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Exact Histogram Specification Considering the Just Noticeable Difference

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** Short Paper*

***Abstract*:** Exact histogram specification (EHS) transforms the histogram of an input image into the specified histogram. In the conventional EHS techniques, the pixels are first sorted according to their graylevels, and the pixels that have the same graylevel are further differentiated according to the local average of the pixel values and the edge strength. The strictly ordered pixels are then mapped to the desired histogram. However, since the conventional sorting method is inherently dependent on the initial graylevel-based sorting, the contrast enhancement capability of the conventional EHS algorithms is restricted. We propose a modified EHS algorithm considering the just noticeable difference. In the proposed algorithm, the edge pixels are pre-processed such that the output edge pixels obtained by the modified EHS can result in the local contrast enhancement. Moreover, we introduce a new sorting method for the pixels that have the same graylevel. Experimental results show that the proposed algorithm provides better image enhancement performance compared to the conventional EHS algorithms.

***Keywords*:** Contrast enhancement, Image enhancement, Histogram equalization, Histogram specification, Human visual system

1. Introduction

Histogram based image processing plays a crucial role in image contrast enhancement due to its conceptual simplicity and reliable performance. One of the widely used histogram based techniques is histogram equalization (HE), which transforms a narrow input histogram into a wide and uniform target histogram. However, HE can result in an annoying visible artifact since the uniformly distributed target histogram tends to excessively enhance a dynamic range of an input image. To this end, many improvements on HE have been proposed in the literature.

Histogram specification (HS) is a generalized version of HE that can change the input histogram into any desired histogram. Thus, HE is equivalent to HS when a desired histogram is the uniform distribution. In HS, HE serves as a link to connect the input and desired histograms [1]. However, since the graylevels of the digital image are discrete, the exact solution, i.e., the uniform distribution, is not achieved for HE in general. Since HS is relying on HE, therefore, only crude approximation of the desired histogram is obtained. In order to more closely approximate the desired histogram, the graylevel grouping [2] and the graph theory [3] were utilized. However, the exact specification of the desired histogram, so called exact HS (EHS), is not accomplished due to the inherent ill-posed characteristics of the problem [4].

In order to exactly specify the uniform histogram, the pixels of the same graylevel are separated randomly or distinguished according to the local average pixel values. The exact histogram equalization is generalized into the EHS in [1, 4]. In [1], the pixels of the same graylevel are sorted by comparing the local average pixel values. If the local averages are the same, the enlarged neighboring filter masks are employed to further discriminate pixels. In [4], the pixel ordering is performed in the wavelet transform domain. By comparing the absolute values of the wavelet coefficients, the local edge information can be examined as well as the local average information.

However, the wavelet based method does not provide the further visual quality improvement as compared to [1]. This is because the pixel value is the first condition of the ordering methods in both [1] and [4]. In other words, regardless of the local perceptual characteristics of the human visual system (HVS), the pixels are firstly sorted solely based on the graylevel. This restriction on the pixel ordering tends to constrain the contrast enhancement capability of the EHS. Therefore, a new ordering method utilizing the characteristics of the HVS is required to successively perform the contrast enhancement.

There are many useful characteristics of the HVS for the contrast enhancement. First, the HVS is sensitive to the contrast rather than the absolute graylevel. Therefore, histogram mapping should consider the contrast changes instead of the pixel value changes. Especially, the just noticeable difference (JND) can explain the perceptual contrast changes of the image [6-9]. Second, changes at or near edges have profound impacts on the HVS. Consequently, histogram mapping should differently process the edge regions of the image. Even though the conventional EHS techniques [1, 4] partially utilize the above HVS characteristics, a perceptual contrast enhancement is limited due to the strong dependency of the pixel ordering on the pixel value.

In this paper, an improved EHS (IEHS) algorithm based on the HVS is proposed. In order to effectively enhance the contrast of the image, the edge pixels are pre-processed so that the output edge pixels obtained by the IEHS can result in local contrast enhancement. Moreover, a new ordering method for sorting the pixels of the same graylevel is introduced. The rest of this paper is organized as follows. A brief description of the EHS is given in Section II, and the proposed IEHS algorithm is presented in Section III. The experimental results are provided in Section IV, and conclusions are given in Section V.

2. Exact Histogram Specification

In this section, we briefly explain the basic HS and review two conventional EHS techniques [1, 4]. Since HS is a technique that converts an original histogram into a desired one, the desired histogram is assumed to be given. Therefore, finding a suitable desired histogram [5, 11] is not a concern of our work.

Let $\mathbf{u}$ and $\mathbf{v}$ denote the random variable (RV) representing the original and desired histograms, respectively. Then, the RVs of the histogram equalized version, $\mathbf{u}_{\mathbf{HE}}$ and $\mathbf{v}_{\mathbf{HE}}$, are obtained as follows:

$$\begin{aligned} \mathbf{u}_{\mathbf{HE}} &= T_{\mathbf{u}}(\mathbf{u}), \\ \mathbf{v}_{\mathbf{HE}} &= T_{\mathbf{v}}(\mathbf{v}), \end{aligned} \tag{1}$$

where $T_{\mathbf{u}}$ and $T_{\mathbf{v}}$ are the cumulative distribution functions (CDFs) of $\mathbf{u}$ and $\mathbf{v}$, respectively. Since the equalized RVs should be identically distributed, the mapping from $\mathbf{u}$ to $\mathbf{v}$ can be represented by

$$\mathbf{v} = T_{\mathbf{v}}^{-1}(\mathbf{v}_{\mathbf{HE}}) = T_{\mathbf{v}}^{-1}(\mathbf{u}_{\mathbf{HE}}) = T_{\mathbf{v}}^{-1}T_{\mathbf{u}}(\mathbf{u}) \ . \tag{2}$$

However, for the discrete RVs, the exact histogram equalization is impossible in general [1]. This is because the pixels of the same graylevel should be mapped to the same output graylevel. Therefore, the equality between $\mathbf{u}_{\mathbf{HE}}$ and $\mathbf{v}_{\mathbf{HE}}$ does not hold for the discrete RV. Consequently, the specified histogram can only crudely approximate the desired histogram.

To solve this problem, a strict pixel ordering algorithm was proposed in [1]. The goal of the strict ordering is to prioritize all pixels that have the same graylevel. In other words, the normal ordering based on the pixel value is maintained while the pixels of the same graylevel are sorted based on their neighboring pixel values. The basic rule of the strict ordering is that the pixel surrounded by bright pixels is assumed to be brighter than that surrounded by dark neighboring pixels. This local average based sorting can discriminate the pixels of the same graylevel. Since it is possible that the local average values are still the same, the number of pixels to be averaged is increased in such a case. In [1], the local average filter masks of different sizes were defined as follows:

$$\begin{aligned} &\phi_1 = [1], \phi_2 = \frac{1}{5}\begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \phi_3 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \\ &\phi_4 = \frac{1}{13}\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}, \phi_5 = \frac{1}{21}\begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}. \end{aligned} \tag{3}$$

The other masks, ϕ_6, ϕ_7, and so on, are constructed in a similar manner. The above masks are sequentially applied until the different local average values are obtained. The experiments in [1] revealed that the strict ordering is satisfied before examining ϕ_7 in most cases. After the strict ordering, the EHS is achieved by assigning the sorted pixels to the desired pixel values.

In [4], the strict ordering is performed in the wavelet domain. For the pixels of the same graylevel, the sorting is performed according to the absolute values of the wavelet coefficients since the wavelet coefficients contain the local edge information as well as the local average information. When the absolute values are the same at a certain subband, a coarser subband is examined until the different values are found. However, the visual quality of the output image by the wavelet based EHS is not noticeably improved compared to the EHS algorithm in [1]. Only for the highly compressed image, the wavelet domain technique slightly improves the visual quality.

In summary, the EHS can be accomplished by utilizing the neighboring pixels. From the viewpoint of the HVS, the wavelet domain technique is more appropriate. However, we found that the initial ordering based on the pixel value restricts the image contrast enhancement capability. In order to improve the performance, the strong dependency of the pixel ordering on the pixel value needs to be relaxed.

3. The Proposed Algorithm

We assume that the goal of the EHS is the image contrast enhancement. From this viewpoint, in this Section, we first propose a preprocessing algorithm that facilitates the image contrast enhancement. Then, we present a modified pixel ordering method that can further improve the image contrast.

3.1 HVS Based Preprocessing

In the classical HE and HS algorithms, the pixels of the same graylevel are always mapped to the same output graylevel. Therefore, this mapping principle can reduce the local contrast of the output image. Also, since the HVS is sensitive to the contrast rather than the graylevel, the pixel sorting based on the graylevel is not suitable to the HVS. In order to improve the conventional algorithms, the HVS characteristics should be more extensively exploited.

The HVS can only perceive the difference above the JND. Due to the HVS characteristics, the JND is dependent on the background luminance and the spatial activity. In [8], the JND is modelled by the combination of two threshold values as follows:

$$jnd(x,y) = Th^l(x,y) + \lambda \frac{Th^t(x,y)}{Th^l(x,y)}, \qquad (4)$$

where (x, y) is the pixel coordinates, = 0.5, Th^l is the threshold for the luminance adaptation, and Th^t is the threshold for the activity masking. Specifically, a piecewise linear approximation in Fig. 1 is used for Th^l, and Th^t is estimated by the maximum pixel difference in the 5x5 spatial neighborhood. The parameters in Fig. 1, f, g, and h, are defined in [8]. Then, with the aid of the JND in (4), the noticeable local contrast (NLC), c_o, is defined as

$$c_o(x,y) = \begin{cases} 0, \text{ if } \left|o(x,y) - \bar{o}(x,y)\right| \le jnd(x,y) \\ \left|o(x,y) - \bar{o}(x,y)\right| / jnd(x,y), \text{ otherwise} \end{cases}, \qquad (5)$$

where o represents the original image and $\bar{o}(x, y)$ is the average pixel value of the 5x5 mask centered at (x, y) [8].

Our remaining problem is how to effectively enhance this NLC by the EHS. In general, the increase of the NLC is advantageous only for the edge pixels. This is because the increase in the non-edge pixels tends to produce annoying artifacts. From this viewpoint, we propose an algorithm that preprocesses the edge pixels so that the NLC can be successfully enhanced by the newly defined IEHS process, whose flowchart is shown in Fig. 2.

First, the Sobel edge mask is applied to the input image o. Then, the binary edge map, Ω_o, is obtained by

$$\Omega_o(x,y) = \begin{cases} 1, & \text{if } G(x,y) > Th^e \\ 0, & \text{otherwise} \end{cases}, \qquad (6)$$

where G is the Sobel filtered result and Th^e is set to 30 [8].

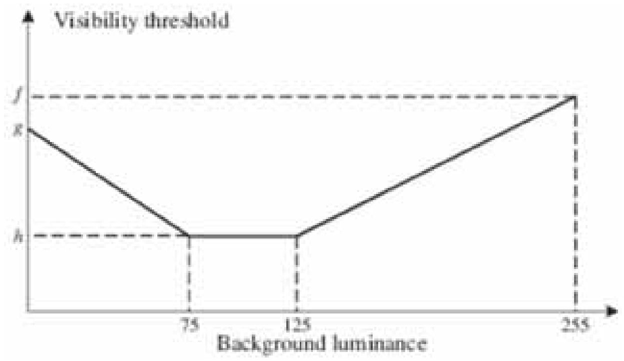

Fig. 1. Visibility threshold against background luminance [8].

While the edge map is constructed, the original HS is performed by using o and the given desired histogram h. After HS, the specified image, d, and the HS mapping function, F_h, are obtained. Specifically, F_h maps the graylevels between o and d. Here, the objective of applying the original HS is to approximately estimate the change of the NLC. If the NLC in the edge pixels is not increased by the original HS, it is beneficial to modify the original pixel value such that the sufficient NLC enhancement can be achieved by the following EHS process.

For each edge pixel, therefore, the NLC of o and d, co and cd, are compared. c_o is defined in (5), and c_d is simply obtained by replacing o by d. Then, at edge position (x,y), if $c_d(x, y) \ge c_o(x, y)$, no modification is required since the NLC is already increased. Otherwise, the original pixel value needs to be updated. For this case, in order to find a proper input pixel value, the desired output pixel value is estimated. Our assumption on the desired HS result is that the NLC should be increased or at least maintained for the edge pixels. Therefore, if $c_d(x, y) < c_o(x, y)$, $d(x, y)$ is updated to $\hat{d}(x, y)$ in a way that $c_d(x, y)$ is mapped into $c_o(x, y)$, i.e.,

$$\hat{d}(x,y) = \begin{cases} \bar{d}(x,y) + c_o(x,y)\cdot jnd(x,y), \text{if} & d(x,y) > \bar{d}(x,y) \\ \bar{d}(x,y) - c_o(x,y)\cdot jnd(x,y), \text{otherwise} \end{cases}. \qquad (7)$$

where $\bar{d}(x,y)$ is the average pixel value of d inside the 5x5 mask centered at (x, y). In (7), the local contrast of d is emphasized by increasing the difference between the current pixel value and its local average. Consequently, a possible loss of the NLC in the edge pixels can be alleviated. This can be checked in (5) by replacing o to $\hat{d}$. Up to this step, the desired specified image is approximated by preventing the decrease of the NLC at the edge pixels. The remaining problem is to convert the original image in a way that the resultant EHS image resembles the updated image, $\hat{d}$. To this end, the input pixel value is modified to produce a pixel value close to the updated value. This is simply done by

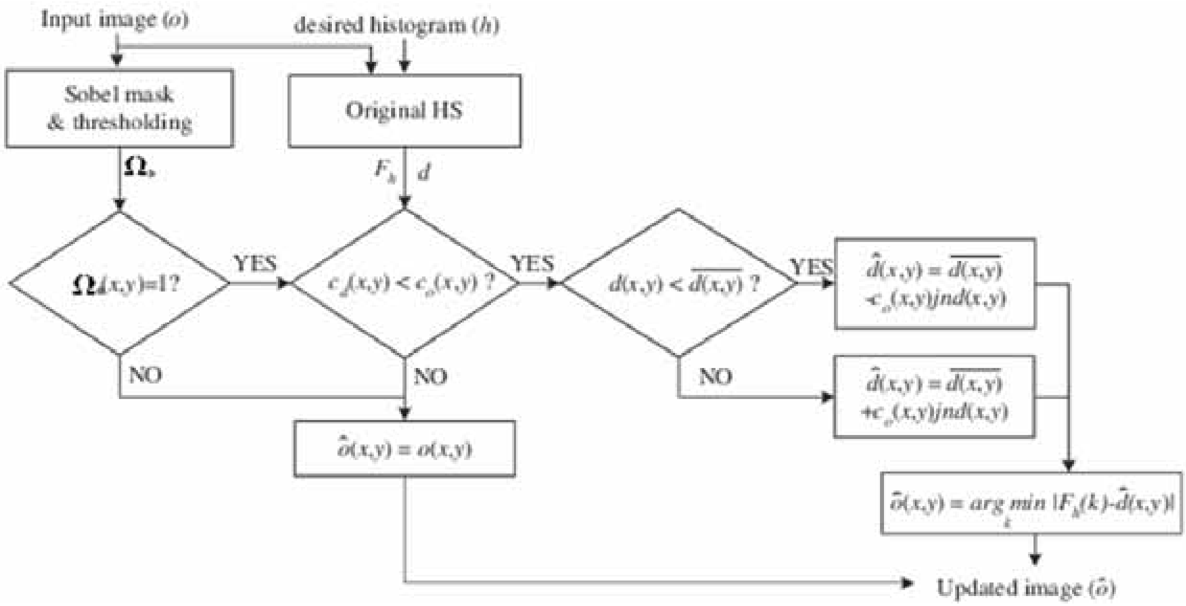

Fig. 2. Flow chart of the proposed preprocessing algorithm.

$$\hat{o}(x,y) = \arg\min_{k} \left| F_h(k) - \hat{d}(x,y) \right|. \tag{8}$$

By modifying the input pixel value in advance, the undesired loss of the NLC can be prevented.

Note that the original HS is used to estimate the output pixel values of the EHS. This simple HS can be replaced by the conventional EHS algorithms [1, 4] at the expense of the computational overhead. However, since our objective is to approximate the output, the complicated EHS process is not necessary in the preprocessing stage. Also, the proposed preprocessing is different from the conventional contrast enhancement algorithms [12-14] in that the pixel values are controlled by the desired histogram. Since the input image is tuned with the consideration of the specified histogram, the following EHS can produce a perceptually enhanced image without a loss of the NLC.

3.2 Pixel Ordering Method

After applying the proposed preprocessing algorithm, the strict pixel ordering should be performed for the EHS. As described in Section II, the neighboring pixels are necessary to discriminate the pixels of the same graylevel. In [1], the filter masks in (3) are sequentially examined until all the pixels are prioritized. Basic intuition behind this approach is that the local average pixel intensities can be viewed as low resolution information. Since the HVS perceives a local region not a certain pixel, it is reasonable to consider the low resolution pixel values. In order to further utilize the HVS characteristics, the strict ordering is performed in the wavelet domain [4]. In the wavelet domain sorting, the horizontal, vertical, and diagonal frequency bands are additionally compared since the significant image

In the proposed EHS, the pixel ordering similar to [4] is used. It is evident that the HVS is sensitive to the high frequency bands. However, for the pixel ordering purpose, it is not necessary to differentiate the high frequency components. Thus, only the difference between the current and neighboring pixels is considered in the proposed pixel ordering. To this end, the filter masks are designed as follows:

$$\phi_1 = [1], \phi_2^l = \frac{1}{5}\begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \phi_2^h = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix},$$
$$\phi_3^l = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \phi_3^h = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}. \tag{9}$$

The larger masks are similarly defined by enlarging the filter support while keeping the symmetry. It can be seen that only the mask, ϕ_i^h , is additionally included to (3). In the proposed pixel ordering, the pixels are firstly ordered based on the pixel value, i.e, the result using ϕ_1 . Then, for the pixels of the same graylevel, the remaining masks are sequentially examined until all pixels are sorted. Note that ϕ_i^h measures the local deviation of the current pixel to the average of neighboring pixels. When the local average values are the same, i.e, the results of ϕ_i^l are equivalent, the results of ϕ_i^h are compared to enhance the local contrast. For instance, if the current pixel is darker than the neighboring pixels, it is advantageous to map that pixel to a more darker value to increase the local contrast. This can be accomplished by sorting the outputs of ϕ_i^h . In addition, the ordering failure problem in [1], which occurs when all the local averages are exhausted without successfully ordering pixels, can be effectively alleviated.

Notice that the proposed pixel ordering method also depends on the pixel value. Without the use of the

Fig. 3. Test images of 256_256 size.

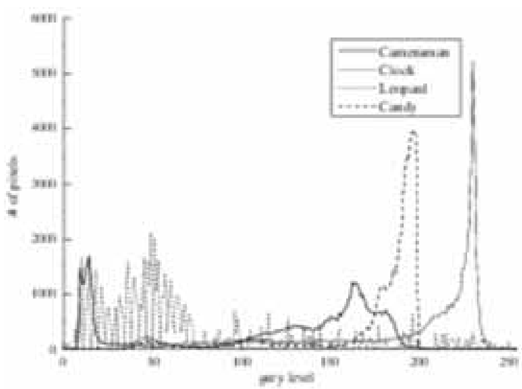

Fig. 4. The histograms of the original images.

preprocessing technique, therefore, the proposed IEHS may not provide a significant difference compared to the conventional EHS algorithms. Together with the preprocessing, however, a possible loss of the NLC can be avoided and the local contrast can be further enhanced by the EHS.

4. Experimental Results

In order to evaluate the performance of the proposed IEHS algorithm, four grayscale images, “Cameraman”, “Clock”, “Leopard”, and “Candy”, in Fig. 3 are tested. The histograms of these four images are shown in Fig. 4. Then, the uniform histogram is assumed as the desired histogram. Since the IEHS is based on the strict ordering, the resultant images can have the exact uniform histogram. For the performance evaluation, the visual quality of the resultant images is compared. In [4], it was shown that Wan et al.’s algorithm slightly outperforms Coltuc et al.’s algorithm [1]. Thus, for the visual quality evaluation, we compare the proposed IEHS only to Wan et al.’s algorithm. Hereafter, the conventional algorithm represents Wan et al.’s

Table 1. Experiment Parameters.

Algorithm	(k,σ^2)	Camera man	Clock	Leopard	Candy
Wan’s	(0.5, 1)	26.33	29.08	25.62	37.30
	(0.5, 2)	24.66	27.34	23.86	35.04
	(0.5, 4)	23.78	26.40	22.90	33.87
	(0.25, 1)	26.21	28.93	25.51	36.70
	(0.25, 2)	24.58	27.21	23.77	34.66
	(0.25, 4)	23.72	26.31	22.81	33.57
Proposed	(0.5, 1)	26.62	29.44	25.94	37.85
	(0.5, 2)	24.85	27.59	24.09	35.46
	(0.5, 4)	23.89	26.57	23.07	34.20
	(0.25, 1)	26.71	29.53	26.06	37.23
	(0.25, 2)	24.90	27.65	24.18	35.17
	(0.25, 4)	23.90	26.60	23.15	33.97

Table 2. The comparison of the computational complexity (ratio).

	Cameraman	Clock	Leopard	Candy
uniform	1.01	1.02	1.08	0.93

algorithm unless otherwise mentioned.

Fig. 5 shows the results of the conventional and proposed algorithms for the uniform specified histogram. Since the proposed technique consists of the two steps, the resultant images after the preprocessing step are shown in the first column. Although the resultant histograms for each target histogram are the same for both algorithms, the proposed algorithm provides superior visual quality compared to the conventional algorithm. As can be seen, the loss of the local contrast is noticeable in the results of the conventional algorithm. Since the proposed preprocessing can prevent the loss of the NLC and the proposed pixel ordering can further emphasize the local contrast, the resultant images obtained by the IEHS have sharper image details.

In order to evaluate the performance objectively, the original images in Fig. 3 are degraded by reducing the contrast and inducing the image blur. To this end, the pixel values are multiplied by k and the Gaussian blur with variance of σ^2 is applied. In Table 1, the peak signal-to-noise ratio (PSNR) results are provided by using different k and σ^2 values. Since the original images are given in this simulation, the histograms of the original images are set as the desired histograms. By comparing the EHS results on the degraded images with the original images, the image restoration capability can be assessed. The objective performance comparison with respect to the PSNR shows that the proposed IEHS outperforms the conventional technique. Note that the effect of the image noise is not considered even the histogram based image processing techniques are inherently sensitive to the image noise. Thus, when dealing with the noisy images, denoising algorithms should be employed before applying the EHS technique.

Table 2 compares the ratio of the computational

Fig. 5. The visual quality comparison for the uniform target histogram. First column: Resultant images after preprocessing, Second column: Specified images by the conventional algorithm, Third column: Magnified regions of the second column, Fourth column: Specified images by the proposed algorithm, Fifth column: Magnified regions of the fourth column. The images are best viewed in the electronic version.

complexity between the proposed and Wan et al.'s methods, where the processing time of the proposed method is divided by that of Wan et al.'s. We see that even though the processing time depends on the image characteristics, the computational complexity of the proposed IEHS is comparable to that of Wan et al.'s method. This is because the computational overhead required for preprocessing is mainly compensated by the proposed pixel ordering. In the ordering stage, we empirically found that the pixel ordering algorithm in [1] utilizes the filter masks up to ϕ_6 or ϕ_7 for the smooth regions. However, in the proposed method, the pixel ordering is frequently finished at ϕ_2^h or ϕ_3^h in such a case. Thus, the proposed preprocessing algorithm does not deteriorate the total computational complexity.

5. Conclusion

In this paper, we have presented an IEHS algorithm consisting of the preprocessing and the strict pixel ordering. In the preprocessing, the pixel values are modified to prevent the loss of the NLC by alleviating the dependency of the pixel value on the EHS result. Then, the pixel ordering concerning the local contrast enhancement is applied to exactly specify the desired histogram. Compared to the conventional EHS algorithm, the proposed IEHS algorithm provides better image enhancement performance.

The proposed algorithm is applicable to a wide variety of multimedia devices. For instance, a user may specify a desirable histogram or the multimedia device can provide a suitable histogram by a certain algorithm. In such a case, the proposed algorithm can not only exactly specify the desired histogram but also provide a perceptually pleasant image. Fast implementation and speedup issues remain a future work of the proposed algorithm.

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