HIGH EFFICIENT CONTRAST ENHANCEMENT USING PARAMETRIC APPROXIMATION

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Abstract-In this study, a local contrast enhancement method, namely Parametric-Oriented Histogram Equalization (POHE), is proposed to effectively yield enhanced results. In general, the grayscale distribution of a specific region in an image can be modeled with a kernel function such as the Gaussian, and thus the corresponding estimated cumulative distribution function (cdf) can be considered as the transformation function for contrast enhancement. The required parameters, however, still need to access all of the pixels in the corresponding region, and thus consume a huge amount of computations. To cope with this, the concept of integral image is adopted to effectively derive the required parameters. In the experimental results, former well-known speed-oriented methods are adopted for comparison, and the results demonstrate that the proposed methods can provide high practical value for biometric and tracking/detection these active issues who desire high efficiency.

Keywords: Image enhancement, histogram equalization, contrast enhancement, integral image, parametric-oriented histogram equalization.

1. INTRODUCTION

Nowadays, image enhancement [1] plays an important role in vision-wise applications, for instance the enhancement of brightness or contrast. These methods are widely-used for providing a better visual perception for Human Visual System (HVS) or higher discernible capability for a signal for rear-end analysis. Among these, the latter issue attracts more attentions because of the rises of some popular fields, such as the medical imaging and pattern recognition. The contrast enhancement is the most popular image enhancement technique throughout these areas. In general, these methods can be roughly grouped into global and local categories according to their purposes and considerations. For the global one, the coordination and the balance of the entire enhanced image should be maintained, and normally the issue of noise influence is also considered since the prospective viewers are HVS. Conversely, the local schemes mostly focus on the stability of the local luminance as well as mining more details from those images. In addition, since the overexpressed information is normally not intuitive for viewers, these methods tend to be utilized in signal analysis related topics, such as object tracking or detection.

The Global Histogram Equalization (GHE) [1] is the most representative global way of contrast enhancement, and typically the target expectation is to shape images having uniform distribution of pixel values. Firstly, this method collects the grayscale histogram (called probability density function (pdf)) of an entire image, and then adopts the corresponding cumulative distribution function (cdf) as the transformation function. This method can be implemented easily and offers high processing efficiency, yet it lacks good brightness preservation and visually pleasurable perception. To improve these issues, some former studies have proposed more effective algorithms/thoughts to reach better performance [2]-[8]. So far the most widely acceptable way to cope with the above issues is to divide this entire histogram into multiple sub-histograms, and enhance each of them. For instance, the Bi-Histogram Equalization (BBHE) [2] and Dualistic Sub-Image Histogram Equalization (DSIHE) [3] separated the histogram into two by the mean and the median value of the given histogram. In addition, the Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) [4] has the same number of sub-histograms, yet it sacrificed processing efficiency for finding a more appropriate location for histogram division. These methods provide two sub-histograms, and also limit the room of brightness preservation. Thus, some methods such as Recursive Mean Separate Histogram Equalization (RMSHE) [5] and Recursive Sub-Image Histogram Equalization (RSIHE) [6] extend the essences of BBHE and DSIHE, respectively, for yielding better performance. Moreover, the Multiple Histogram Equalization (MHE) [7] and Celik-Tjahjadi's method [8] also achieved an improvement through the same concept. In recent years, the adoption of wavelet transform comes to another popular way for global contrast enhancement [9]-[11]. Normally, the wavelet coefficients are modified individually to yield the expected effect, while an independent way which thresholds these coefficients is also usually utilized for easing noises. To further improve the visual quality, the method in [9] decomposed the high-frequency bands by the Haar transform to extract more image details for enhancement. In addition, to obtain a higher accuracy of coefficient representation, the method in [10] offered multiple available wavelet transforms during process. Although these wavelet-based methods are able to offer good enhanced results and noise suppression simultaneously, the required transformation and its inverse process also raise the entire computations (4.9 seconds were needed for a frame of size 256x384 when the Pentium 4 2.4GHz CPU was adopted). Hence, these methods are widely-used in medical imaging which has less demand on processing efficiency.

Conversely, to give more discernible details of images, the regional enhancement perspective is considered for each pixel in the local methods, while the computation requirement are also raised more intuitively. For instance, the region of size 21x21 was supposed to be used in Sakellaropoulos et al.'s wavelet-based method [12], and thus a relatively higher computational complexity is also accompanied (122 seconds are needed for a frame of size 1400x2300 when the Pentium 4 1.5GHz CPU and 1GB RAM were used). Meanwhile, respecting to the GHE, the

Local HE (LHE) the local form of the HE technique also induces an unacceptable complexity since each pixel has a specific transformation function. For some applications, e.g., intelligent surveillance system, biometric, tracking, and detection, due to the processing efficiency is a rather crucial factor, some specific studies toward computation simplification are motivated. For instance, Stark [13] proposed an adaptive contrast enhancement method to leave a room for further adjustment to meet different applications and the corresponding preferred effect. In this method, the concept of the signed power-law and the local-mean replacement method were adopted to generate the required transformation functions, whereas two adjustable parameters, the cumulation function power and the proportion of local-mean, were retained. Moreover, the Yu-Bajaj's method [14] employed the isotropic and anisotropic propagations to yield the required maximum, minimum, and average maps for contrast enhancement. Since the propagation information replaces the role of the Gaussian filtering [15], the computational complexity is also reduced. Kim et al.'s Partially Overlapped Sub-block Histogram Equalization (POSHE) [16] utilized the concept of block-wise processing to replace the former pixel-wise concept. In this method, the pixels in a block use an identical group of cdfs (involving the neighboring blocks, and the weights of each cdf according to a low-pass filter) to obtain the shared transformation function, and the processing efficiency is further increased. Since this method consumed lots of computations on the filtering, the method called Cascaded Multistep Binomial Filtering Histogram Equalization (CMBFHE) [17] is proposed to utilize a binomial filter with fewer computations to replace the role of the formerly used low-pass filter. Although all of the above improved local methods offer well contrast enhancement and more discernible details, the processing efficiency still has quite a big gap to reach the real-time requirement of speed-oriented applications. In particular, when a bigger neighborhood size is considered (the region size to enhance a pixel), the processing efficiency is normally reduced exponentially.

In this study, the Parametric-Oriented Histogram Equalization (POHE) is proposed to meet the requirements of locally contrast-enhanced results, and which simply requires extremely low computations. In this method, the concept of the integral image is employed to enable these functions. With this strategy, the processing efficiency does not affected by the size of the considered neighborhood.

2. Parametric-Oriented Histogram Equalization (POHE)

In general, although the traditional LHE [1] provides better descriptions on the details of a given image compared to the GHE, it requires much more computational time to construct the transformation function (cdf) for each pixel. To reduce the high required payload, the proposed POHE attempts to use an estimated model to yield the transformation function. As a result, the computations can be significantly reduced with this strategy.

2.1. Traditional LHE

To have a better understanding of the proposed POHE, the traditional LHE is briefly introduced in this subsection. In the LHE, each pixel has an independent transformation function. The relationship between an input image and the enhanced image can be formulated below,

$$y_{i,j} = f(x_{i,j}), \text{ where } x_{i,j} \in \mathbb{Z} \text{ and } y_{i,j} \in \mathbb{Z}, \tag{1}$$

where $x_{i,j}$ and $y_{i,j}$ denote the given grayscale value and the corresponding contrast enhanced grayscale value, respectively. This transformation function is obtained by considering the grayscales of its neighborhood. The traditional HE (no matter the global or local HE) supposes that a uniform grayscale distribution is able to provide the best contrast, and thus the cdf of the grayscale distribution is considered as the transformation function as below,

$$p(g) = \frac{1}{|\mathrm{R}_{i,j}|}\sum_{(m,n)\in\mathrm{R}_{i,j}} \delta(x_{i+m,j+n} - g), \text{ where } g \in [0, L], \tag{2}$$

$$c(g) = \sum_{i=0}^{g} p(i), \tag{3}$$

where g denotes the possible values (in an 8-bit digital image, $L = 2^8 - 1 = 255$); $\mathrm{R}_{i,j} = \left\{x_{i+m,j+n} \,\middle|\, |m| \le \left\lfloor\frac{M}{2}\right\rfloor, |n| \le \left\lfloor\frac{N}{2}\right\rfloor\right\}$ of size *M*x*N* denotes the neighborhood (referred to as a block in this paper) centered at coordinate (i, j); $|\mathrm{R}_{i,j}|$ denotes the cardinality of $\mathrm{R}_{i,j}$; $2 \nmid M$ and $2 \nmid N$; $p(\cdot)$ and $c(\cdot)$ denote the pdf and cdf, respectively. Subsequently, the transform function can be obtained through the stretching as below,

$$f(x_{i,j}) = L \times c(x_{i,j}). \tag{4}$$

2.2. Concept description

Most of the time consumptions in the traditional LHE can be separated into two parts: 1) The pdf construction which has to access the entire $\mathrm{R}_{i,j}$, and 2) the construction of cdf for each grayscale (as represented in Eqs. 2 and 3, respectively). In this work, these two issues are separately discussed and simplified in terms of computational complexity conceptually.

Considering a common viewpoint that the grayscale distributions of natural images are in Gaussian, in particular the well-exposed images normally confirm this observation. This indicates that few statistical parameters can be used for estimating an approximate distribution from an image of interest. The cdf of the Gaussian distribution has an error function according to its definition as defined below,

$$\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt, \text{ where } x \in \mathbb{R}. \tag{5}$$

To simplify this formula, the corresponding approximation [18] can be rewritten as below,

$$\mathrm{erf}(x) \approx 1 - \left(\sum_{i=1}^{5} a_i t^i\right)e^{-x^2}, \text{ where } t = \frac{1}{1+px} \text{ and } x \ge 0, \tag{6}$$

where p =0.3275911, a_1 =0.254829592, a_2 =-0.284496736, a_3=1.421413741, a_4=-1.453152027, and a_5=1.061405429; for negative x, $\mathrm{erf}(-x) = -\mathrm{erf}(x)$. Thus the transformation function for the LHE can be obtained through

$$c_{Gaussian}(x_{i,j}) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{x_{i,j} - \mu_{i,j}^{est}}{\sqrt{2}\sigma}\right)\right], \tag{7}$$

where

$$\mu_{i,j}^{est} = \frac{1}{|\mathrm{R}_{i,j}|}\sum_{(m,n)\in\mathrm{R}_{i,j}} x_{i+m,j+n}, \tag{8}$$

$$\sigma = \sqrt{\frac{1}{|\mathrm{R}_{i,j}|}\sum_{(m,n)\in\mathrm{R}_{i,j}} \left(x_{i+m,j+n} - \mu_{i,j}^{est}\right)^2}. \tag{9}$$

The superscript "est" represents that the labeled variable is obtained through estimation. By this distributive assumption, the required cdf construction intuitively does not have to be calculated. Figure 1 shows a simple visual comparison which involves the traditional global/local HEs, and the parametric estimated approach using Gaussian kernel function. It is clear that the proposed simple method is still able to provide high local contrast, in particular the words appeared on the Buddha's strap comparing to that of the GHE.

2.3. Simplification

The above parametric method still has to access the entire $\mathrm{R}_{i,j}$ for estimating distribution, in particular the derivations of the two variables, $\mu_{i,j}^{est}$ and σ. To reduce the required computations, the concept of the integral image is adopted in this work as described below,

$$I_{i,j} = \sum_{m=0}^{i} \sum_{n=0}^{j} x_{m,n}, \quad (10)$$

where $x_{m,n}$ denotes the grayscales. This derivation is possible to be simplified when raster scan path is applied. For instance, to calculate the integral value at a specific location (i, j), the above equation can be rewritten as

$$\begin{aligned} I_{i,j} &= x_{i,j} + \sum_{m=0}^{i-1} \sum_{n=0}^{j} x_{m,n} + \sum_{m=0}^{i} \sum_{n=0}^{j-1} x_{m,n} - \sum_{m=0}^{i-1} \sum_{n=0}^{j-1} x_{m,n} \\ &= x_{i,j} + I_{i-1,j} + I_{i,j-1} - I_{i-1,j-1}. \end{aligned} \quad (11)$$

In addition, to extend this formula to derive the kth moment ($m_{i,j}^{(k)}$) of a specific region, this equation can be rewritten as below,

$$I_{i,j}^{(k)} = \sum_{m=0}^{i} \sum_{n=0}^{j} x_{m,n}^{k} = x_{i,j}^{k} + I_{i-1,j}^{(k)} + I_{i,j-1}^{(k)} - I_{i-1,j-1}^{(k)}, \quad (12)$$

$$m_{i,j}^{(k)} = \left(I_{i+\lfloor \frac{M}{2} \rfloor, j+\lfloor \frac{N}{2} \rfloor}^{(k)} - I_{i-\lceil \frac{M}{2} \rceil, j+\lfloor \frac{N}{2} \rfloor}^{(k)} - I_{i+\lfloor \frac{M}{2} \rfloor, j-\lceil \frac{N}{2} \rceil}^{(k)} + I_{i-\lceil \frac{M}{2} \rceil, j-\lceil \frac{N}{2} \rceil}^{(k)} \right) / \left| \mathrm{R}_{i,j} \right|, \quad (13)$$

where the operations $\lfloor \cdot \rfloor$ and $\lceil \cdot \rceil$ denote round down and round up, respectively. Thus, the required computations of $\mu_{i,j}^{est} = m_{i,j}^{(1)}$ and $\sigma = \sqrt{m_{i,j}^{(2)} - \left(m_{i,j}^{(1)}\right)^2}$ can be significantly simplified, and the computation is independent to the size of $\left| \mathrm{R}_{i,j} \right|$ theoretically.

2.4. Implementation

Similar to the traditional LHE, the two parameters, M and N, are left to control the enhanced region size as needed. First, the whole integral images $I_{i,j}^{(1)}$ and $I_{i,j}^{(2)}$ should be calculated in advance through Eq. 12. Subsequently, Eqs. 4 and 7 are adopted to enhance each pixel independently, in which the required variables $\mu_{i,j}^{est}$ and σ can be simply derived by $m_{i,j}^{(1)}$ and $m_{i,j}^{(2)}$, and they need to use the calculated $I_{i,j}^{(1)}$ and $I_{i,j}^{(2)}$ as defined in Eq. 13. Finally, the LHE contrast enhancement effect is simulated when all pixels are accessed.

3. Experimental Results

In this section, the performance of the proposed POHE is evaluated. Three aspects are considered to conduct the comparisons among various methods, including processing efficiency, intensity of the enhanced local contrast, and visual perception quality. In this work, the testing platform is geared with Microsoft Windows 7 (32-bit), Visual Studio 2008 C++ compiler, Intel Q6600 CPU, and 3.5GB RAM for the following experiments. To provide an objective evaluation, the traditional local histogram equalization is considered as a ground truth for the proposed method, while the four well-known speed-oriented local contrast enhancement methods with the corresponding settings are also adopted for comparisons as below:

1) Local Histogram Equalization (LHE) [1].
2) Stark's method [13], in which the two parameters, cumulation function power and proportion of local-mean are set at 0.5.
3) Yu-Bajaj's method [14], in which the resistance factor of the anisotropic propagation is set at 0.1.
4) Partially Overlapped Sub-block Histogram Equalization (POSHE) [16]: Since the filter size will greatly affect the performance of processing speed and visual quality, two sets of settings are adopted: 1) The smallest filter size (3x3) to yield the fastest computation (labeled "speed"), and 2) the suitable filter size (around a half of the tested block size) to obtain the nearly artifact-free results (labeled "quality"). Notably, since this method is only workable on even block size, the employed block size in the following experiments equals to the block size minus one for simplicity. In addition, the block size should be greater than 1/2 of the used filter size.
5) Cascaded Multistep Binomial Filtering Histogram Equalization (CMBFHE) [17]: Since this method is an improvement of the POSHE, the features and the constraints are also inherited.

Figure 2 shows the comparison in terms of processing efficiency to evaluate the above and the proposed method, where the computational time is the average time, and the test images are of size 512x512. As it can be seen, the block size does not affect the processing time of the proposed method, and the corresponding average time is 50.2 milliseconds. Thus, the proposed method is proved to be able to yield excellent performance on this evaluation, yet some former methods such as the LHE and Yu-Bajaj's method provide even better results when block size is smaller or equal to 5. Nonetheless, since these small block sizes are rarely used for contrast enhancement, the superiority of them does not provide an essential value in practical applications as well. On the other hand, the processing efficiency of the former POSHE and CMBFHE schemes with the speed-oriented setting (labeled "speed") are superior to the proposed POHE when block size is greater or equal 17, while the visual quality and the effect of local enhancement will significantly degrade as discussed below.

Figure 3 shows some practically enhanced results of the above methods, in which four different blocks including 17, 65, 257, and 513 are applied to obtain the corresponding results. Herein, the result of the LHE as shown in Fig. 3(c) is considered as the ideal case for comparison. Basically, all of the methods are able to provide the local contrast enhanced results, though Stark's and Yu-Bajaj's methods offer a relatively weak performance. Focusing on the POSHE and CMBFHE, although the two methods adopt a big filter size in the quality-oriented setting to achieve artifact-free visual quality, the filtering also removes high-frequency details, and thus smooth outputs are presented. In addition, the local contrast of these methods are inversely proportional to the block size as tending to the result of the GHE (it can be observed from the results of Fig. 3(g), (i)-(j) at block of size 513 (512 for POSHE and CMBFHE)). These drawbacks can also be observed from the results generated with the speed-oriented setting. Moreover, the blocking artifact is also enhanced when smaller block sizes are employed, in particular the cases shown in Figs. 3(f) and (h) at block of size 64. Conversely, the proposed method can provide excellent contrast enhancement result even a bigger block size is utilized. As a result, the proposed method can yield significant improvement in terms of processing efficiency and image quality, and thus which can be considered as an excellent candidate in coping with the contrast enhancement applications in most of the pattern recognition fields.

4. Conclusions

In this paper, a local contrast enhancement method, namely Parametric-Oriented Histogram Equalization (POHE), is proposed to meet the high speed processing requirement of practical pattern recognition applications. According to the experimental results, it is proved that the computational time can be maintained in a constant level when different block sizes are adopted. As documented in the experimental results, the proposed method effectively simulate the enhancement effect of the local histogram equalization as well as offering extremely low computational complexity. Furthermore, the proposed method also provide a number of superiorities simultaneously, including the distinguishable local image details, artifact-free results, and the key element of high efficiency (these are hard to be achieved simultaneously by the former methods). Consequently, it is evident that the proposed methods can be a very competitive candidate for practical pattern recognition related enhancement applications.

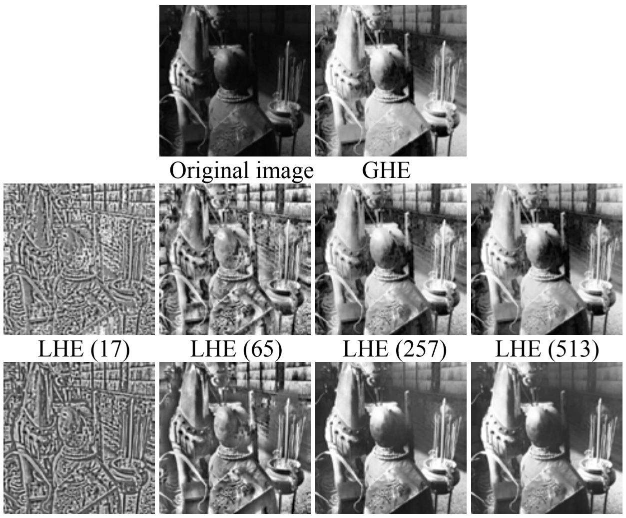

Fig. 1. Results of the traditional global/local HEs, and the proposed POHE with Gaussian kernel function. (The test image is of size 512x512; $\sqrt{|R_{i,j}|}$ are represented as $(\cdot)$, and for simplicity, M=N)

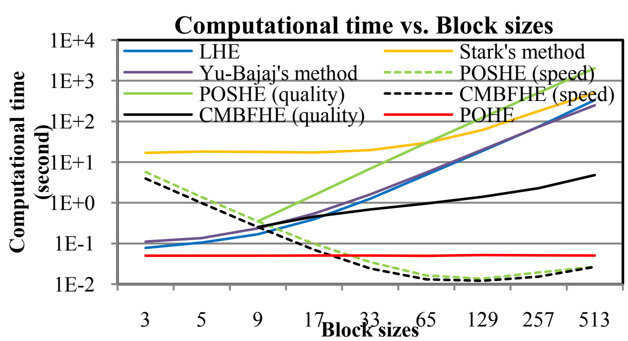

Fig. 2. Comparison of averaged processing efficiency with various contrast enhancement methods. (Note that the block size for the methods of POSHE and CMBFHE are the used block size minus one since they are only workable at even block size)

(a) (b)

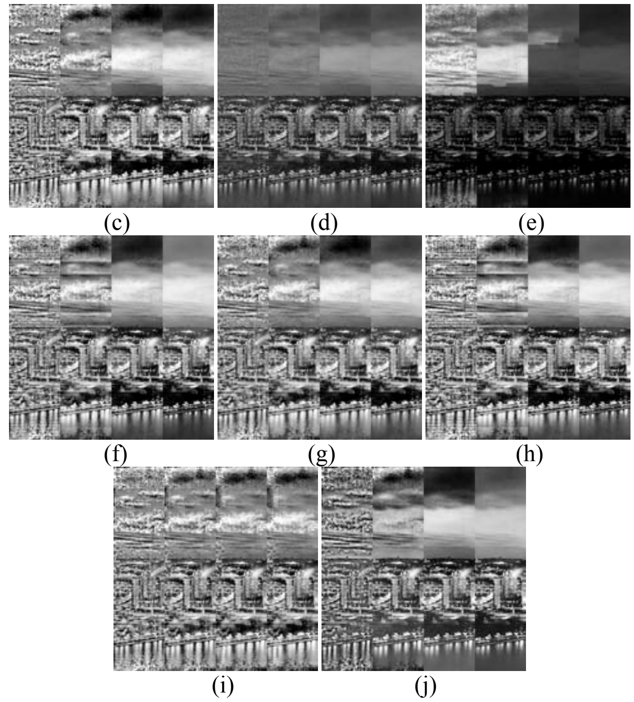

Fig. 3. Contrast enhanced results of various methods. (The subfigures (c)-(j) are the combination of four results generated with four different block sizes. Moreover, the left 1/4 columns of the enhanced images are cropped to construct the results as these subfigures; the results from left to right are the results enhanced with block sizes of 17, 65, 257, and 513, respectively) (a) Original image. (b) GHE. (c) LHE. (d) Stark's method [13]. (e) Yu-Bajaj's method [14]. (f) POSHE (speed) [16]. (g) POSHE (quality) [16]. (h) CMBFHE (speed) [17]. (i) CMBFHE (quality) [17]. (j) Proposed POHE.

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