Histogram-Based Locality-Preserving Contrast Enhancement

Jeyong Shin, *Student Member, IEEE*, and Rae-Hong Park, *Senior Member, IEEE*

***Abstract*—Histogram equalization (HE), a simple contrast enhancement (CE) method, tends to show excessive enhancement and gives unnatural artifacts on images with high peaks in their histograms. Histogram-based CE methods have been proposed in order to overcome the drawback of HE, however, they do not always give good enhancement results. In this letter, a histogram-based locality-preserving CE method is proposed. The proposed method is formulated as an optimization problem to preserve localities of the histogram for performing image CE. The locality-preserving property makes the histogram shape of the enhanced image to be similar to that of the original image. Experimental results show that the proposed histogram-based method gives output images with graceful CE on which existing methods give unnatural results.**

***Index Terms*—Contrast enhancement, histogram equalization, image enhancement, image processing.**

I. Introduction

CONTRAST ENHANCEMENT (CE) techniques have been widely used for image enhancement in various applications. One of the most popular and simple CE techniques is histogram equalization (HE) [1]. However, it has a severe problem that it gives unnatural effects or artifacts on some images with high peaks in their histograms.

There are a lot of histogram-based CE algorithms that improve HE using various approaches. For example, bi-HE (BHE) is an algorithm that splits a histogram into two sub-histograms and applies HE to each sub-histogram. Brightness preserving BHE (BBHE) uses the mean intensity value of the input image to split its histogram [2]. Minimum mean brightness error BHE (MMBEBHE) splits a histogram based on the absolute mean brightness error (AMBE) [3]. Brightness preserving dynamic HE (BPDHE) divides a histogram into several sub-histograms and applies HE to each sub-histogram separately, which is followed by the normalization that makes the contrast-enhanced image have the same mean intensity value as the input image [4]. These existing histogram-based CE methods tend to preserve global average intensity value with the contrast of the whole image improved. There are other well-known methods that improve HE [5]–[7], however, they are parameter-sensitive, which gives good quality only when the parameters are carefully chosen.

In the meanwhile, CE using local statistical properties has been also studied. Adaptive HE (AHE) [8] successfully takes local statistical properties into consideration and gives local details in the output images. However, it does not consider the global look of the images and the computational complexity is very high. Partially overlapped sub-block HE (POSHE) [9] and cascaded multistep binomial filtering HE (CMBFHE) [10] enhance AHE to consider overall look of the images and to decrease the computational complexity. However, these methods are still computationally expensive, which keeps them from commercial use.

In this letter, a CE method that preserves the locality of the histogram is proposed. The proposed method, so-called histogram-based locality- preserving CE (HBLPCE), solves an optimization problem to calculate an intensity transformation with the histogram of an input image. The objective function of the optimization problem is formed to find a least squares solution of locality conditions. The experimental results show that HBLPCE adapts well on images with various statistical properties.

II. Proposed Histogram-Based CE Method

A. Locality Condition

Locality condition is defined using the intensity level in image histogram. The purpose of the locality condition is to realize a local CE. By combining local CE at each intensity level, we form a global CE with the locality-preserving property, meaning that the local structure of the histogram is preserved after histogram processing.

In this letter, image histograms are described by the probability mass function (PMF), i.e., normalized histograms. Note that the sum of PMFs is equal to one. The PMF vector $\mathbf{p} = [p_0, p_1, \cdots, p_{N-1}]^T$ is specified with respect to the input intensity vector $\mathbf{r} = [r_0, r_1, \cdots, r_{N-1}]^T$, where N denotes the total number of intensity levels. Then, an intensity transformation can be defined by specifying the transformed intensity vector $\mathbf{x} = [x_0, x_1, \cdots, x_{N-1}]^T$.

Locality condition at ith transformed intensity level with respect to two neighboring intensity levels is defined as

$$(x_i - x_{i-1})p_{i+1} = (x_{i+1} - x_i)p_i, \tag{1}$$

which represents that the histogram is stretched in inverse proportion to the PMF value in a local sense, as shown in Fig. 1. The locality condition is designed to represent local structures of a

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The authors are with the Department of Electronic Engineering, Sogang University, Seoul, Korea (e-mail: rockilica@sogang.ac.kr; rhpark@sogang.ac.kr).

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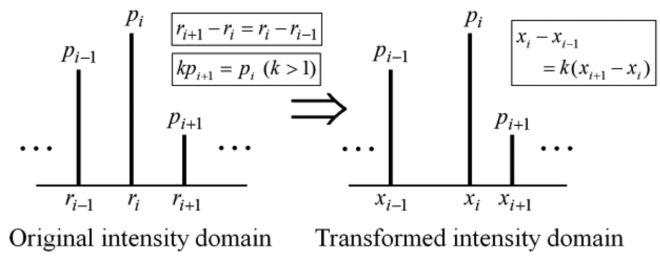

Fig. 1. Example of locality condition.

stretched histogram. It is assumed that the two consecutive intensity difference ($(x_i - x_{i-1})$ and $(x_{i+1} - x_i)$) are stretched proportional to the PMF values (p_i and p_{i+1}), which maximizes the CE by giving larger intensity difference to larger PMF-valued intensity level, where the larger PMF-value also means larger number of pixels in that intensity level.

The locality condition can also be interpreted as local HE, in which the HE can be written as $x_i = (L-1)\sum_{k=0}^{i} p_k (0 \leq i \leq N-1)$, where L denotes the number of intensity levels allowed in the image [1]. By subtracting x_i from x_{i+1}, we obtain a recursive equation

$$x_{i+1} - x_i = (L-1)p_{i+1}. \tag{2}$$

The recursive equation is equivalent to (1), obtained by combining two consecutive equations ($i \leftarrow i$ and $i \leftarrow i-1$).

If there are zero PMFs in the input histogram, the locality condition in (1) is modified as

$$w_{i,i-1}(x_i - x_{i-1})p_{i+1} = w_{i+1,i}(x_{i+1} - x_i)p_i, \tag{3}$$

where the weight factor $w_{i,j} = \exp(-(r_i - r_j)^2/2\sigma^2)$ is defined using a decreasing Gaussian function with a controllable parameter σ. If $(r_i - r_{i-1})$ is larger than or equal to two quantization units, $w_{i,i-1}$ becomes small, which gives a more stretched histogram, i.e., large $(x_i - x_{i-1})$. A Gaussian function is used as an intensity-domain distance measure, inspired by bilateral filtering [11], which uses a Gaussian function in the range domain (intensity domain).

B. Optimization Problem Formulation

To calculate $\mathbf{x}$, an optimization problem is formed in the context of locality conditions over the entire intensity range. The optimization problem using a least square method can be written as

$$\begin{aligned} &\text{minimize} && \sum_{i=1}^{N-2} [w_{i,i-1}(x_i - x_{i-1})p_{i+1} - w_{i+1,i}(x_{i+1} - x_i)p_i]^2 \\ &\text{subject to} && x_0 = 0, x_{N-1} = L-1, \\ &&& x_i - x_{i-1} \geq 0 (1 \leq i \leq N-1), \end{aligned} \tag{4}$$

where L denotes the total number of intensity levels of the image, which equals 256 with 8-bit representation of the intensity level. The objective function is expressed in terms of the sum of squared errors of locality conditions over the entire intensity levels. Locality condition at each intensity level has a CE effect in a local sense and the objective function is formulated by combining locality conditions at all intensity levels over the entire intensity range of an input image. Two equality constraints in (4) represent that the enhanced image should use the full dynamic range, where x_0 and x_{N-1} are the minimum and maximum intensity levels in the transformed image, respectively. Note that these two levels can be arbitrarily chosen by a user. The inequality constraint in (4) states that the intensity transformation should be a monotonically increasing function.

By dropping a known value x_0, the transformed intensity vector is redefined as $\mathbf{x} = [x_1, x_2, \cdots, x_{N-1}]^T$, so that the objective function can be written in a matrix form. Let the difference matrix D be defined as

$$D = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \ddots & \ddots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & -1 & 1 & 0 & 0 \\ 0 & 0 & \cdots & 0 & -1 & 1 & 0 \\ 0 & 0 & \cdots & 0 & 0 & -1 & 1 \end{bmatrix}, \tag{5}$$

where D is an $(N-1) \times (N-1)$ matrix. By using the redefined $\mathbf{x}$ and D, the optimization problem can be rewritten as

$$\begin{aligned} &\text{minimize} && \mathbf{x}^T D^T Q D \mathbf{x} \\ &\text{subject to} && x_0 = 0, x_{N-1} = L-1, \\ &&& x_i - x_{i-1} \geq 0 (1 \leq i \leq N-1), \end{aligned} \tag{6}$$

where a tridiagonal matrix Q is formed with coefficients in (4).

C. Solution of the Optimization Problem

To solve the optimization problem, $\mathbf{x}$ is substituted by $\mathbf{y} = D\mathbf{x}$, where $\mathbf{y} = [x_1, x_2 - x_1, \cdots, x_{N-1} - x_{N-2}]^T$ represents the difference vector between consecutive intensity levels in the transformed histogram. Then, (6) can be rewritten as

$$\begin{aligned} &\text{minimize} && \mathbf{y}^T Q \mathbf{y} \\ &\text{subject to} && \mathbf{1}^T \mathbf{y} = L-1, \\ &&& y_{\mathrm{i}} \geq 0 \ (0 \leq i \leq N-2), \end{aligned} \tag{7}$$

where $\mathbf{1}$ denotes an all-one $(N-1) \times 1$ vector. Note that the minimum value x_0 is set to 0 from $y_0 = x_1$ and the maximum value x_{N-1} is fixed to $L-1$ by setting the equality condition $\mathbf{1}^T \mathbf{y} = \sum_i y_i = x_{N-1} = L-1$. The optimization problem can be solved by using a general quadratic programming method. In this letter, the interior-point method [12] is used.

III. Experimental Results and Discussions

The proposed HBLPCE is tested on various color images with different statistical properties and compared to existing HE [1], BPDHE [4], BBHE [2], MMBEBHE [3], and recursively separated and weighted HE (RSWHE) [7] methods. The parameters of RSWHE method are chosen based on the authors' suggestion. The proposed method is compared with global CE methods only because local ones give very different tendency and are hard to compare with. In this letter, each CE method is realized in HSV color space, manipulating the V channel with the H and S channels unchanged. HSV color space is chosen to avoid color distortion in enhanced images. HBLPCE can also be performed in

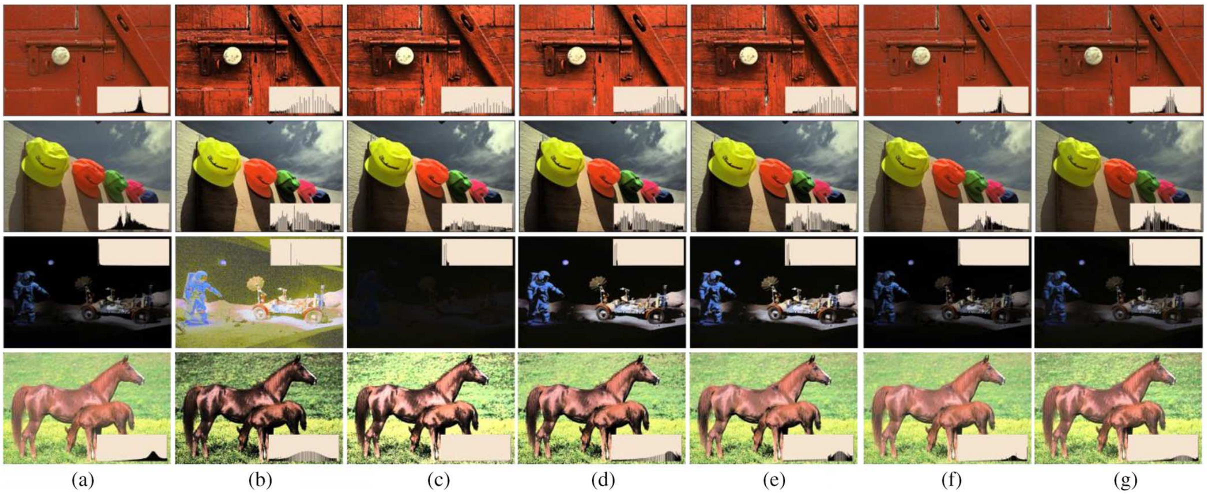

Fig. 2. Experimental results on *kodim02.png*, *kodim03.png*, *moon.bmp*, and *horse.jpg* images (from top to bottom), (a) original image, (b) HE, (c) BPDHE, (d) BBHE, (e) MMBEBHE, (f) RSWHE, (g) proposed HBLPCE.

YCbCr, YUV, and Lab color spaces. The user-controllable parameter σ that adjusts the weight factor is experimentally set to 10.

Fig. 2 shows experimental results with their histograms. The top left image is an original image (*kodim02.png*) with a unimodal histogram. Compared to other methods, RSWHE and the proposed HBLPCE produce histograms of which the shape is similar to that of the original histogram. The locality-preserving property on histogram gives a shape-preserving result while histogram stretch can also be observed, whereas RSWHE gives weaker histogram stretch. The result images of HE, BPDHE, BBHE, and MMBEBHE show rather excessive CE, which lead to unnatural artifacts in the contrast-enhanced images. On the other hand, HBLPCE shows a graceful CE with a natural contrast-enhanced image.

The left image in the second row is an original image (*kodim03.png*) with a multimodal histogram. The histograms of MMBEBHE, RSWHE, and HBLPCE results are similar to the original histogram compared to the histograms of the other methods. HE, BPDHE, and BBHE give somewhat excessive CEs, which make details of the images hardly observed (see the top of the yellow cap and the texture in the wood board against the wall). The result images of MMBEBHE and HBLPCE show better enhanced results while details in the images are well-preserved.

An extremely dark original image (*moon.bmp*) with a left-skewed histogram is illustrated on the left in the third row. HE gives an excessive CE and shows a severe color distortion. BPDHE fails to enhance the contrast of the input image while preserving the mean intensity value. BBHE and MMBEBHE produce acceptable contrast-enhanced images, however these methods do not preserve details in the bottom of the images. On the contrary, HBLPCE and RSWHE give graceful CEs and preserves details in the bottom (around the rocks between a man and vehicle).

A saturated original image (*horse.jpg*) is shown at the bottom left. The PMF shows its highest value at the highest intensity value, which is caused by saturation in the image. HE gives a too dark image. BPDHE gives a much lighter image, saturating the result image much further. RSWHE does not show a significant change in the output image. BBHE and MMBEBHE produce unnatural results, while PMF of the result images are unnaturally dense at some intensity levels. The proposed HBLPCE gives a very natural-looking image. The enhanced image reveals a lot of details in the background regions and the body of the horses. Additional experiments show that the proposed HBLPCE gives better contrast-enhanced results for images with multimodal histograms as well.

TABLE I
QUANTITATIVE COMPARISON OF DIFFERENT HISTOGRAM-BASED CE METHODS

Image	Method	AMBE	CII	H	HI
kodim02.png	Original	N/A	N/A	6.24	N/A
	HE [1]	12.5	4.34	6.01	0.11
	BPDHE [4]	0.9	3.84	5.63	0.14
	BBHE [2]	18.3	3.04	6.04	0.20
	MMBEBHE [3]	0.4	3.92	6.02	0.14
	RSWHE [7]	0.5	1.29	6.19	0.78
	HBLPCE	10.0	1.53	6.11	0.54
kodim03.png	Original	N/A	N/A	7.24	N/A
	HE [1]	10.0	2.18	7.02	0.39
	BPDHE [4]	0.4	1.93	6.92	0.46
	BBHE [2]	3.8	2.37	7.03	0.43
	MMBEBHE [3]	0.6	2.33	7.02	0.42
	RSWHE [7]	2.2	1.31	7.20	0.79
	HBLPCE	10.0	1.29	7.17	0.72
moon.bmp	Original	N/A	N/A	4.15	N/A
	HE [1]	134.5	0.32	3.89	0.00
	BPDHE [4]	0.3	0.30	2.92	0.04
	BBHE [2]	21.7	0.43	3.83	0.11
	MMBEBHE [3]	21.4	0.43	3.81	0.10
	RSWHE [7]	1.1	0.47	3.85	0.66
	HBLPCE	6.1	0.88	4.04	0.49
horse.jpg	Original	N/A	N/A	7.05	N/A
	HE [1]	64.7	3.22	6.85	0.36
	BPDHE [4]	11.3	2.53	4.89	0.23
	BBHE [2]	18.3	2.29	6.80	0.53
	MMBEBHE [3]	7.3	1.73	6.78	0.64
	RSWHE [7]	1.3	1.13	6.97	0.92
	HBLPCE	6.9	1.38	6.81	0.61

Table I shows quantitative comparisons on the four test images. AMBE, contrast improvement index (CII), and discrete entropy (H) are used as measures of CE [3], [13], [14]. AMBE

TABLE II
COMPARISON OF EXECUTION TIMES ON DIFFERENT SIZE IMAGES

Method	Execution time (ms)		
	768×512	2048×1080	4096×2160
HE [1]	11	61	349
BPDHE [4]	15	64	357
BBHE [2]	12	67	380
MMBEBHE [3]	26	123	626
RSWHE [7]	13	71	386
CMBFHE [10]	1013	1992	5596
HBLPCE	40	97	385

is defined as the absolute difference of the mean intensity between the original and the contrast enhanced images. If AMBE is small, the average brightness of the image is well preserved. The CII is defined as CII $= C_{\text{processed}}/C_{\text{original}}$, where $C_{\text{processed}}$ and C_{original} are the average values of the local contrast measured in the processed and original images, respectively. The local contrast is computed as

$$C_{\text{local}} = \frac{\max - \min}{\max + \min}, \tag{8}$$

where max and min represent the maximum and minimum intensity values in a 3×3 window, respectively. In the case of both max and min values are zeros, C_{local} is not defined by (8) and is set to zero in this letter. The CII ranges from zero to infinity since C_{local} varies between zero and one. However, CII does not reach infinity typically, because C_{original} becomes zero if and only if the original image has constant intensity value over the entire image plane. Larger CII indicates more CE while CII equals to one if there is no CE. Note that CII is not reliable in the extremely dark image (*moon.bmp*), because C_{local} reaches its maximum value of 1 if there are one or more zero-valued pixels in the 3×3 window ($\min = 0$ in (8)), regardless of max value in the window. The discrete entropy is defined as $H = -\sum_{i=0}^{N-1} p_i \log_2 p_i$. Histogram intersection (HI) is used to measure the similarity of the processed histogram with the original histogram, which is defined as $\mathrm{HI}(\mathbf{p},\mathbf{q}) = \sum_{i=0}^{N-1} \min(p_i, q_i)$, where $\mathbf{p}$ and $\mathbf{q}$ denote PMFs of the original and processed images, respectively.

BPDHE and MMBEBHE aim to minimize AMBE, which preserve the average intensity of the original image, however, they do not guarantee better enhanced results. BBHE gives larger CII than HE does on *kodim03.png*, meaning that it fails to reduce excessive CE by HE. RSWHE shows the largest HI values, which indicates that the shape of the histogram is well-preserved, however the result images do not show significant differences from the original ones. HBLPCE gives lower CII values than other methods, however the CII values are more stable than those of other methods. Other methods except for RSWHE give varying CII value, which indicates that their CE performance varies from the statistical properties of the input images. HBLPCE also gives moderate and stable AMBE, H, and HI values, showing better trade-offs than other methods.

The execution times on different size images are shown in Table II. The experiment is performed on 20 images on each resolution and the average execution time is shown. All CE methods are tested on Core i5 processor using MATLAB. The proposed HBLPCE is compared with the global CE methods and CMBFHE [10]. CMBFHE is a local CE method, which implements well-known POSHE [9] very efficiently with the identical results. CMBFHE takes much longer time than global CE methods, which increases drastically with the size of the input image. HBLPCE takes the longest time among the global CE methods for small images, while the execution times of global CE are similar for large images.

IV. CONCLUSION

In this letter, a novel histogram-based CE method, which aims to preserve locality of the original histogram while enhancing the global contrast, is proposed. An optimization problem is formulated by combining proposed locality conditions of the histogram to achieve locality-preserving CE. The proposed method gives graceful CE on various images of different histogram profiles. While the existing histogram-based CE methods show excessive enhancement and unnatural artifacts, the proposed method gives better contrast-enhanced images with locality-preserved histograms. Future work will focus on extension of the proposed HBLPCE method to video sequences. Also, studies will be done on reflecting local statistical properties to perform a better CE.

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