high. The sum of the first local gain and the second local gain may be the same as the local gain.

The high and low local gains can be calculated as

$$\begin{aligned} G^L_{low} &= (G^T - G^G)/2 \\ G^L_{high} &= (G^T - G^G)/2 \end{aligned} \tag{23}$$

where G^T, G^G, G^L_{low}, and G^L_{high} respectively represents the total gain, the global gain, the first local gain, and the second local gain, respectively.

G^T is the ratio of a clipped portion to the original brightness histogram, so its distribution is similar to those of G^G, G^L_{low} and G^L_{high}. The global gain is uniformly distributed throughout the clipped histogram.

The local gain is distributed to a particular region of the clipped histogram. The global gain may be controlled in the range of [0-100]. For example, when the global gain is 100%, the local gain is 0%. In this case, a uniform gain is used over the entire region without the control of the local gain, which corresponds to the existing CHE. When Equation (23) is used, the first gain is the same to the second gain. For example, when the clipping rate is 20%, the upper 20% of the original histogram is clipped and total gain becomes 20 which are distributed as a local gain and a global gain. When the global gain is determined to be 50%, it has a value of 10. When the first and the second local gains are determined using Equation (23), each of them has a value of 5. Here, the first and the second local gains may be the same or different from each other.

After the global gain and the local gain are determined, the clipped histogram is corrected using the corresponding gains. The clipped histogram is corrected by summing the clipped histogram and the ratio of the global gain to the total number of gray levels as

$$H^G = \tilde{P} + \frac{G^G}{k}, \tag{24}$$

where k represents the total number of gray levels, H^G the histogram corrected using the global gain, and $\tilde{P}$ the clipped histogram. Thereafter, black level correction using the first local gain may be accomplished using

$$H^B = \begin{cases} \tilde{P}, & if \quad k \geq k_B \\ \tilde{P} + \dfrac{2 \bullet G^L_{low}}{k_B^2} \times k, & otherwise \end{cases}, \tag{25}$$

where H^B represents the black-level corrected histogram and k_B the gray level defining the black level region. According to (25), the histogram remains the same in the region brighter than k_B, and is corrected to become darker than k_B.

White level correction using the second local gain is expressed as

$$H^w = \begin{cases} \tilde{P}, & if \quad k \geq k_w \\ \tilde{P} + \dfrac{2 \bullet G^L_{high}}{k_w^2} \times k, & otherwise \end{cases}, \tag{26}$$

where H^w represents the white-level corrected histogram and k_w the gray level defining the white level region. According to (26), the histogram remains the same in the region brighter k_w and is corrected to become brighter than k_w.

IV. Experimental Results

A. Test Environment

In order to implement and test the proposed contrast enhancement algorithm in the real-time environment we made a graphical user interface (GUI) that can interactively control parameters and display mages before and after contrast enhancement, as shown in Fig. 3. The computer on which the GUI is running combines a CCD camera module and a frame-gabber. In order to control the amount of contrast enhancement, we adjust the clipping value, and control the noise amplification using local gain control. In addition to input and output images, the proposed GUI provides the histogram and the intensity to transformation function.

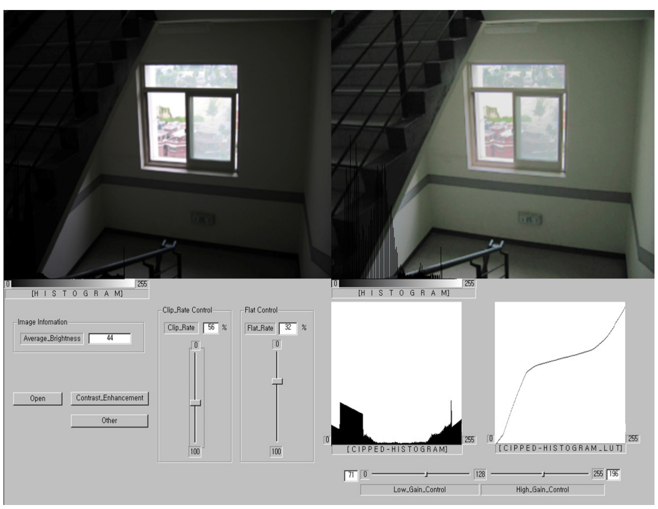
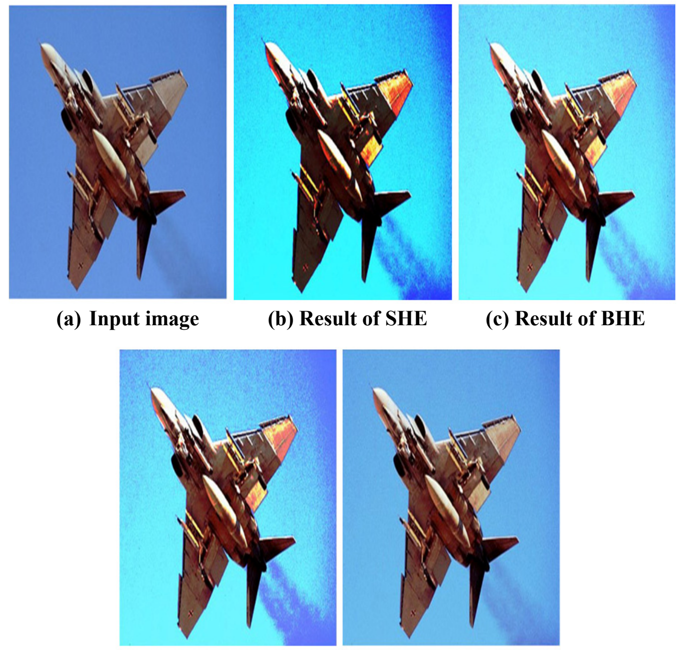


Fig. 3. The proposed GUI for testing the contrast: enhancement algorithm including input and output images, parameter control, histogram, and the intensity transformation function.

B. Performance Evaluation

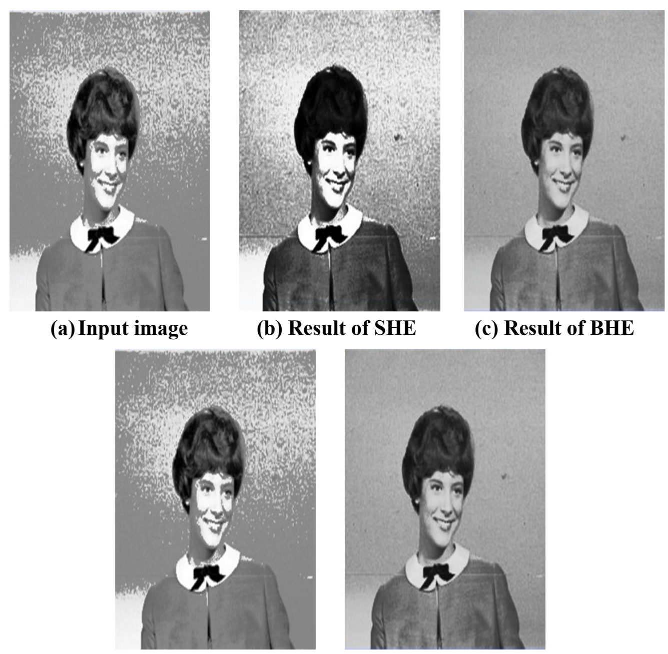
In order to analyze and compare the proposed algorithm with existing methods we use *Jet* and *Girl* images as shown in Fig. 4 and Fig. 5. It is to note that the result of SHE, BHE, and RMSHE are all exhibit unnaturally enhanced contrast. The result of GC-CHE shows that the proposed algorithm can preserve the brightness up to the required level as well as gives natural enhancement the entire image.



(a) Input image (b) Result of SHE (c) Result of BHE

(d) Result of RMSHE (e) Result of the GC-CHE

Fig. 4. Performance comparison using *Jet* image.



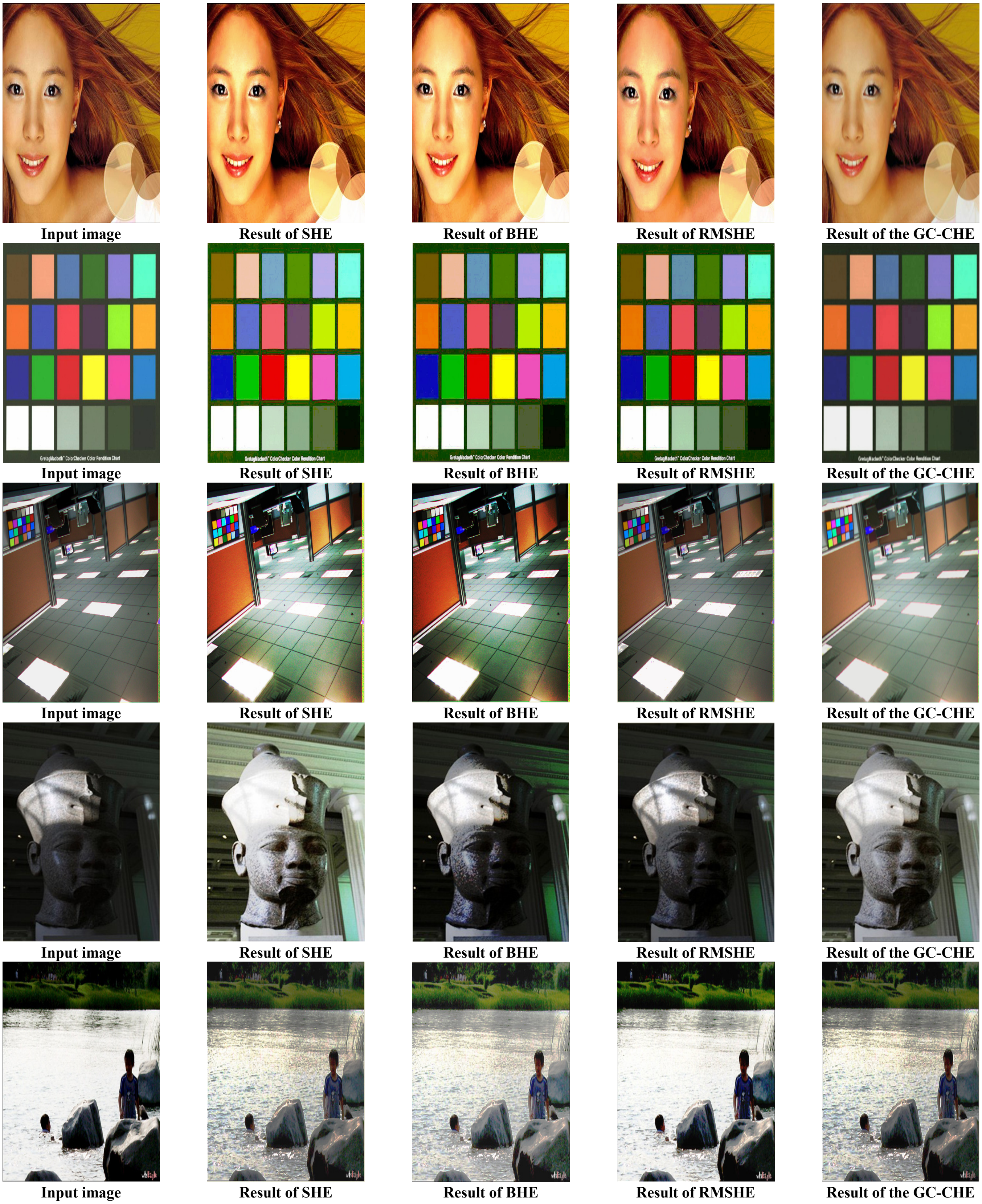
(a) Input image (b) Result of SHE (c) Result of BHE

(d) Result of RMSHE (e) Result of the GC-CHE

Fig. 5. Performance comparison using *Girl* image.

C. Comparative Analysis

For the comparative analysis of GC-CHE, we also implemented existing histogram-based contrast enhancement algorithm such as SHE, BHE, and RMSHE. We used 24 test images for both objective and subjective evaluations.


Input image
Result of SHE
Result of BHE
Result of RMSHE
Result of the GC-CHE
Input image
Result of SHE
Result of BHE
Result of RMSHE
Result of the GC-CHE
Input image
Result of SHE
Result of BHE
Result of RMSHE
Result of the GC-CHE
Input image
Result of SHE
Result of BHE
Result of RMSHE
Result of the GC-CHE
Input image
Result of SHE
Result of BHE
Result of RMSHE
Result of the GC-CHE

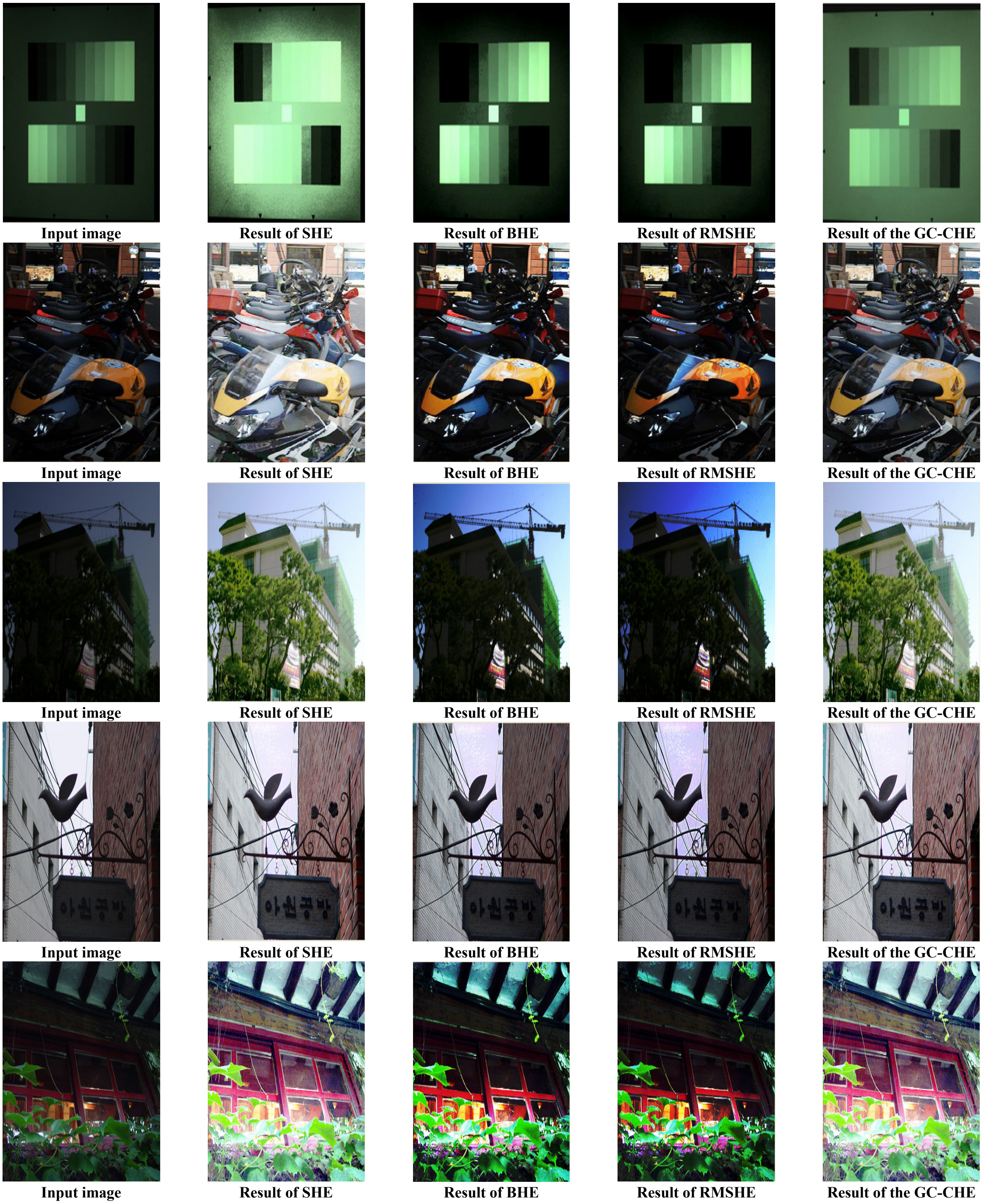


Fig. 7. Contrast enhancement results.

The entire set of experimental results are shown in Fig. 7 which only the proposed GC-CHE method successfully enhanced all the test images without introducing undesirable artifacts, such as saturation.

For the objective measure of the enhancement performance we use average absolute mean brightness error (AAMBE), defined as

$$AAMBE = \frac{1}{N}\sum_{n=1}^{N}\left|E_n(X) - E_n(Y)\right|, \tag{27}$$

where N represents the total number of test images, $E(X)$ the average intensity of $N-th$ the test image N, and $E(Y)$ the average intensity of the corresponding output image. Smaller value of AAMBE shows that the average intensity of the input and the output images are similar, and that the corresponding method can preserve the mean brightness of the image.

TABLE I
AAMBE MEASURE OBTAINED FROM 24 INPUT IMAGES.

Method	AAMBE
SHE	28.19
BHE	8.64
RMSHE	4.09
GC-CHE (Proposed)	**17.32**

Table 1 presents AAMBE measure for all methods tested in this work. From the table, we found that GC-CHE can preserve the mean brightness better than any existing methods. Both noise amplification and mean brightness variation problems have been successfully dealt with using the proposed method.

Fig. 6 shows the comparison of brightness variations for some test images, where the proposed method gives the minimum variation.

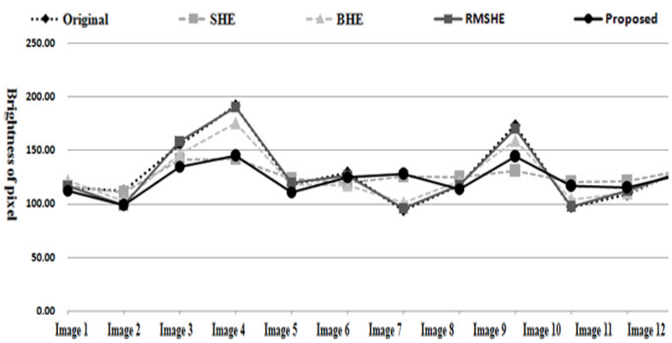


Fig. 6. Comparison of brightness variations of all test methods for 12 selected test images.

V. CONCLUSIONS

In this paper, an adaptive contrast enhancement algorithm, referred as gain controllable clipped histogram equalization (GC-CHE), is proposed to preserve brightness of the input image using the clipped histogram.

The GC-CHE is a generalization of the existing SHE, BHE, and RMSHE in terms of brightness preservation. The main idea is to preserve the original brightness based on the clipped histogram equalization.

Simulation results on various test images prove that the proposed algorithm outperforms the existing methods in terms of both objective and subjective criteria. Furthermore, similar other HE-based algorithm GC-CHE has a simple, regular computational structure, and can be implemented in real-time on either an embedded system or a system-on-chip.

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Taekyung Kim was born in Pusan, Korea in 1974. He received his B.S. degree in computer engineering from Silla University, Pusan, Korea, in 2002. He received his M.S. degree in computer information engineering from Silla University, Pusan, Korea, in 2004. Currently he is pursuing Ph.D. degree in image processing at Chung-Ang University. His research interests include image enhancement and segmentation of image and video, background generation and surveillance video applications.

Joonki Paik was born in Seoul, Korea in 1960. He received the B.S. degree in control and instrumentation engineering from Seoul National University in 1984. He received the M.S. and the Ph.D. degrees in electrical engineering and computer science from Northwestern University in 1987 and 1990, respectively. After getting the Ph.D. degree, he joined Samsung Electronics, where he designed the image stabilization chip sets for consumer's camcorders. Since 1993, he has worked for Chung-Ang University, Seoul, Korea, where he is currently a professor in the Department of Imaging. From 1999 to 2002, he was a visiting professor at the Department of Electrical and Computer Engineering at the University of Tennessee, Knoxville. He is currently the Director of Seoul Future Contents Convergence Cluster supported by Seoul R&BD Project and the head of the Image Processing and Intelligent Systems Laboratory supported by the Korean Ministry of Education under the Brain Korea 21 Project and by the Korean Ministry of Information and Communication under ITRC-HNRC.