

Chapter 2

Locally-Equalized Image Contrast Enhancement Using PSO-Tuned Sectorized Equalization

N. M. Kwok, D. Wang, Q. P. Ha, G. Fang and S. Y. Chen

Abstract Contrast enhancement is a fundamental procedure in applications requiring image processing. Indeed, image enhancement contributes critically to the success of subsequent operations such as feature detection, pattern recognition and other higher-level processing tasks. Of interest among methods available for contrast enhancement is the intensity modification approach, which is based on the statistics of pixels in a given image. However, due to variations in the imaging condition and the nature of the scene being captured, it turns out that global manipulation of an image may be vulnerable to a noticeable quality degradation from distortion and noise. This chapter is devoted to the development of a local intensity equalization strategy together with mechanisms to remedy artifacts produced by the enhancement while ensuring a better image for viewing. To this end, the original image is subdivided randomly into sectors, which are equalized independently. A Gaussian weighting factor is further used to remove discontinuities along sector boundaries. To achieve simultaneously the multiple objectives of contrast enhancement and viewing distortion reduction, a suitable optimization algorithm is required to determine sector locations and the associated weighting factor. For this, a particle-swarm optimization

N. M. Kwok (✉) · D. Wang
The University of New South Wales, Sydney, NSW 2052, Australia
e-mail: nmkwok@unsw.edu.au

D. Wang
e-mail: d.wang@unsw.edu.au

Q. P. Ha
University of Technology Sydney, Sydney, NSW 2007, Australia
e-mail: quangha@eng.uts.edu.au

G. Fang
University of Western Sydney, Sydney, NSW 2751, Australia
e-mail: g.fang@uws.edu.au

S. Y. Chen
Zhejiang University of Technology, Hangzhou 310023, China
e-mail: sy@ieee.org

algorithm is adopted in the proposed image enhancement method. This algorithm helps optimize the Gaussian weighting parameters for discontinuity removal and determine the local region where enhancement is applied. Following comprehensive descriptions on the methodology, this chapter presents some real-life images for illustration and verification of the effectiveness of the proposed approach.

2.1 Introduction

The use of image processing technology can be found in a large number of applications including computer vision, optical classification, augmented reality, feature detection, medical and morphological signal processing. For example, in manufacturing [3], three-dimensional model construction could be facilitated by the use of properly structured illumination. In industrial automation where reliable perception of the workspace is required, a vision system can be used to detect surface defects on civil structures, enabling a maintenance [13]. Image processing techniques have been applied to restore valuable ancient paintings [16], which is an important step towards their preservation. Images from cephalic radiography could be enhanced for better diagnosis of illnesses [6]. The quality of remote sensing data could be improved using image processing techniques [14]. Numerous interesting applications can be found in the literature. One fundamental operation in image processing technique is the contrast enhancement, which critically determines the quality of its subsequent operations.

In the context of contrast enhancement, there are also a number of possible approaches. In [17], a morphological filter was used for image sharpening. The contrast could also be improved by making use of the curvelet transform [20]. In the field of soft computing [7], the image contrast could be increased by a fuzzy intensification process. In [8], image enhancement was tackled from the point of view of noise-filtering and edge boosting, where the method was applied in color images. Color image processing and enhancement is a more complicated process than its counterpart for black-and-white images [12] due to the involvement of multiple color channels and the need to preserve the color information content [15] while enhancing the contrast. Novel techniques that address these problems are in great demand. For instance, in [1] it was proposed to enhance the image quality by making use of local contrast information and fusing the morphologically enhanced image with the original.

There are other attempts to enhance an image, e.g. by color rendition [18], where a neural network is used to model the color relation from a natural scene. An approach to intensify an image using a fuzzy system was also presented in [7] where the intensity gradients of neighboring pixels are adjusted according to a rule base. Alternatively, the genetic algorithm, an evolutionary computation technique, was applied to enhance image contrast [19]. Although satisfactory results could be obtained with these specific approaches, the use of histogram equalization is still a popular, effectively proven method due to its simplicity [4] and satisfactory performance. In this

class of methodology, statistics of pixel intensities collected in a histogram are constructed, and pixel intensities are modified accordingly for contrast enhancement.

Image enhancement approaches adopting histogram equalization can be broadly categorized into classes of global and local equalization implementation. The former method conducts equalization over all image pixels concurrently. In a canonical implementation, the resultant image has a histogram resembling a linear transformation or stretching from its original image histogram. In [10], spatial relationships between neighboring pixels were taken into consideration.

On the other hand, local equalization tackles image enhancement by dividing the image into multiple sectors and equalizing them independently, see [11]. In the work by Stark [21], the generation of a desired target histogram is made dependent on the characteristics of local windows. For this, a predetermined scheme can be applied to divide the image into subblocks, where each block is equalized independently. In this context, a local histogram equalization scheme was proposed in [25]. In [24], the input images were subdivided, independently equalized, and finally fused to produce a contrast-enhanced image. This approach was further developed in Kim et al. [9], where the original image is divided into overlapping subblocks and equalized according to the pixel characteristics within the block. In [21], the image histogram is matched to a distribution determined from a windowed and filtered version of the original histogram. Manipulations on the histograms were also frequently suggested by researchers. These include specific considerations in minimizing the mean brightness error between the input and output images [2]. In [22], the maximum entropy or information content criterion was invoked in contrast enhancement.

A computational intelligence optimization-based method is presented in this chapter as an alternative approach to the contrast enhancement problem for color images. The image is first randomly divided into sectors, and their contrast is increased by individual histogram equalization. The enhanced sectors are then modulated by a Gaussian mask to mitigate abrupt changes at the sector boundaries. This process is repeated, where new sectors are generated and the final output is derived from a weighted summation of the intermediate images with the weights determined via information-based weighted sum average. The performance of the approach is evaluated by using a collection of color images taken under diverse conditions. Moreover, it should be nontrivial to obtain an optimal selection of sectors, including their numbers, the boundaries and the smoothing needed to remove discontinuities along the boundaries. Here, the particle-swarm optimization (PSO) algorithm is adopted as an optimization procedure to obtain the above-mentioned settings such that the resultant image can provide the information to the viewer and for the success of subsequent processing. The PSO algorithm [5] is a multiagent-based search method mimicking the flights of bird flocks. For example, PSO is adopted to find optimal parameters for multiple-robot motion planning [23] or, more relevantly, for enhancement of an image while preserving its brightness, as reported in [12].

The Chapter is organized as follows. Section 2.2 describes the global histogram equalization process for image enhancement and its limitations. The proposed local sector-based enhancement method is developed in Sect. 2.3. Experiments conducted

using a variety of color images are described in Sect. 2.4, followed by some discussion. A conclusion is drawn in Sect. 2.5.

2.2 Global Histogram Equalization

Histogram equalization is a technique used to enhance the contrast of an image. The statistics of the image are collected and represented in a graphical representation showing the distribution of image data. Color images are frequently delivered from cameras in red green blue (RGB) signals or spaces. It is also a common strategy to enhance a color image by first converting the image to its intensity-related space, where enhancement operations are applied. The intermediate results are then converted to eventually give an enhanced color image.

Let the input or original color image be represented by

$$\mathcal{I} = \{\mathbf{I}_{uv}\}, \quad \mathbf{I}_{uv} = [R_{uv} G_{uv} B_{uv}]^T, \quad (2.1)$$

where u, v are pixel coordinates in the width and height dimensions, respectively. Since the RGB space contains three color-related signals, it is intuitive to operate on the three signal spaces simultaneously for image enhancement. Furthermore, since the human visual system is sensitive to intensity variation when accessing image contrast, the image is converted before applying enhancement. For example, the image is commonly converted to the hue saturation value (HSV) format:

$$\begin{bmatrix} H \\ S \\ V \end{bmatrix}_{uv} = \mathbf{T} \left(\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{uv} \right) = \begin{bmatrix} \arctan(\sqrt{3}(G - B)/(2R - G - B)) \\ 1 - 3 \times \min(R, G, B)/(R + G + B) \\ \max(R, G, B) \end{bmatrix}, \quad (2.2)$$

where the H component represents the color tone, S denotes saturation and V corresponds to the image intensity. The restoration from HSV to RGB space is conducted using $\mathbf{T}^{-1}()$, the inverse transform of $\mathbf{T}()$.

A histogram is obtained from intensities V_{uv} , giving

$$\mathcal{H} = \{h_i\}, \quad \sum_{i=1}^L h_i = N, \quad (2.3)$$

where h_i is the number of pixels having the i th intensity level and N is the total number of pixels. The number of levels is taken as $L = 256$, corresponding to 8-bit ($2^8 = 256$) electronic display.

In principle, image contrast will be enhanced as long as one can make use of the whole available intensity range. A uniform histogram is therefore used, where the numbers of pixels that fall inside each intensity level are equal. That is, the desired histogram is

$$\mathcal{H}^d = \{h_j^d\}, \quad h_j^d = NL^{-1}, \quad j = 1, \dots, L. \quad (2.4)$$

To perform enhancement, two cumulative histograms are constructed from the input and desired histograms, respectively. We have

$$\mathcal{C} = \{c_i\}, \quad c_i = \sum_{k=1}^i h_k; \quad \text{and} \quad \mathcal{C}^d = \{c_j^d\}, \quad c_j^d = \sum_{k=1}^j h_k^d. \quad (2.5)$$

For a pixel with original intensity i in the cumulative histogram $\mathcal{C}$ at the c_i th position, its equalized intensity value is obtained by referring to the c_j^d th element in the cumulative desired histogram $\mathcal{C}^d$ and overriding. That is,

$$j = \{i : c_i = c_j^d\}. \quad (2.6)$$

The aforementioned process is referred to as global histogram equalization because all pixels in the image are used in constructing the histograms. This method is easy to implement but there are also limitations in its performance, particularly in viewing. To illustrate this remark, an image is taken for an indoor scene where the camera is being saturated from the background high-level illumination magnitude (Fig. 2.1a). The result from global histogram equalization is given in Fig. 2.1b. It is observed that some degree of enhancement is obtained for the people sighted at the bottom-right corner. Further comparison can be made with results from a canonical implementation of a local equalization scheme as well as the proposed approach, discussed in what follows, for which the results are shown respectively in Figs. 2.1c and d. It is noted that further contrast enhancements can be obtained, also illustrated by the bottom-right corner portion of the image, via the sectorized approach, while a better result is obtained from the proposed method. Histograms of the intensities of these images are plotted in Fig. 2.1e. For the global equalization process, the histogram shown in cyan illustrates that there are occasions where some of the intensity ranges, with zero counts of pixel intensity, have not been utilized for conveying scene information. On the other hand, intensity ranges are more utilized in the two other sector-based equalization methods, as can be seen in Figs. 2.1c and d.

2.3 Local Histogram Equalization

In order to enhance the contrast of a color image and to extract details not deliverable by global histogram equalization, a local equalization method is developed and reported in the remainder of this chapter. In brief, the proposed method consists of three major steps: (i) to independently equalize image sectors or blocks, (ii) to reduce intensity discontinuity along sector boundaries, and (iii) to aggregate an enhanced image using a weighted-sum scheme.

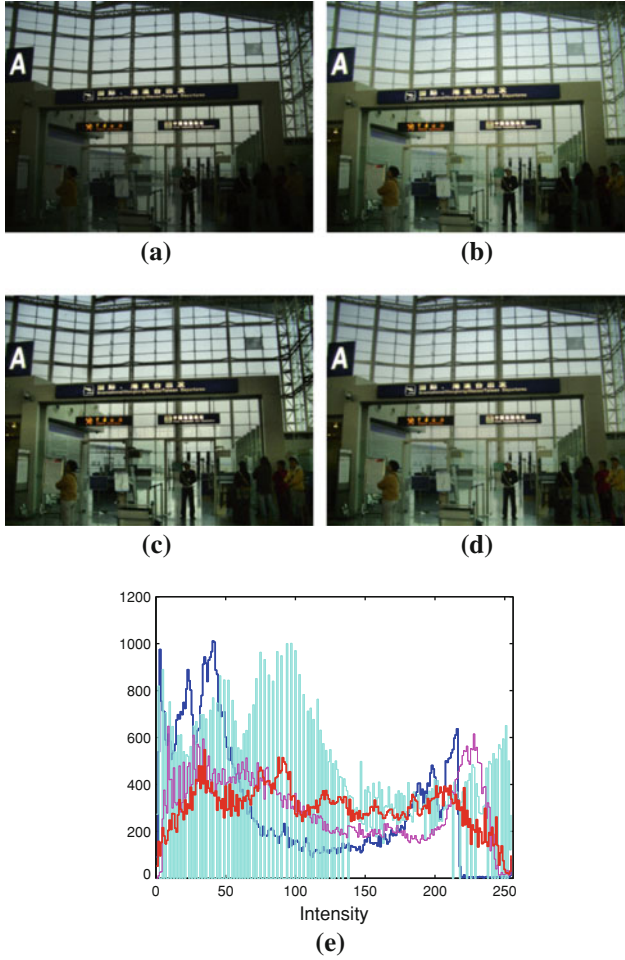


Fig. 2.1 Performance of global against local/sectorized histogram equalization: **a** original image, **b** globally equalized image by a uniform target distribution, **c** canonical sectorized equalization result, **d** proposed sectorized equalization result, **e** resulting histograms, *blue*: original **a**; *cyan*: globally equalized image **b**; *magenta*: canonical sectorized equalization **c**; *red*: proposed sectorized equalization **d**, to be discussed in Sect. 2.3

2.3.1 Sectorized Equalization

Given an image to be enhanced, the process starts first with its conversion from the RGB space to the HSV space, where the intensity component is denoted as V_{uv} . Four sectors are then generated. The center point (p, q) of dividing the sectors is determined by randomly drawing a sample in the image. That is,

Fig. 2.2 An intermediate image showing independently equalized sectors. Note intensity differences along the sector boundaries



$$p \sim \mathcal{U}(1, u_{\max}), \quad q \sim \mathcal{U}(1, v_{\max}), \quad (2.7)$$

where $u_{\max}, v_{\max}$ are the width and height of the given image in pixels, respectively; $\mathcal{U}$ is a uniform distribution; and $\sim$ stands for the sampling operation. The choice of the center point is constrained so as not to produce a too-small or too-narrow sector. In this work, the center is not allowed to lie within 10 % from the image edges. That is,

$$0.1u_{\max} \leq p \leq 0.9u_{\max}, \quad 0.1v_{\max} \leq q \leq 0.9v_{\max}. \quad (2.8)$$

Four sectors that are formed using the point (p, q) as the center, indexed by superscript $s = 1, \dots, 4$, are given by

$$\mathcal{S}_{pq}^s = \begin{cases} \mathcal{I}_{1:p, 1:q} \\ \mathcal{I}_{p+1:u_{\max}, 1:q} \\ \mathcal{I}_{1:p, q+1:v_{\max}} \\ \mathcal{I}_{p+1:u_{\max}, q+1:v_{\max}} \end{cases}. \quad (2.9)$$

Each sector $\mathcal{S}_{pq}^s$ is then equalized to the desired uniform distribution using the procedure described in Sect. 2.2, giving equalized sectors as

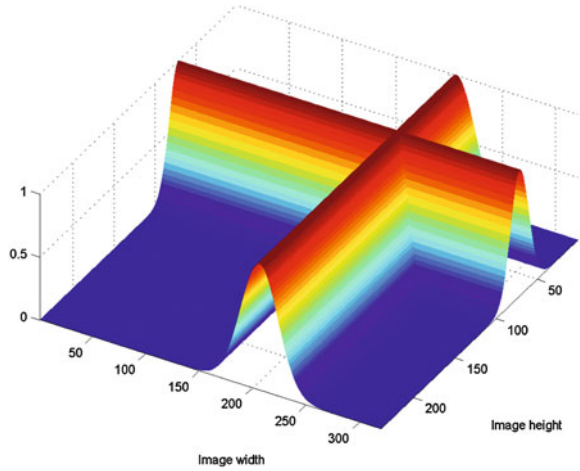
$$\mathcal{E}_{pq}^{sd} = \{\mathcal{S}_{pq}^s : \mathcal{S}_{pq}^s(c_i) = \mathcal{E}_{pq}^{sd}(c_j)\}. \quad (2.10)$$

The result is depicted in Fig. 2.2, where it can be seen that for each individual sector, the contrast is increased. However, it is also observed that along the sector boundaries, intensity differences or discontinuities are noticeable and need to be mitigated.

2.3.2 Mitigation of Sector Discontinuities

In order to reduce the difference of intensities along sector boundaries, an arithmetic mean aggregation approach is adopted in order to combine the locally equalized

Fig. 2.3 The Gaussian weighting kernel to remove boundary discontinuities corresponding to the sectors shown in Fig. 2.2



sectors. In addition, enhancements in each sector should be retained as much as possible. Here, these requirements are satisfied by weighting the sectors with a Gaussian kernel and then integrating with the original image.

Let a normalized one-dimensional Gaussian for each boundary be given by

$$\mathbf{G}^b(\delta, \sigma) = \exp\left(\frac{-\delta^{b^2}}{2\sigma^{b^2}}\right), \quad (2.11)$$

where superscript $b \in \{u, v\}$ denotes if the Gaussian is for the height (v) or width (u) for the image dimension, δ is the distance from the boundary along the associated dimension, and σ is the Gaussian standard deviation. The overall Gaussian used to remove the boundary discontinuities is obtained from an element-wise maximization operation, that is,

$$\mathbf{G}_{uv} = \max\{\mathbf{G}^u(\delta, \sigma), \mathbf{G}^v(\delta, \sigma)\}. \quad (2.12)$$

The resultant Gaussian weighting kernel is shown in Fig. 2.3.

The original image $\mathcal{I}$ and the complete image $\mathcal{E}$, formed by aggregating the independently equalized sectors $\mathcal{E}_{pq}^s$, are then fused to obtain a smoothed image $\mathcal{I}_{sm}$. For this, the Gaussian weights and an element-wise operator $\odot$ defined by

$$\mathcal{I}_{sm} = \mathbf{G} \odot \mathcal{I} + (\mathbf{I} - \mathbf{G}) \odot \mathcal{E}, \quad (2.13)$$

are used, where $\mathbf{I}$ is a matrix having dimension $u \times v$ for all elements equal to unity. The smoothed image is depicted in Fig. 2.4.

Fig. 2.4 The boundary smoothed image is obtained by fusing the equalized and original images via the Gaussian weighting kernel



2.3.3 Iterated Enhancement

The smoothed image in Fig. 2.4 is obtained from a randomly selected center point (p, q) . A further improvement can therefore be expected from deliberate determination of a proper center point. For the purpose of ensuring enhancement across all possible cases of scene variations, a number of center points and sectors have to be generated and their enhancement conducted iteratively using histogram equalization. To this end, a collection of smoothed images is created. Moreover, in order to produce an enhanced image from the smoothed images, a strategy for their combination using an information-based weighted-sum technique is adopted.

The quality of the smoothed intermediate image $\mathcal{S}_{sm}$ is taken as information entropy. That is,

$$H_t = - \sum_{i=0}^L \log(p_i) p_i, \quad (2.14)$$

where subscript t stands for the iteration count, $L = 255$ is the maximum intensity, p_i is the probability of pixel that takes on the i th intensity. The values of p_i are obtained as normalized histogram elements h_i .

In local and sectorized equalization, through the selection of a certain center point to sector the original image as well as repeated calculation of the quality metric for, say, τ iterations, the final output can be obtained by first normalizing the information contents as

$$\bar{H}_t = \frac{H_t}{\sum_{t=1}^{\tau} H_t}, \quad (2.15)$$

and then by combining this with a weighted-sum average of the intermediate resultant images, yielding

$$\tilde{\mathcal{J}} = \sum_{t=1}^{\tau} \bar{H}_t \mathcal{S}_{sm,t}. \quad (2.16)$$

The result is depicted in Fig. 2.5. It can be seen that intensity discontinues are removed and contrast is increased in local sectors. This image then replaces the

Fig. 2.5 Resultant image obtained from fusion of sectorized equalization and smoothing



V-component in the HSV domain and is finally converted back to the RGB space as a color image.

2.3.4 PSO-Based Parameter Optimization

In the above development and illustration, it is observed that effective results are obtained by incorporating an iterative smoothing operation into the sectorized local equalization approach. A nontrivial question can then be raised as to what should be the proper sector that divides the image and how should smoothing weighting be assigned. To this end, we solve these unknowns by the use of a multiobjective optimization algorithm for which the computational effectiveness remains a requirement. For this, particle-swarm optimization (PSO) [5] is used as described in the following.

The PSO algorithm can be viewed as a stochastic search method for solving nondeterministic optimization problems. For example, in the problem at hand, the sector center point (p, q) and the standard deviation σ of the smoothing Gaussian are coded as particles:

$$\mathbf{x} = [p_1, q_1, \sigma_1, \dots, p_\tau, q_\tau, \sigma_\tau]^T, \quad (2.17)$$

where each set of parameters or part of the particles $\{p, q, \sigma\}$ gives one smoothed image from the sectorized histogram equalization approach.

At the start of the algorithm, the particle positions are generated to cover the solution space. These positions may be deterministically or randomly distributed and the number of particles is predefined. In general, a small number reduces the computational load but at the expense of extended iterations required to obtain the optimum (but the optimal solution is not known *a priori*). The velocities $\mathbf{v}_0^i$ can also be set randomly or simply assigned as zeros. A problem-dependent fitness function is evaluated, and a fitness value is assigned to each particle. Here, the fitness function is taken from the entropy of the image given in Eq. (2.14). For the set of fitness values, the one with the highest value is taken as the global best $\mathbf{g}_{best}$ (for a maximization

problem). This set of initial fitness values is denoted as the particle-best $\mathbf{p}_{best}^i$. The velocity is then calculated using the random gain coefficients. The particle positions are updated, and the whole procedure repeats. Finally, as the satisfaction of some termination criteria, the global-best particle is reported as the optimal solution to the problem.

The essence of the algorithm can be described by the following expression,

$$\begin{aligned}\mathbf{v}_{k+1}^i &= w\mathbf{v}_k^i + \mathbf{c}_1 \otimes (\mathbf{g}_{best,k} - \mathbf{x}_k^i) + \mathbf{c}_2 \otimes (\mathbf{p}_{best,k}^i - \mathbf{x}_k^i) \\ \mathbf{x}_{k+1}^i &= \mathbf{x}_k^i + \mathbf{v}_{k+1}^i,\end{aligned}\tag{2.18}$$

where $\mathbf{x}$ is the particle position in the solution space, $\mathbf{v}$ is the velocity of the particle motion assuming a unity time step, w is the velocity control coefficient, $\mathbf{c}_1$, $\mathbf{c}_2$ are the gain control coefficients, $\mathbf{g}_{best}$ is the global-best position, $\mathbf{p}_{best}$ is the position of a particular particle where the best fitness is obtained so far, operator $\otimes$ denotes the external multiplication of scalars with velocities, subscript k is the iteration index, and superscript i is the particle index.

For the local equalization in the contrast enhancement problem tackled in this work, the optimization process is proposed in Algorithm 2.1 as follows:

Algorithm 2.1 PSO-tuned sector equalization

```

1: Input: Image  $\mathcal{I}$  of size  $v, u$ 
2: Define PSO parameters: generations  $nG$ , particles  $nP$ , iterations  $nS$ 
3: Initialize: particles  $P$ , velocities  $V$ , inertia weight  $w$ 
4: Initialize: group best  $\mathbf{G}_{best}$ , personal best  $\mathbf{P}_{best}$ 
5: for generations  $g = 1 : nG$  do
6:   for particles  $p = 1 : nP$  do
7:     for iterations  $s = 1 : nS$  do
8:       Get the sector center point from particle  $s$ 
9:       Partition input image into four sectors
10:      Conduct uniform histogram equalization
11:      Get the smoothing Gaussian standard deviation  $\sigma$ 
12:      Smooth sector boundaries to give smoothed image  $\mathcal{S}$ 
13:      Calculate entropy  $H$  for smoothed image
14:    end for
15:    Normalize entropies from each smoothed image
16:    Aggregate enhanced image  $\mathcal{E}_p$  for particle  $p$ 
17:    Calculate entropy for each aggregated image
18:  end for
19:  Determine  $\mathbf{G}_{best}$  and  $\mathbf{P}_{best}$  from all particles
20:  Update particle position in solution space
21: end for
22: Output: overall contrast enhanced image  $\mathcal{E}$ 

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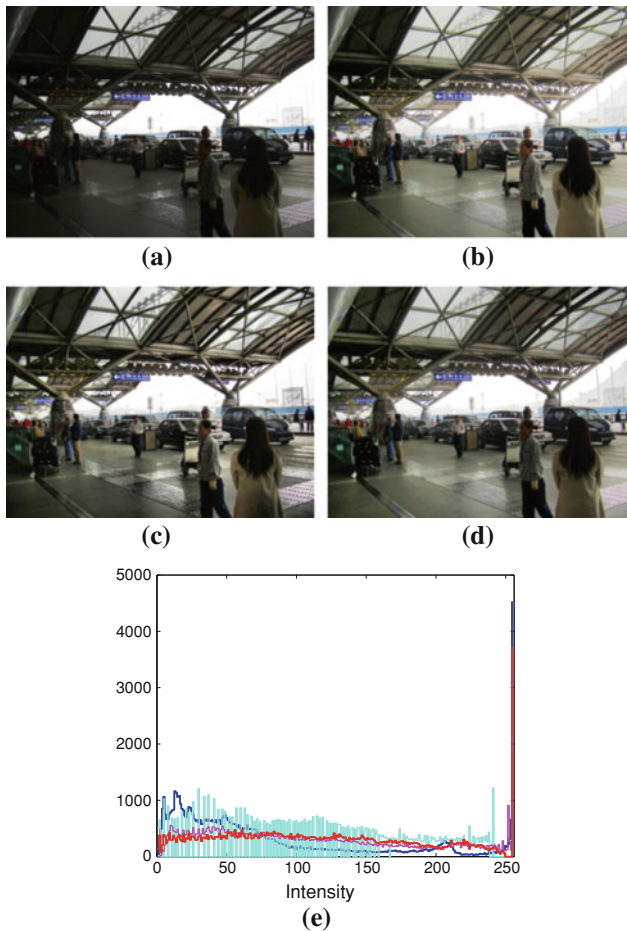


Fig. 2.6 Test results 1: **a** original image, **b** result from global equalization, **c** result from CLAHE, **d** result from proposed method, **e** plot of histograms, *blue*: original; *cyan*: globally equalized image; *magenta*: CLAHE; *red*: proposed method

2.4 Experiments and Discussion

Experiments were conducted to verify the proposed local equalization approach. A collection of 30 test images was taken under a variety of environment conditions including indoor, outdoor and cases of insufficient illuminations. The objective of enhancement includes recovering details in dark sectors that cannot be seen in the original images. In addition to objective viewing, a further assessment metric is also examined via the normalized entropy in Eq. (2.15). Here, the Shannon's entropy is adopted and calculated for all test images.

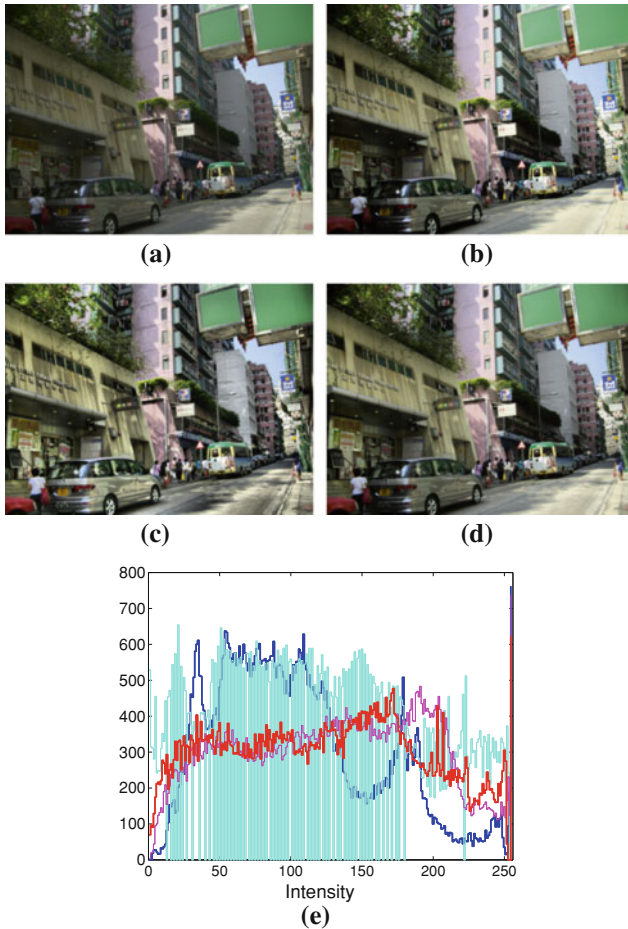


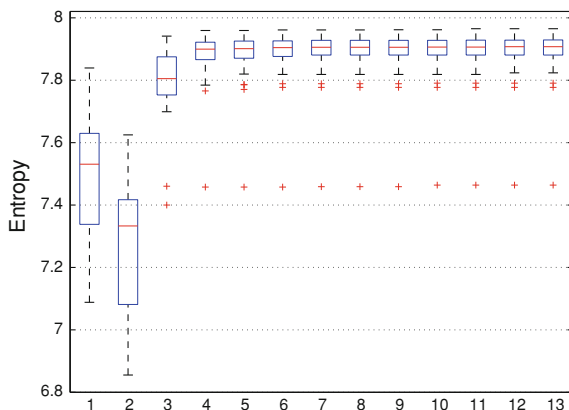
Fig. 2.7 Test results 2: **a** original image, **b** result from global equalization, **c** result from CLAHE, **d** result from proposed method, **e** plot of histograms, *blue*: original; *cyan*: globally equalized image; *magenta*: CLAHE; *red*: proposed method

Each image is captured in the RGB color space and of size 320×240 in width height dimensions. The PSO algorithm parameters are chosen as: ten PSO iterations, ten particles, and ten sectors encoded in each particle.

A sample of test images and their enhanced results is shown below. In the tests, the proposed method is compared to the canonical global histogram equalization method. Furthermore, results from the contrast-limited adaptive histogram equalization (CLAHE) method [26] in the Matlab implementation are also included.

As can be seen in Fig. 2.6, the performance of the CLAHE and the proposed methods both exhibit better performance than the globally equalized image in terms of contrast viewing. On the other hand, the performance of the CLAHE and the

Fig. 2.8 Box plots of image entropies, original and enhanced. *First column* original image, *second column* global histogram equalization, *third column* clipped adaptive histogram equalization, fourth to 13th columns: traces of entropy over the iterations using the proposed method



local equalization method are comparable. Moreover, it is also observed subjectively that the CLAHE result contains some degree of over-equalization, particularly in the texture on the bottom-left corner of the image (Fig. 2.6c), where the CLAHE method produces a darker appearance. A careful inspection of the relevant histograms indicates that the one obtained from the proposed method is more uniform and thus contains a higher information content according to the Shannon's entropy measure.

Results from another test image are depicted in Fig. 2.7. Similar observations are also obtained for this test case. In the region around the mid-bottom of the image shown in Fig. 2.7c, the CLAHE approach also gives an over-equalization artefact that does not appear in the locally equalized image. The advantage of the proposed method over the CLAHE method is attributed to its randomly chosen sectorization and optimal tuning from the PSO algorithm.

The overall results from testing the total 30 images in separate runs are summarized in a box plot of information contents (entropies) shown in Fig. 2.8. Meritorious performance of the proposed method in comparison with others is illustrated using descriptive statistical quantities such as the median, quartiles and indications of outliers. The first column in the left represents the entropy of the original image. The second column denotes results from global histogram equalizations. It is seen that the information content with these methods generally drops down in value because part of the intensity range has not been fully utilized. This is indicated by the zero entries in the histogram as shown in Figs. 2.6e and 2.7e. The third column is obtained from results using the CLAHE approach where improvements in the information are noticeable. From column 4 to column 13, the entropies are shown with respect to the iterations performed during the proposed contrast enhancement process. It is evident that the proposed method has made an overall improvement over other methods implemented in the test. Furthermore, it is observed that the information content increases along with the iterations. This further verifies the effectiveness of the local equalization scheme proposed.

2.5 Conclusion

An image contrast enhancement method based on the concept of local histogram equalization is reported in this chapter. This method is useful for images with dark and low clarity regions due to severe limitations in the illumination condition when first captured. In this work, equalization is performed on a sectorized basis where the image is divided by a chosen division point. Each image sector is enhanced by matching to a uniformly-distributed target histogram. To reduce abrupt changes at the sector boundaries, a Gaussian mask is used with a weighted sum being obtained from information contents. The choice of the sector center and the mitigation of boundary discontinuities are determined optimally by adopting a PSO algorithm. The algorithm introduces iterative contrast enhancement, applicable to a vast variety of real-life scenes. The optimized procedure has been verified in a set of test results from real-world images by a comprehensive comparison with a number of contrast-enhancement approaches available in the literature.

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