A Simple Histogram Modification Scheme for Contrast Enhancement

Yen-Ching Chang and Chun-Ming Chang

Abstract —*Histogram equalization (HE) is a widely used contrast enhancement (CE) method in image processing applications. The algorithm can be easily implemented; however, it tends to transform the average brightness of an image toward the middle of the gray scale. In addition, unpleasant artifacts often appear in the enhanced images. In order to overcome these drawbacks, various HE-based methods which aim at specific issues were proposed. Some of them might overlook the problems inherent in the implementations of histogram equalization and histogram specification (HS). This paper presents a simple histogram modification scheme to solve those problems according to the characteristic of implementation. Two boundary values of the support of histogram are found and set to corresponding values, respectively. The probability density function of an image is then recomputed and the updated mapping function is used to perform histogram equalization. Experimental results show that the proposed approach can effectively improve the quality of images enhanced by histogram equalization and specification methods, and even histogram redistribution methods such as gray-level grouping (GLG).*[1]

Index Terms —Histogram equalization, contrast enhancement, histogram specification, histogram modification .

I. INTRODUCTION

Contrast enhancement plays an important role in the field of image processing applications. The objective of this method is to make an image clearly recognized for a specific application. One of the most popular contrast enhancement methods is histogram equalization (HE). The mechanism of HE is to transform the gray levels of an image to a uniform histogram based on the probability of occurrence of gray levels in an input image. In general, HE will flatten out the probability distribution of an image and increase its dynamical range. However, the effectiveness of HE depends on the contrast of the original image. The lower the contrast, the more the effectiveness is. Since its simplicity and ease to implement, it is usually applied in many areas including medical image processing, texture synthesis, and speech recognition.

Theoretically, the output histogram of a histogram equalized image is supposed to be uniform [1], but it is generally not due to the discrete nature of pixel intensities. Therefore, in spite of its high performance for a large portion of applications, it is seldom applied in consumer electronic such as TV. In addition, HE will also make the average brightness toward the middle gray level of an image regardless of the input image, and introduce objectionable artifacts and unnatural contrast effects. This makes the visual quality of processed imagery unsatisfactory.

In order to overcome those problems, Kim proposed a brightness preserving bi-histogram equalization (BBHE) method [2]. His algorithm preserves the mean brightness of a given image very well, compared to typical or global HE. The mechanism of BBHE is to first decompose an input image into two subimages based on the mean of the input image. Two histograms are then histogram equalized independently. Similar to BBHE, Wang *et al*. proposed a dualistic sub-image histogram equalization (DSIHE) method, which separates an input image into two subimages based on the median of an image, to improve the performance of HE [3]. The basic idea of the algorithm is to maximize the entropy of an output image. For comparison, the authors illustrated its effectiveness in an image with a large PDF being at gray level 0. They claimed that the quality of an image enhanced by DSIHE is better than that of BBHE according to the criteria of mean, average information content (AIC), and background gray level (BGL).

In order to achieve higher degree of brightness preservation without annoying artifacts, Chen and Ramli proposed minimum mean brightness error bi-histogram equalization (MMBEBHE) [4]. Their method uses the minimum absolute mean brightness error (AMBE)—the absolute difference between input mean value and output mean value, to compute the threshold gray level to separate the input histogram. The function of the threshold gray level is similar to that of the mean value for BBHE or that of the median value for DSIDE. Since this algorithm is time consuming, the authors adopted an approximation approach to compute integer values of AMBE recursively to facilitate real time implementation. At the same time, Chen and Ramli also proposed another enhancement scheme called recursive mean-separate histogram equalization (RMSHE) [5]. The mean of each subhistogram is computed as the threshold gray level iteratively. This process is repeated r times, and generates 2^r subhistograms. It is mathematically confirmed that the mean brightness of the output image will converge to the one of the input image as the iteration number increases. In addition, the repeating nature of RMSHE provides scalable brightness preservation.

[1] Y.-C Chang is with Department of Applied Information Sciences, Chung Shan Medical University, Taichung, 40201, Taiwan, R.O.C. (e-mail: nicholas@csmu.edu.tw).

C.-M. Chang is with Department of Information Science and Applications, Asia University, Taichung, 41354, Taiwan, R.O.C. (e-mail: cmchang@asia.edu.tw).

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Similar to RMSHE, Sim et al. proposed a recursive sub-image histogram equalization (RSIHE) approach [6], which separates the histogram based on the median separation approach, instead of the mean separation one used by the RMSHE. RMSHE and RSIHE improve the results enhanced by BBHE and DSIHE, but also invoke two problems: how to choose the optimal value of r and the number of subhistograms must be power of two.

In order to deal with above problem, Abdullah-Al-Wadud et al. proposed a dynamic histogram equalization (DHE) technique [7]. DHE partitions the image histogram into subhistograms based on the local minima of the smoothed histogram and assigns a specified gray level range to each partition before equalizing them separately. However, DHE does not consider the preserving of brightness. For this purpose, Ibrahim and Kong proposed brightness preserving dynamic histogram equalization (BPDHE) [8]. This method partitions the image histogram based on the local maxima of the smoothed histogram. It then assigns a new dynamic range to each partition. Finally the output intensity is normalized to make the mean intensity of the resulting image equal to the input one.

On the other hand, Wang and Ward proposed a convenient and effective mechanism to control the enhancement process, called weighted thresholded histogram equalization (WTHE) [9]. The results using WTHE method show well enhanced contrast and little artifacts. In addition, in order to achieve optimal brightness preserving based on maximum entropy, Wang and Ye proposed brightness preserving histogram equalization with maximum entropy (BPHEME) [10], which is a novel extension of histogram specification (HS). This method maximizes the entropy under the constraint of fixed mean brightness. Experimental results showed that BPHEME can enhance an input image while preserving the mean brightness. It is very suitable for consumer electronics such as TV.

Even though each method plays a very important role for its proposed problem, some common drawbacks still exist. No matter using histogram equalization or histogram specification in the method, washed-out appearance, patchiness effects, or/and other artifacts will emerge because of the characteristics of implementation. In order to resolve this problem, we propose a simple histogram modification scheme in this paper. This scheme is appropriate for histogram equalization or specification related methods, even histogram redistribution methods such as gray-level grouping (GLG) [11]. GLG is an automatic method for optimized image contrast enhancement and whose optimal gray-level transformation function is constructed according to the maximum average distance (AD) between pixels on the grayscale. It is a time consuming algorithm and induces patchiness effects at the highest gray level.

In this paper, the traditional HE method and its variants will be reviewed in Section II. We propose a simple histogram modification scheme in Section III. Experimental results and discussions are presented in Section IV. Finally, Section V concludes this paper.

II. HISTOGRAM EQUALIZATION AND ITS VARIANTS

Consider a digital image, $\mathbf{F} = \{F(i, j)\}$, which has the total number of N pixels with gray levels in the range $[0, L-1]$. The histogram of the image with gray levels in this range is a discrete function $h(r_k) = n(k)$, where r_k is the kth gray level and $n(k)$ is the number of pixels in the image with gray level r_k. For convenience, we use k instead of r_k. The probability density function (PDF) of the image is approximately by the following relative frequency:

$$p(k) = n(k)/N \text{, for } k = 0, 1, \ldots, L-1 . \quad (1)$$

The cumulative distribution function (CDF) of the image is then obtained by

$$c(k) = \sum_{i=0}^{k} p(i) \text{, for } k = 0, 1, \ldots, L-1 . \quad (2)$$

Histogram equalization will map an input gray level k into an output gray level $T(k)$ using the following transformation or mapping function:

$$T(k) = (L-1) \cdot c(k). \quad (3)$$

It is obvious from equation (3) that the mapping function is a scaled version of CDF. The method is referred to as global or traditional histogram equalization, simply called histogram equalization (HE). In the other words, HE uses the histogram of the input image to obtain the mapping function. As will be seen, other histogram-based methods obtain the mapping function via the modified histogram. It can be shown from (3) that the increment at the output gray level $T(k)$ is as follows:

$$\Delta T(k) = T(k) - T(k-1) = (L-1) \cdot p(k). \quad (4)$$

From (4), we know that the increment of gray level $T(k)$ is proportional to the probability of its corresponding gray level k in an input image. The probability of the continuous version of the mapping function $T(k)$ can be proved to be a uniform probability density function. In general, the enhanced or output image processed by corresponding discrete version of HE will not be uniform. A mapping function of HE will be found to make an output image with a histogram that is as close to a uniform distribution as possible. Therefore, it is inevitable that HE will invoke undesirable phenomenon such as washed-out appearance, patchiness effects, and other artifacts.

In order to overcome these problems, several methods were proposed for certain purposes. For example, BBHE is proposed for preserving the mean brightness of a given image while enhancing the contrast. The concept will be introduced in the remainder of this section.

Let the mean of an image is denoted by μ, which can be calculated by the following equation:

$$\mu = \frac{1}{N} \sum_{k=0}^{L-1} k \cdot n(k) = \sum_{k=0}^{L-1} k \cdot p(k), \quad (5)$$

and suppose that $m = \lfloor \mu \rfloor \in \{0, 1, \ldots, L\}$, which is called the threshold gray level. Using this threshold value, the input image is decomposed into two subimages $\mathbf{F}_L$ and $\mathbf{F}_U$ as

$$\mathbf{F} = \mathbf{F}_L \cup \mathbf{F}_U , \quad (6)$$

where

$$\mathbf{F}_L = \{F(i, j) | F(i, j) \le m, \forall F(i, j) \in \mathbf{F}\}, \quad (7)$$

and

$$\mathbf{F}_U = \{F(i, j) | F(i, j) > m, \forall F(i, j) \in \mathbf{F}\}. \quad (8)$$

Therefore, the subimage $\mathbf{F}_L$ consists of gray levels $\{0, 1, \ldots, m\}$, whereas the subimage $\mathbf{F}_U$ consists of gray levels $\{m+1, m+2, \ldots, L-1\}$. Under these structures, the PDF of the subimages $\mathbf{F}_L$ and $\mathbf{F}_U$ can be obtained by

$$p_L(k) = n(k)/N_L , \text{ for } k = 0, 1, \ldots, m , \quad (9)$$

and

$$p_U(k) = n(k)/N_U , \text{ for } k = m+1, m+2, \ldots, L-1 , \quad (10)$$

where N_L and N_U denote the number of pixels in the subimages $\mathbf{F}_L$ and $\mathbf{F}_U$, respectively, i.e.,

$$N_L = \sum_{k=0}^{m} n(k), \quad (11)$$

$$N_U = \sum_{k=m+1}^{L-1} n(k), \quad (12)$$

and $N = N_L + N_U$. The cumulative density functions of $\mathbf{F}_L$ and $\mathbf{F}_U$ are obtained by

$$c_L(k) = \sum_{i=0}^{k} p_L(i), \text{ for } k = 0, 1, \ldots, m , \quad (13)$$

and

$$c_U(k) = \sum_{i=m+1}^{k} p_U(i), \text{ for } k = m+1, m+2, \ldots, L-1 . \quad (14)$$

Similar to the case of HE, the mapping functions of the subimages are adopted as

$$T_L(k) = m \cdot c_L(k), \text{ for } k = 0, 1, \ldots, m , \quad (15)$$

and

$$T_U(k) = m + 1 + (L - m - 2) \cdot c_U(k), \text{ for } k = m+1, m+2, \ldots, L-1 . \quad (16)$$

Based on these two mapping functions, the decomposed subimages are histogram-equalized independently, and then combined into the output image. The overall mapping function can then be obtained by combining (15) and (16)

$$T(k) = \begin{cases} T_L(k) & k = 0, 1, \ldots, m \\ T_U(k) & k = m+1, m+2, \ldots, L-1 \end{cases}. \quad (17)$$

Histogram equalization is directly applied to the input image using the above mapping function. This method is called BBHE. Several related methods were proposed later as the variants of BBHE. The main technique of these methods is to find out an appropriate threshold or some thresholds for certain purposes. Unfortunately, these methods possess a potential problem in the upper and lower boundary values (i.e., the first and last nonzero values) of the support of histogram because of the characteristic of histogram equalization. This problem can be solved by a simple histogram modification scheme which is proposed in the next section.

III. Histogram Modification Scheme

According to the mechanism of histogram equalization and histogram specification, an image with a large upper boundary value (and therefore PDF) of the support of histogram will result in washed-out appearances after equalizing histogram. On the other hand, one with a large lower boundary value (and therefore PDF) of the support of histogram will show up patchiness effects after equalizing histogram. One or both of these effects may also occur in the scheme of histogram redistribution methods such as GLG. In this section, we shall propose a simple histogram modification scheme to remove these effects. The procedure of the scheme is summarized as follows:

1. Find the first two and last two values of the support of histogram.
2. Set the first value to be zero and replace the last one with the minimum between the last two values.
3. Perform histogram equalization.

Suppose that the first nonzero $n(k)$, i.e., the first value of the support of histogram, occurs at gray level b_f , i.e., $n(b_f) \ne 0$ but $n(k) = 0$ for $k \in \{0, 1, \ldots, b_f - 1\}$. It is well-known from (4) that if the PDF of gray level b_f is big enough, the gray level will be shifted to the right a lot. This will cause washed-out appearances. The bigger the PDF of a gray level is, the more the gray level will be shifted to the right. To improve contrast enhancement and avoid washed-out appearances, the number of gray level b_f could be set to 0, i.e., $n(b_f) = 0$, before HE is applied.

On the other hand, suppose that the last nonzero $n(k)$, i.e., the last value of the support of histogram, occurs at gray level b_l , i.e., $n(b_l) \ne 0$ but $n(k) = 0$ for $k \in \{b_l + 1, b_l + 2, \ldots, L-1\}$. Let b_{l-1} denote the last second nonzero $n(k)$. Patchiness effects often occur between gray levels $T(b_{l-1}) = (L-1) \cdot c(b_{l-1})$ and $T(b_l) = (L-1) \cdot c(b_l) = L-1$ as long as the PDF of gray level b_l is big enough. In order to eliminate these effects, the following technique could be adopted:

$$n(b_l) = \min\{n(b_{l-1}), n(b_l)\}. \quad (18)$$

Next, we compute the PDF of the modified histogram. Let $\bar{c}$ denote the CDF of the modified histogram. It is obvious from the following equation that gray level b_f must be located at gray level 0:

$$T(b_f) = (L-1) \cdot \bar{c}(b_f) = 0 . \quad (19)$$

Under this histogram modification, the gray scale will be detained in the interval $[0, L-1]$ since the mapping of gray level $L-1$ must be $L-1$, which can be verified as follows:

$$T(L-1)=(L-1)\cdot\bar{c}(L-1)=L-1\,. \tag{20}$$

Finally, traditional histogram equalization is performed on the modified CDF to obtain updated gray levels. The modified image will show that contrast is enhanced and washed-out appearances are phased out.

The above approach is valid for a single threshold case. For multithreshold histogram equalization methods such as BBHE and DSIHE, the same scheme can be applied to both subhistograms, respectively. This is also true for the GLG method, except for the first value of the support of histogram being replaced with $\min\{n(b_f), n(b_{f+1})\}$ instead of 0, where b_{f+1} denotes the second nonzero $n(k)$. It will be improved a lot for an image with a large lower boundary value of the support of histogram. The experimental results will be compared and shown in the next section.

IV. Experimental Results and Discussions

Since our proposed histogram modification scheme is to aim at the common problem inherent in the two boundary values of the support of histogram, it is appropriate for HE-based and HS-based methods as well as histogram redistribution methods. In order to show its effectiveness, our scheme was applied to two images, including the "*hands*" and its negative. Fig.1 illustrates these two images and their corresponding histograms. The supports of histogram are spread between 0 and 255. Notice that both histograms have a significant peak value in the boundary of the support of histogram, respectively.

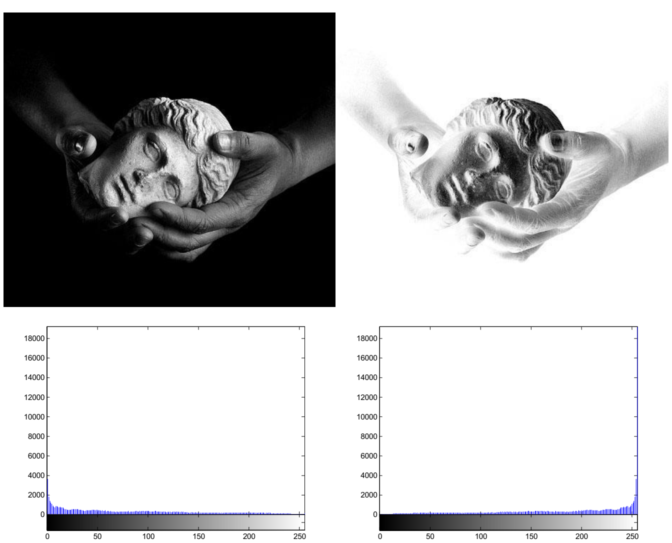

Fig. 1. Top row: Images for *hands* and its negative. Bottom row: the corresponding histograms.

Fig. 2 shows the processed results of "*hands*" by histogram equalization and proposed method, respectively. The left figure has a clearly washed-out look. This can be validated from the histogram on the bottom. The dynamic range of histogram is reduced and toward the right side, and there is a sharp peak in the middle of histogram. The processed results of the negative of "*hands*" are shown in Fig. 3. The right figure which is processed by HE has visual graininess and patchiness around the objects. The dynamic range of histogram is also reduced and toward the left side. The right figures in Fig. 2 and 3 are processed by our proposed method. Both of them yield natural appearance while enhancing contrast, without arousing adverse effects.

The enhanced images based on BBHE, BPHEME, GLG and corresponding proposed methods are demonstrated in Figs. 4, 5, and 6, respectively. Those images on the left which have washed-out appearance and patchiness are disappeared after applying proposed method, as shown in the images on the right.

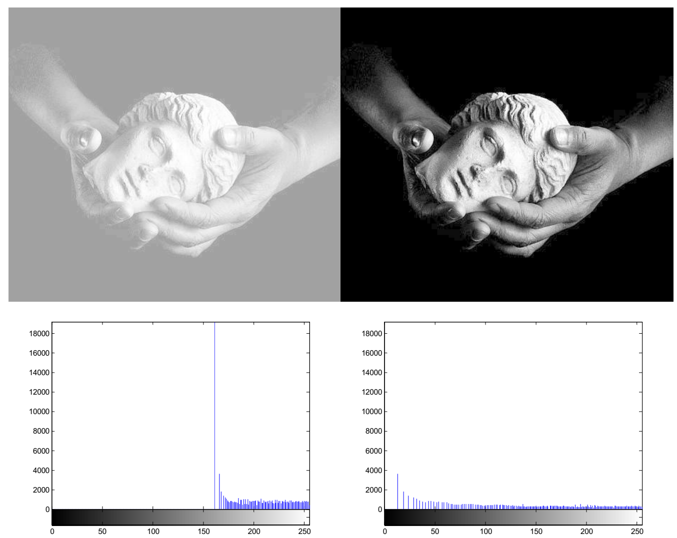

Fig. 2. Contrast enhancement for *hands* based on HE. Top row: HE and proposed method. Bottom row: the corresponding histograms.

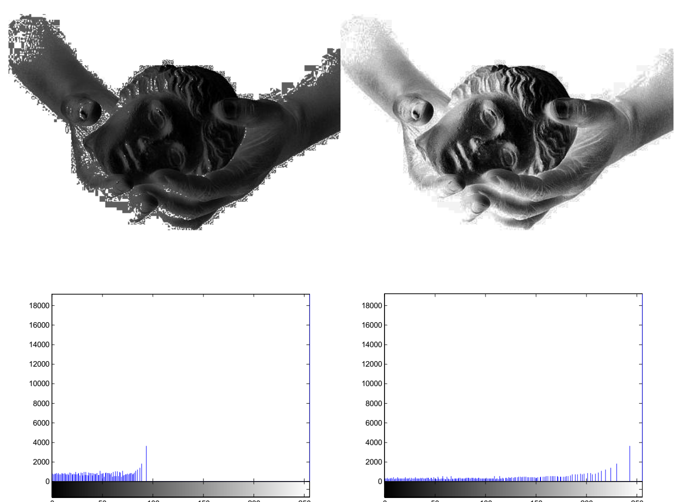

Fig. 3. Contrast enhancement for the negative of *hands* based on HE. Top row: HE and proposed method. Bottom row: the corresponding histograms.

Fig. 4. Contrast enhancement for *hands* and its *negative* based on BBHE. Left column: BBHEs. Right column: proposed method.

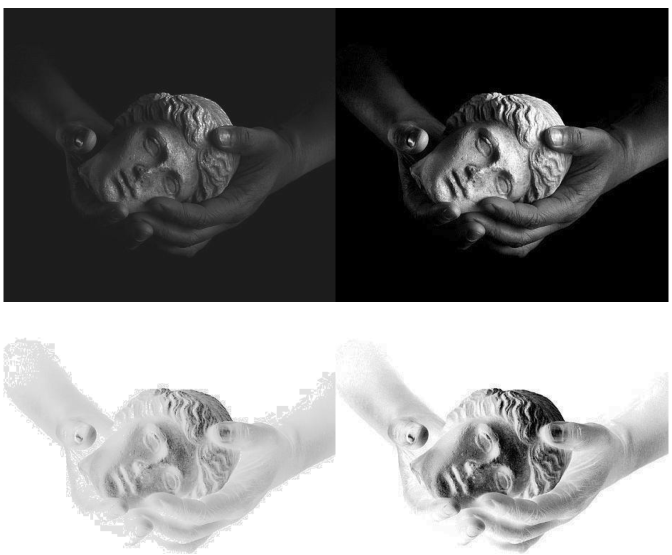

Fig. 5. Contrast enhancement for *hands* and its *negative* based on BPHEME. Left column: BPHEMEs. Right column: proposed method.

In order to compare our results with those of the existing approaches quantitatively, four criteria are adopted: mean, AIC, BGL, and AD [3, 11]. The first criterion is to find average brightness of an image. It is better to be close to that of the original image. The "average information contents" or entropy is defined as [3]

$$AIC = -\sum_{k=0}^{L-1} p(k)\log p(k). \tag{21}$$

The log is a base-2 logarithm and AIC is expressed in bits. Here, we set $0\log 0 = 0$, which is easily justified by continuity since $x\log x \to 0$ as $x \to 0$. Thus, adding terms of zero probability does not affect the AIC value [12]. The bigger the AIC is, the better the result. The third one is to find the background gray levels. This value should be kept as close to the original value as possible. The last criterion "average distance" is defined as [11]

$$AD = \frac{1}{N(N-1)}\sum_{i=0}^{L-2}\sum_{j=i+1}^{L-1} n(i)n(j)(j-i) \text{ for } i,\, j \in [0,\, L-1], \tag{22}$$

where $n(i)$ denotes the number of pixels in an image with gray level i and N is the total number of pixels. The AD value is expected to be bigger.

Fig. 6. Contrast enhancement for *hands* and its *negative* based on GLG (α = 0.8). Left column: GLG. Right column: proposed method.

TABLE I
COMPARISONS FOR METHODS ON HANDS

	Mean	AIC	BGL	AD
Original	28.48	3.72	0	23.08
HE	178.46	3.28	161	13.13
HE*	47.30	3.62	0	35.58
BBHE	53.68	3.27	24	24.55
BBHE*	37.22	3.62	0	29.71
BPHEME	38.39	3.22	28	8.49
BPHEME*	28.39	3.65	0	22.65
GLG	54.17	3.53	0	39.81
GLG*	41.80	3.56	0	32.77

* denotes the method using a simple histogram modification scheme.

TABLE II
COMPARISONS FOR METHODS ON THE NEGATIVE OF HANDS

	Mean	AIC	BGL	AD
Original	226.52	3.72	255	23.08
HE	178.65	3.29	255	50.43
HE*	206.19	3.61	255	36.41
BBHE	216.83	3.39	255	29.91
BBHE*	218.02	3.62	255	29.52
BPHEME	234.15	3.23	255	15.10
BPHEME*	226.71	3.64	255	22.41
GLG	193.37	3.40	255	42.63
GLG*	212.13	3.53	255	33.37

* denotes the method using a simple histogram modification scheme.

Results of the comparison are summarized in Tables I and II. From these results, it can be observed that the proposed method outperformed each of these methods in all four criteria in Table I, except for the AD of GLG. However, our proposed method has better appearance. Note that the background gray levels of our proposed method are kept intact, while those of most approaches have significantly changed. In Table II, our approach is still better than other methods in the first three criteria, only a little shy in the AD criterion. It is worth noting that the visual effects of our proposed method are consistently better than those of other approaches.

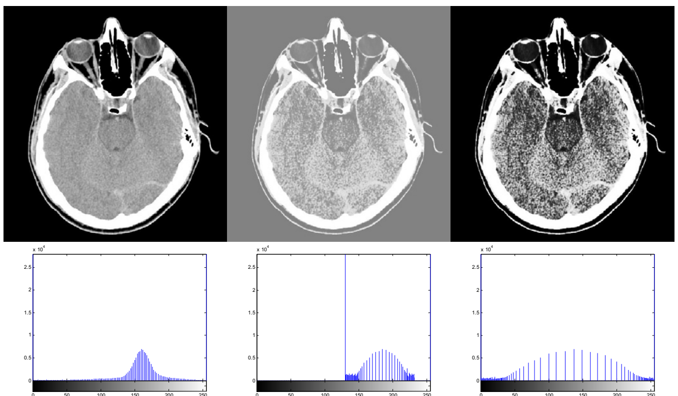

Fig. 7. Top row: CT scan of a human head, HE, and proposed method. Bottom row: their corresponding histograms.

For medical applications, since most images have a large PDF being at gray level 0 and/or L-1, it is suitable to use our proposed method. We apply the proposed scheme to a medical image to show that a simple histogram modification scheme will achieve very good performance. The image shown on the upper left of Fig. 8 is a 512 x 512 CT scan of a human head [1]. The histogram of our proposed method is spread over the whole gray levels and the details of the original image can then be recognized easily. From the upper right of Fig. 7, it is shown that a natural look is obtained to use our method while enhancing contrast.

V. Conclusion

Most existing contrast enhancement methods do not consider the problem with a large area of gray level being in the boundary values of the support of histogram. In this paper, we propose a simple histogram modification scheme to deal with this issue. This scheme can be applied in histogram equalization methods, histogram specification methods, and histogram redistribution methods. Experimental results demonstrate that our proposed scheme can effectively and significantly eliminate washed-out appearance and adverse artifacts induced by several existing approaches. Furthermore, it can be expected that the processed image using the proposed method, which considers the problems inherent in the boundaries of histogram, will have a natural look.

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Biographies

Yen-Ching Chang was born in Changhua, Taiwan, R.O.C., in 1966. He received the B.S. degree in electrical engineering from National Taiwan Institute of Technology, Taipei, Taiwan, in 1991 and the M.S. and Ph. D. degrees in electrical engineering from National Tsing Hua University, Hsinchu, Taiwan, in 1993 and 2002. Since 2003, he has been with Department of Applied Information Sciences, Chung Shan Medical University, Taichung, Taiwan, where he is currently an associate professor. His research interests include statistical signal processing, image processing, and medical image processing.

Chun-Ming Chang received the B.S. degree from National Cheng Kung University, Taiwan, in 1985 and the M.S. degree from National Tsing Hua University, Taiwan, in 1987, both in electrical engineering. He received the Ph.D. degree in electrical and computer engineering from University of Florida in 1997. From 1998 to 2002, Dr. Chang served for two communication companies as a senior technical staff member and a senior software engineer, respectively. He joined the faculty of Asia University in Taiwan in 2002. His research interests include computer vision/image processing, video compression, virtual reality, computer networks and robotics.