Available online at www.sciencedirect.com
SCIENCE DIRECT®
Image and Vision Computing 23 (2005) 51–57
www.elsevier.com/locate/imavis

Image enhancement based on the statistics of visual representation

Huang Kaiqi[a,*], Wu Zhenyang[b], Wang Qiao[b]

[a]National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, South Road 95, P.O. Box 2728, Beijing 100080, China
[b]Department of Radio Engineering, Southeast University, Nanjing, Jiangsu 210096, China

Received 9 February 2004; accepted 23 July 2004

Abstract

This paper introduces a novel algorithm to image enhancement that exploits the multi-scale wavelet and statistical characters of visual representation. Processing includes the global dynamic range (brightness) correction and local contrast adjustment, whose parameters are picked automatically by the information contained in the image itself. Experimental results show that the new algorithm outperforms other many existing image enhancement methods and is highly resilient to the effects of both the image-source variations.

Keywords: Image enhancement; Visual representation; Brightness; Contrast

1. Introduction

Image enhancement algorithms have been designed to process a given image so the results are better than the original image for their applications or objectives [1–3]. When the objective is to improve perceptual aspects, desirable image enhancement can be performed by the contrast and dynamic range modification.

Processing techniques for image enhancement can be classified into spatially uniform operators and spatially non-uniform operators. Linear contrast stretch, histogram equalization are two of the most widely used spatially uniform technique. Adaptive histogram-equalization (AHE) [4], contrast-limited adaptive histogram equalization (CLAHE) [5] and multi-scale enhancement [7,8] belong to the second class of image-contrast enhancement methods. While the spatially uniform methods use a transformation applied to all the pixels of the image, the later methods use an input–output transformation that varies adaptively with the local characteristics of the image. Spatially non-uniform operators usually provide a better performance than spatially uniform operators, but these methods reveal the some drawbacks. Some characteristic drawbacks of these techniques follow. The linear contrast-stretch method can hardly enhance all parts of the image simultaneously. Histogram equalization tends to over-enhance the image contrast if there are high peaks in the histogram. AHE applies locally varying gray-scale transformation each small region (block) of the image, thus requiring the determination of the block size. An improvement on this technique is represented by the CLAHE method and JND-guided adaptive contrast-enhancement methods (JGACE) [6]. In CLAHE the local contrast-gain is limited by restricting the height of local histograms. This method does not completely eliminate noise enhancement in smooth regions, and the selection of the contrast-gain limit is image-dependent. The JGACE method is general technique including certain basic human visual properties, but it requires the choice of a series of parameters. The other drawback with those basically following the HE as above is that the brightness is changed and the enhanced images look far from natural and the extend of enhancement is not controllable, though some works have been done [15,17,18], it is still has no means to solve this problem in a better manner.

Unlike traditional signal scale techniques, wavelet-based algorithms offer the capability of modifying/enhancing image components adaptively based on their spatial-frequency properties. Based on multi-scale edge

* Corresponding author. Tel.: +86 10 6265 3768; fax: +86 10 6255 1993.
E-mail address: kqhuang@nlpr.ia.ac.cn (H. Kaiqi).

0262-8856/$ - see front matter © 2004 Elsevier B.V. All rights reserved.
doi:10.1016/j.imavis.2004.07.005

representation, Lu and Hearly's algorithm enhances the image contrast by choosing 'scale variable stretching factor' to enhance the image edges [8], which just aimed at low contrast reduction.

Another important aspect is that a performance evaluation of these different algorithms is inherently difficult to obtain, due to the lack of objective measures (not depending on display devices, observers performance studies and viewing conditions). Most of digital contrast-enhancement techniques that have been proposed in the literature, especially those based on histogram modifications, try to enhance the contrast of the input image without measuring the contrast itself. A high-performance contrast enhancement algorithm should take into account not only local image characteristics but also some basic human visual properties.

In this paper, based on the statistics of visual representation [9], we present a novel robust image enhancement algorithm and a contrast evaluation method. The algorithm adjusts the dynamic range (brightness) and local contrast in wavelet domain. Similar to the contrast defined in [10], our contrast also has a multi-scale structure that corresponds the human vision system [11,12]. Based on this contrast definition, an image enhancement algorithm is proposed to enhance the image by manipulating the wavelet coefficients according to contrast defined. The local contrast and dynamic range (brightness) adjusting parameters can be decided by the statistics of visual representation automatically to achieve the 'optimal' visual image.

The paper is organized as follows: The statistics of visual representation is described in Sections 2–4 describe the novel image enhancement algorithm and how to decide the parameters in the algorithm based on the statistics characters of visual representation; Section 5 illustrates the experimental results.

2. The statistics of visual representation

In [9], Jobson investigates the connection between a well-defined consistent statistical character and good visual representations. In his experiments, the overall lightness is measured by the image mean, $\mu = \bar{I}_{\mathrm{f}}$, which is also the ensemble measure for regional lightness. The overall contrast, $\bar{\sigma}_{\mathrm{f}}$, is measured by the mean of regional standard deviations, σ_f, and it provides a gross measure of the regional contrast variations. As formula (1) and (2)

$$I_{\mathrm{f}}(i,j) = \frac{1}{(2P+1)(2Q+1)} \sum_{m=i-P}^{i+P} \sum_{n=j-Q}^{j+Q} f(m,n) \tag{1}$$

$$\sigma_{\mathrm{f}} = \frac{1}{(2P+1)(2Q+1)} \sum_{m=i-P}^{i+P} \sum_{n=j-Q}^{j+Q} [f(m,n) - I_{\mathrm{f}}(i,j)]^2 \tag{2}$$

where $(2P+1)$ $(2Q+1)$ is the extent of the analysis window, the blocks used to computer the regional parameters are 50×50 pixels in [9].

obson finds that all good visual renderings share convergent statistical characters. Fig. 1 (a) shows the clustering of actual data points. These data support the idea that the visually optimized representations compared to original data do converge in two senses: (1) mean values cluster and do reasonably tightly around an average of about 165 whereas original image distributions exhibit mean values that scatter rather more evenly across a wider range, and (2) the frame average of regional standard deviations for the visually optimized images all shift to significantly higher values. Fig. 1 (b) summarizes two primary trends. Further, Jobson tells that the 'ideal image' will exhibit values of contrast (standard deviation) in the range of 60–90.

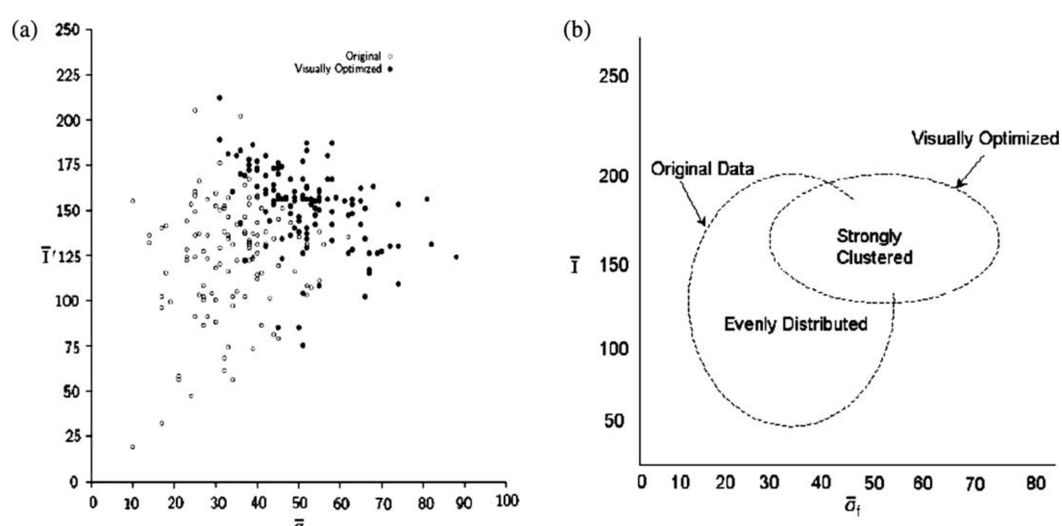

Fig. 1. Ideal visual representation experiments. (a) Large sample of original and optimized images. (b) Large sample-overall trends in optimization [1]. (Visual optimized image achieved by some preliminary experiments).

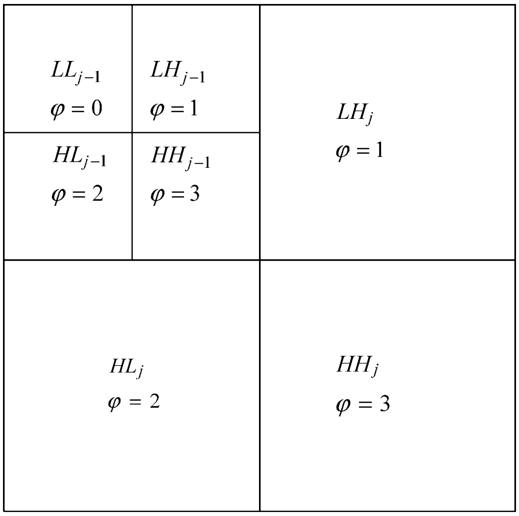

Fig. 2. Image reconstruction using wavelets.

Based on the statistics of visual representation, we can give a novel image enhancement algorithm that automatically enhances images.

3. A novel image enhancement algorithm

The product of the wavelet transform is a hierarchy of resolution information at many different levels and orientations [14]. At each level, the wavelet transform can be reapplied to the low-resolution subband to further decorrelate the image. Fig. 2 shows the image reconstruction, defining level and subband conventions used in enhancement algorithm. The label HL_jrefers to those coefficients at the jth level of reconstruction, which are the output of the highpass filter in the horizontal direction and the lowpass filter in the vertical direction. The subbands HH_j, HL_j, LH_j, $j=1,2,\ldots,N$ are called the details, where $j$is the level, with Nbeing the largest (or coarsest) level. The subband LL_0 is the low resolution residual. ϕ is orientation marked with 0,1,2,3. The properties of the wavelet coefficients provide a natural way for us to define a contrast in the wavelet domain. Here the contrast can be defined as the ratio of luminance mean between high-frequency and low-frequency bands in the wavelet domain similar to the contrast defined in [10].

The contrast at the jth band and different orientations is defined as

$$C_j = \frac{E_{H_j}}{E_{L_j}} \tag{3}$$

where E is the subband luminance mean as follow:

$$E = \frac{\sum\sum |W_{\mathrm{coe}}|}{M} \tag{4}$$

where W_{coe} is the wavelet coefficient, M is the subband resolution. We assume the same enhancement algorithm in $\phi=1,2,3$. The proposed image enhancement algorithm is based on the contrast defined in (3). Let the contrast of the origin block be $C=(c_1,c_2,\ldots,c_N)$, where c_j is the contrast at the jth frequency band, and let the contrast of the enhanced block be denoted by $\bar{C}=(\bar{c}_1,\bar{c}_2,\ldots,\bar{c}_N)$.

We enhance the contrast uniformly for all frequencies, then

$$\bar{c}_j = \lambda c_j \tag{5}$$

leading to

$$\frac{\bar{E}_{H_j}}{\bar{E}_{L_j}} = \bar{c}_j = \lambda c_j = \frac{\lambda E_{H_j}}{E_{L_j}} \tag{6}$$

Here λ is an image enhancement control factor that is decided in Section 4.

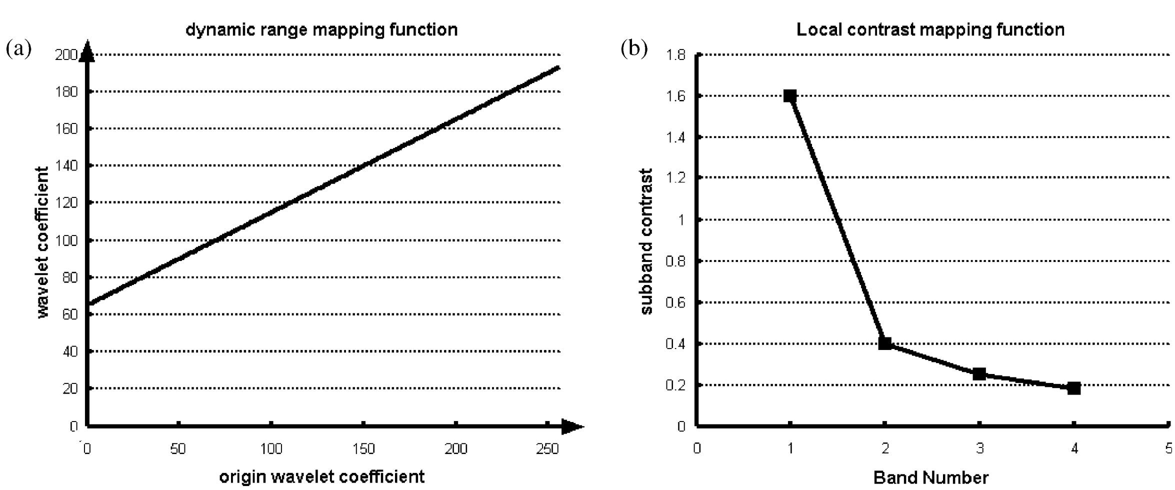

Fig. 3. Two parameters functions (a) dynamic range mapping function, $\beta=0.5$ (b) Local contrast mapping function, $\lambda=1.6$.

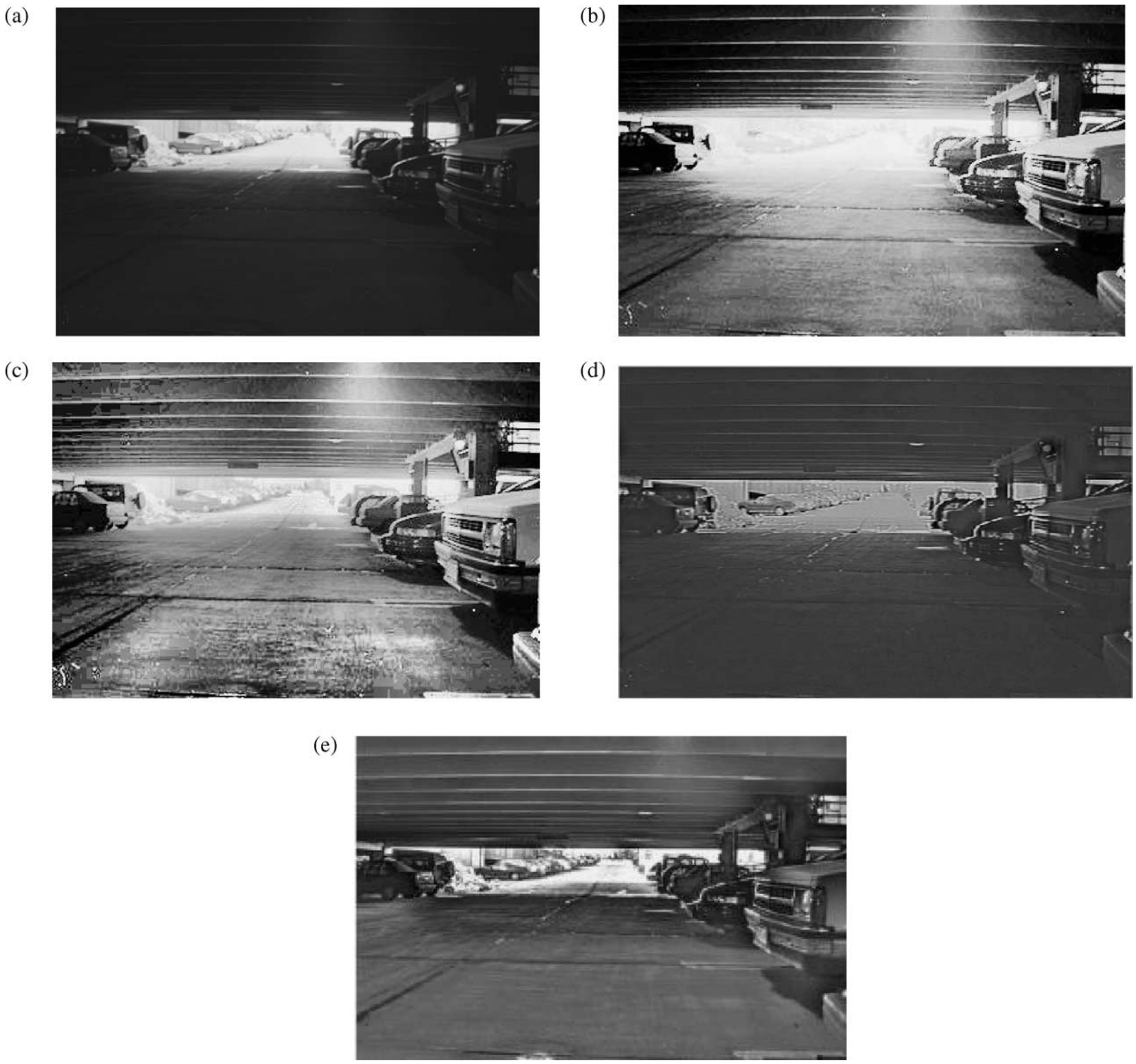

Fig. 4. Result of image enhancement (3 levels): (a) original image; (b) histogram equalization result; (c) CLAHE result; (d) previous wavelet method, (e) our algorithm result.

From (4) and (6) we can obtain the enhanced wavelet coefficients W_{coe} as

$$\bar{W}_{\text{coe}} = \lambda H_j W_{\text{coe}} \tag{7}$$

where

$$H_j = \frac{\bar{E}_{L_j}}{E_{L_j}} \tag{8}$$

H_j can be obtained by recursion. The proposed algorithm can be summarized as follows:

Step 1 Let $j=0$ and

$$\bar{E}_{L_0} = K_\beta(E_{L_0})$$

$$\bar{E}_{H_0} = E_{H_0} = (\bar{E}_{L_0})$$

Table 1
Quantitative comparison of four algorithms

Methods	Statistic value				
	Park image	HE	CLAHE	Previous wavelet method	Our Algorithm
Mean (μ)	0.2375	0.4996	0.5293	0.3356	0.6247 ($\approx$ Statistic optimal 0.63)
Standard derivation (σ)	0.1772	0.2935	0.3272	0.2822	0.3000 ($=$Statistic optimal chosen)

Step 2 If $j \le N-1$, let $j=j+1$ and use (8) to compute H_j, *else* end.
Step 3 Use (7) to obtain $\bar{W}_{\mathrm{coe}}$.
Step 4 Use (4) to compute E_{H_j}, E_{L_j} and $\bar{E}_{H_j}, \bar{E}_{L_j}$
Step 5 Return to Step 2.

Here E_{L_0} is luminance mean of the low-resolution residual. $K_\beta(\cdot)$ is a function to control the dynamic range of the enhanced image to be in the range of the display device. For $K_\beta(\cdot)$, the following function is used similar to [13]:

$$\bar{\hat{W}}_{\mathrm{coe}} = K_\beta(\hat{W}_{\mathrm{coe}}) = 65 + \beta \cdot \hat{W}_{\mathrm{coe}} \tag{9}$$

Here $\hat{W}_{\mathrm{coe}}$ is the wavelet coefficient of low-resolution residual, $\bar{\hat{W}}_{\mathrm{coe}}$ is the wavelet coefficient after dynamic range adjusting by function $K_\beta(\cdot)$. Enhancement control factors λ and β are chosen in Section 4.

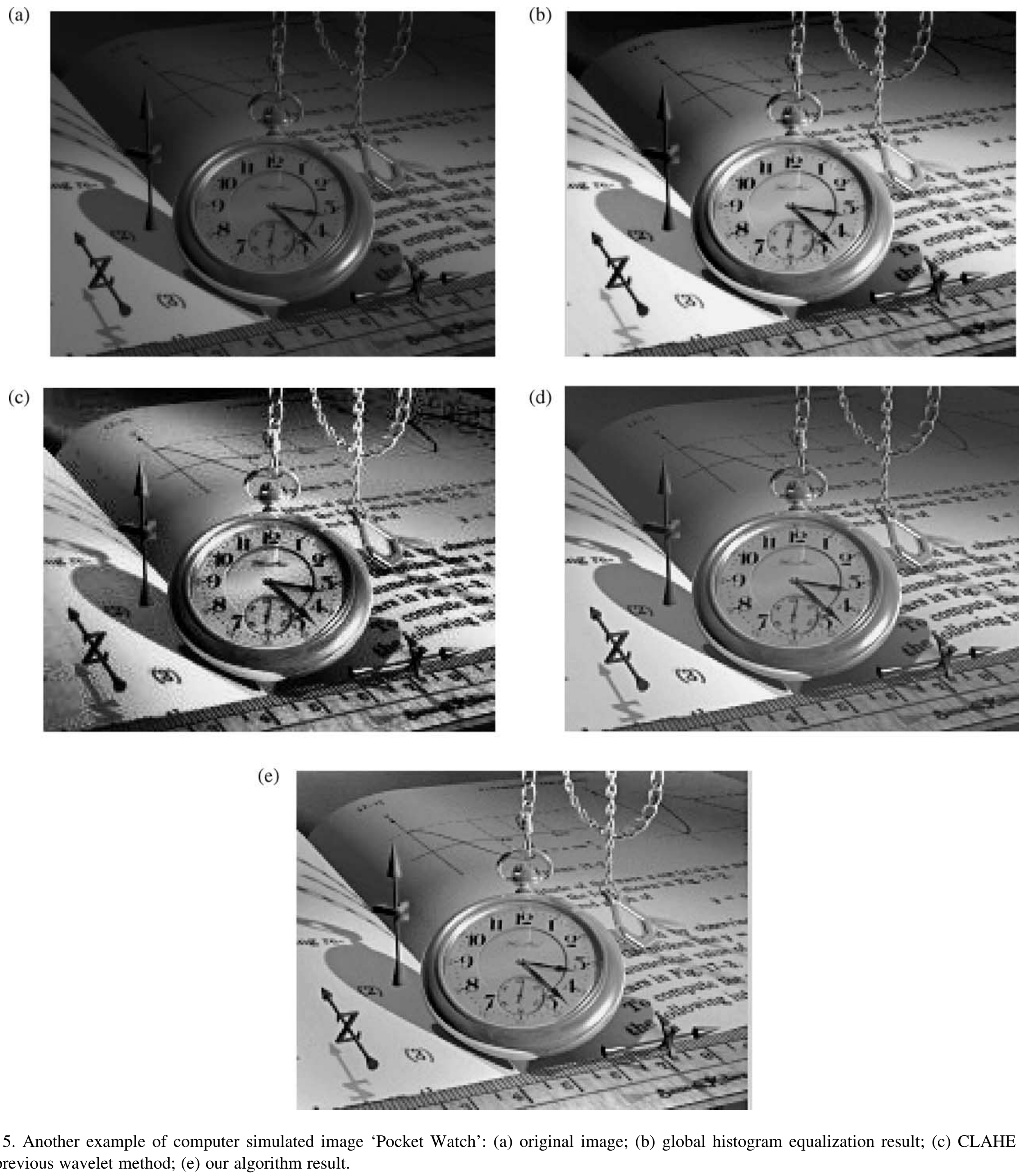

Fig. 5. Another example of computer simulated image ‘Pocket Watch’: (a) original image; (b) global histogram equalization result; (c) CLAHE result; (d) previous wavelet method; (e) our algorithm result.

4. How to choose the optimal enhancement control factors

We notice that, in the enhancement algorithm, the enhancement control factors (λ) and β play important role. Parameter λ can enhance or reduce the contrast to get optimal perceptual effect and β can adjust the global dynamic range (brightness) of the image. But how to pick the right value? It is known that the mean and standard deviation of ideal visual image is 0.63, 0.25–0.35, respectively, [9], which gives us an idea to get right values. We assume σ_{optimal} is the standard deviation of optimal visual image and μ_{optimal} is the mean of the image wanted, $\mu_{\text{WT}}(\beta)$, $\sigma_{\text{WT}}(\lambda)$ is the mean and standard deviation of enhanced image in above section. We can solve Eqs. (10) and (11) to get λ, β.

$$\mu_{\text{WT}}(K_\beta) = \mu_{\text{optimal}} \tag{10}$$

$$\sigma_{\text{WT}}(\lambda) = \sigma_{\text{optimal}} \tag{11}$$

Eqs. (10) and (11) is classic nonlinear parameter estimation and solvability can refer to [16]. By above method, the λ, β can adjust the image contrast and brightness to the value of ideal visual image. Fig. 3 is the two parameters mapping function of image 'park' in experimental results part by choosing the parameters according to (10) and (11).

5. Experimental results

To verify the usefulness of the proposed method, experiments were performed with a set of digitized monochrome images of size 512×512 with 256 gray levels. Two of them, park, HDR (high dynamic range) image from http://www.cs.utah.edu/~reinhard/cdrom/, and 'Pocket Watch', computer simulated image from http://www.cl.cam.uk/~fapp2/watermarking/image/image database/, are presented. The original images have areas of details that are in high illumination levels and other areas that in low illumination levels. In the following, we shall present the results obtained by applying our algorithm and a few other algorithms.

Fig. 4 shows the HRD test image and the results of processing by four different algorithms. HRD image is a kind of image whose ratio between the brightest part and the darkest part is very large. The first method applied is the HE (global histogram equalization). The second algorithm is CLAHE (contrast-limited adaptive histogram equalization). The third method is the result by previous method. We do not compare our results with AHE and JGACE algorithms, because the results of CLAHE are better than the former and similar to JGACE in most cases if background noise is low [6]. The fourth technique employed for comparison is our algorithm for which the $\beta=0.5$, $\lambda=1.6$. From the results shown in Fig. 4, it is clear that HE caused a saturation for the high illumination areas (park entrance) and over-enhanced the this area while other area enhanced less, CLAHE are better than HE and enhanced local areas by blocks. But the result shows some artifact block effect and the enhanced image looks unnatural, the previous wavelet enhancement method has little effect on this HDR image. Our algorithm provided faithful reproduction of the visual impression for the considering both the image global dynamic range (brightness) and local contrast in the statistics characters of 'optimal' images.

Table 1 shows the quantitative comparison results of four algorithms. It is clear that our algorithm perform well in the two aspects of statistical characters of optimal visual image. Others algorithms may only do well in one way, either lightness or contrast. The mean of previous wavelet method is less than statistic optimal, so the enhancement result is also bad.

Fig. 5 shows computer simulated image results of four enhancement algorithms. The original test image is a computer simulated image, which is not a high contrast image. It is clear that HE and CLAHE also over enhanced the image, in this image, the wavelet method performed better than HE and CLAHE, but in some area, such as the right up of the image, the detail of 'wave line' can not be seen clearly, in Fig. 5(e), most of the areas can be seen as expected. It shows that our algorithm gets the optimal visual effect both in global dynamic range and local contrast.

We also test many other images and the results reveal that the new statistical algorithm has high resiliency.

6. Conclusions and future works

In this paper, a new algorithm of image enhancement has been presented. It makes novel use of the statistic optimal visual representation and automatically adjusts the parameters in wavelet domain. Local contrast adjustment can be executed based on global dynamic range correction. The results show that the new methods produce both good visual effect and quantitative metrics compared to other algorithms. Our algorithm can be extended directly to luminance component of color image after color space transformation and is effective in common case, while completely considers the color human visual characteristics will achieve better effects [19,20]. In the future, the statistics model of visual representation also needs to be improved better.

Acknowledgements

The part of work is finished in Southeast University and is supported by 973-Project of China under Grant No. 2002 CB312102 and NSF of China under Grant No. 60002008.

References

[1] A. Rosebfield, A.C. Kak, Digital Picture Processing, Academic Press, San Diego, CA, 1976.

[2] R.C. Gonzalez, P. Wintz, Digital Image Processing, Addison-Wesley, Reading, MA, 1977.

[3] J.S. Lim, Two-Dimensional Signal and Image Processing, Prentice-Hall, Englewood Cliffs, NJ, 1999.

[4] R.H. Sherrier, G.A. Johnson, Regionally adaptive histogram equalization of the chest, IEEE Trans. Med. Image Mi-6 (1987) 1–7.

[5] S.M. Pizer, E.P. Amburn, et al., Adaptive histogram equalization and its variations, Comput. Vision, Graph. Image Process. 39 (1987) 355–368.

[6] T.L. Ji, M.K. Sundareshan, H. Roehrig, Adaptive image contrast enhancement based on human visual properties, IEEE Trans. Med. Imaging 13 (4) (1994) 573–586.

[7] A. Laine, J. Fan, W. Yang, Wavelets for contrast enhancement of digital mammorgraphy, IEEE Egn. Med. Biol. Mag. 145 (1995) 536–550.

[8] J. Lu, D.M. Healy Jr., J.B. Weaver, Contrast enhancement of medical images using multiscale edge representations, Opt. Engng 33 (7) (1994) 2151–2161.

[9] D. Jobson, Z. Rahman, G.A. Woodell, The statistics of visual representation, Visual Information Processing XI, Proc. SPIE 2002; 4736–4748 invited paper.

[10] E. Peli, Contrast in complex images, J. Opt. Soc. Am. A 7 (1990) 2032–2040.

[11] J.G. Daugman, Two-dimension spectral analysis of cortical receptive field profiles, Vision Res. 20 (10) (1980) 847–856.

[12] D. Marr, Vision, W.H. Freeman and Compant, San Fransisco, CA, 1982.

[13] T. Peil, J.S. Lim, Adaptive filtering for image enhancement, Proc. ICASSP81, Atlanta 1981; 1117–1120.

[14] S. Mallat, S. Zhong, Characterization of signals from multiscale edges, IEEE Trans. Pattern Anal. Machine Intell. 14 (1992) 710–732.

[15] T. Zong, H. Lin, T. Kao, Adaptive local contrast enhancement method for medical images displayed on a video monitor, Med. Engng Phys. 22 (2000) 79–87.

[16] J.C. Nash, S.M. Walker, Nonlinear parameter estimation: an integrated system in basic, Marcel Dekker, New York, 1987.

[17] Y.-T. Kim, Contrast enhancement using brightness preserving bi-histogram equalization, Consumer Electr., IEEE Trans. 43 (1) (1997).

[18] S.-Y. Kim, et al., Image contrast enhancement based on the piecewise-linear approximation of CDF, Consumer Electr. IEEE Trans. 45 (3) (1999) 828–834.

[19] K. Huang, W. Zhenyang, Color image denoising with wavelet thresholding based on human visual system model, Proceedings of Visual Communication and Image Processing Conference (VCIP2003), 5150, Lugano, Switzerland, July 8–11, 2003, pp. 1667–1676.

[20] K. Huang, Q. Wang, W. Zhenyang, Color image enhancement and evaluation algorithm based on human visual system, Proceedings of the International Conference of Speech, Acoustics, and Signal Processing (ICASSP-04), Montreal, Canada, III, 2004, pp. 721–724.