Image enhancement algorithm based on NF-ICM

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Received September 18, 2009

Utilizing the intersecting cortical model (ICM) to enhance degraded images under poor illumination is presented. As the key point, the general mapping function (MF) for image enhancement is deduced firstly on the basis of the nature-firing ICM (NF-ICM), which restrains the traditional autowave effect of blurring details and contrast. Then, the sigmoid MF is especially proposed to map the input gray-level to a more proper range for visual looking, and it solves over-enhancement and artifact by the classical logarithm one. For image enhancement application, the optimized parameters, initial threshold, and stopping condition in NF-ICM are all analyzed in detail. Simulation results prove that the proposed method has more contrasted, colorful, and good-visual performance.

OCIS codes: 100.0100, 100.2980, 100.4996, 330.1720.

doi: 10.3788/COL20100805.0474.

Saturation and underexposures are common in images due to the limited dynamic range of the imaging and display equipment. Especially, when insufficient or non-uniform illumination occurs, the image may contain dark regions in which objects or scenery are hard to recognize. Abundant algorithms for image enhancement have been brought about but they are too complex. From the optimization or even greedy point, the image enhancement algorithm should be simple but to fit for different and complicated scenes. Luckily, human visual characteristics and visual cortex theory witness the improvement on application and bring about the guidance for image processing[1,2]. We learn from such a development and present a new algorithm for image enhancement.

The intersecting cortical model (ICM) derived from several visual cortex models was especially designed for image processing[3]. The minimal system consists of two coupled oscillators, a small number of connections, and a nonlinear function. This system is described by[4]

$$\begin{cases} F_{ij}[n+1] = f \cdot F_{ij}[n] + S_{ij} + W_{ij}\{Y[n]\} \\ Y_{ij}[n+1] = \begin{cases} 1 & \text{if} \quad F_{ij}[n+1] > T_{ij}[n] \\ 0 & \text{else} \end{cases}, \\ T_{ij}[n+1] = g \cdot T_{ij}[n] + h \cdot Y_{ij}[n+1] \end{cases} \tag{1}$$

where S_{ij} is the stimulus; Y_{ij} is the firing state of the neuron (Y is the output image); f, g, and h are scalars; $W_{ij}\{Y\}$ describes the inter-neuron communications; i and j are indices denoting each individual node.

Various forms of output and derivative ones give rise to a wide range of application, and image enhancement is the typical one[1]. But there is another focus for $W_{ij}\{Y\}$ in the original ICM model. It is described as the source of interference between objects and tendency to blur the details and contrast. The solution to the interference effect is based on curvature flow theory and requires a re-definition for the $W\{\cdot\}$ item[5]. Actually, there leave a lot of questions about how to give the proper form of so-called centripetal autowave (CA)[3,6]. So a compromise has to be made for performance and computational complexity. We have to leave out the $W\{\cdot\}$ term to leave the ICM model without the connection function, which is always called nature-firing ICM (NF-ICM)[3]. Simulation results show that such a tradeoff really works with the removal of a time-consuming part: the convolution one.

For the realization of enhancement, the key point is how to design the mapping function (MF) to map the input gray-level to the proper range for visual looking with the use of Y, the only output of the ICM. Based on the Weber theory, Zhang *et al.* introduced the logarithm space to give the example of the output to apply the human visual characteristics about the Mach band effect[7]:

$$I\_en[n] = \ln[\mathrm{Max_p} - (n-1) \cdot \theta] \cdot Y[n], \tag{2}$$

where at the nth time, I_en is the output with the threshold θ, the maximum intensity $\mathrm{Max_p}$ and the output image Y by such MF. Obviously, the sum of I_en is the final output image. The kernel of Eq. (2) is the process that a step-by-step decreasing value set by θ is conducted by the following logarithm operation. With the high-to-low firing condition, the result is obtained from the highest gray-level to the lowest one. Noticeably, the results are similar to but not the same as that obtained with global MF applied to the original images directly, owing to the whole firing process given by Eq. (1).

However, there exists a key weak point of this MF that over-enhancement often occurs in the darkest and the brightest regions just for the logarithm effects. More importantly, if it is used in the NF-ICM, a certain number of pixels in the image matrix surely will be never fired under general parameters, which will lead to artifact similar to the random noise for color image and degrade the image quality seriously. Such phenomenon is easy to be found, e.g., in the results of Ref. [8].

So, for those degraded images stated above, the logarithm-MF is not very suitable but suggestive, and a new proper one should be considered and adopted. From the above analysis, the general MF for image enhancement is easy to be deduced, that is:

$$I\_en = \sum_n f(\theta) \cdot Y[n]. \tag{3}$$

For a different application, we can introduce a different MF $f(\cdot)$ to operate on the decreasing value set by a step parameter θ. The sum is the final result we desire, experiencing the stepwise firing process. With the simplified ICM model, NF-ICM, we propose the sigmoid-output MF to enhance degraded images under poor illumination especially. There are several key points, as illustrated in detail below.

Actually, human vision is apt to have a more precise or high-level resolution for the middle gray-level image, especially the gray-level 127 nearby[9]. The mean of an ideal visual image is often above the average gray-level of 100[10].

The adaptive transfer function for pixel-to-pixel operation is often applied in the conventional tonal correction techniques which usually bring about satisfactory results. The sigmoid function is a continuous nonlinear activation with the basic form as $f(x)=1/[1+\exp(-a{\cdot}x)]$, where a controls the curvature. We introduce a more parameterized sigmoid function as the MF:

$$y = c/[1 + \exp(-a \cdot x + b)]. \tag{4}$$

In comparison with the logarithm operator, such a sigmoid function focuses more on the middle gray-level and produces much more contrast in this field. We set $a = 3$, $b = 1$, and $c = 1+\exp(-\mathrm{a}+\mathrm{b})$ as default values. The enhancement framework is determined by Eq. (3) and $f(\cdot)$ is assumed to act on the $\mathrm{Max_p}-(n-1)\cdot\theta$ all the same for simplicity. The whole procedure is depicted in Fig. 1.

Now we consider the optimization of parameters in NF-ICM. The scalars f and g are decay constants and thus less than 1. In order to ensure that F_{ij} eventually becomes Y_{ij}, we will have $f > g$ and the values of f, g, h are typically 0.9, 0.8, and 20.0, respectively[14]. But for the image enhancement process, parameters must be adjusted and basic assumptions for firing carry-on must be made. h must be large enough to have only one chance to fire, which means a value exceeding the threshold. The degradation of the output and the threshold must be slow, leaving a small θ and a large g. f must be smaller while g must be larger, which ensures the efficient firing for almost all the pixels. θ is determined by the gray-level to let the adjacent ones fire at different time. According to the above assumption and analysis, we have $\theta = 1/300$, $f = 0.1$, $g = 0.99$, and $h = 300$ for default.

The initiation of threshold matrix plays an important role in the firing process. It determines the order and time between adjacent pixels. The ordinary Laplacian kernel was introduced to form an initial T matrix[7]. We adopt this simple but effective way and make an improvement by using the more noise-robust kernel K=[−1 −1 −1; −1 8 −1; −1 −1 −1]/3[11] which really works for deep analysis. The initial T matrix is

$$T[0] = E - K \otimes S, \tag{5}$$

where E stands for the identity matrix, S stands for the input image which is first scaled so that the largest pixel value is 1.

The global operation calls for the stopping condition and the iteration should be ended at the proper time. To avoid repeating firing of the same pixel and to affirm the performance, we introduce the two conditions: Y is set to 0; the presetting iteration number is smaller than the firing period of each neuron, which is $N_{ij}<-\ln(1+h/S_{ij})/\ln(g)$. For a more robust and special case, we leave the ending condition with no changing output from a temporary cell matrix storing five outputs, which gives a direct anding quick ending for those unused and unnecessary iterations.

Subject and objective standards representing visual statistics are all needed for evaluating the image enhancement performance[12]. We introduce the statistical characteristics of images given by the National Aeronautics and Space Administration (NASA) of USA[10] to illustrate the assessment. The average of image (Av) and the mean of zonal standard deviation of non-overlapping blocks (MZ_Std) form the coordinate. Especially, the overall contrast is measured by taking the mean of regional standard deviations instead of global standard deviation for its weak relation with the overall visual sense of contrast.

For color images, we often introduce the basic cognitive color space HSV/HSI, and apply the algorithm to the value/intensity (V/I) component. Those typical testing images include portraits and scenes with poor illumination. Firstly, we compare the proposed algorithm under different conditions, such as evaluating the effects caused by autowave (Fig. 2) and the Laplacian kernel's effect (Fig. 3). More enhanced results for efficiency testing are shown in Fig. 4. The statistical characteristics are illustrated in Fig. 5 with the corresponding objective values in Table 1.

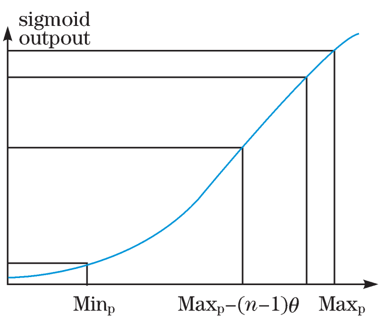

Fig. 1. Sketch map for ICM output with typical sigmoid function.

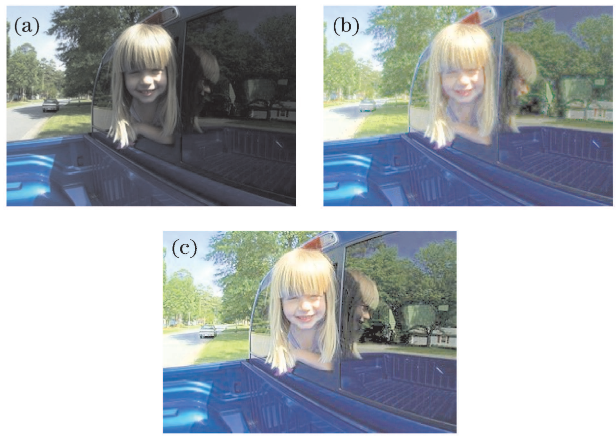

Fig. 2. Example of enhanced effects by autowave. (a) Original image, (b) by autowave, (c) by nature firing.

Fig. 3. Example of enhanced effects by different Laplacian kernels. (a) Original image, (b) by original kernel, (c) by noise-robust kernel.

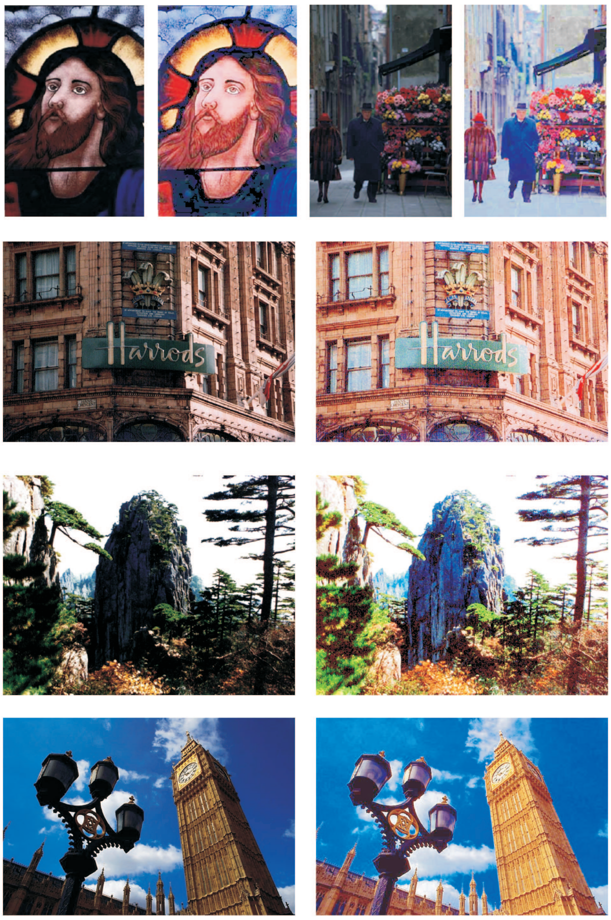

Fig. 4. More simulation results.

From the results and open-and-shut statistical data, except the enhanced one of "Flower" is out of the "visually-optimal window" but nearby for too dark regions, while all the others fit it. Realistic scenes regain proper luminance compensation with higher Av and good visualization of details at previous lower brightness with higher MZ_Std which presents the global contrast truely. Furthermore, circumspect considerations of the model and initiation setting assuredly avoid blur and much magnification of block effects, especially for those in the format of ∗.jpg.

In conclusion, we present a new algorithm for image enhancement based on the NF-ICM model. The results show up the pleasing performance for those images captured under poor illumination. Good visual representation witnesses and validates the algorithm. While, due to the lack of the item representing the inter-neuron connection, the iteration process is inevitably slow but very effective.

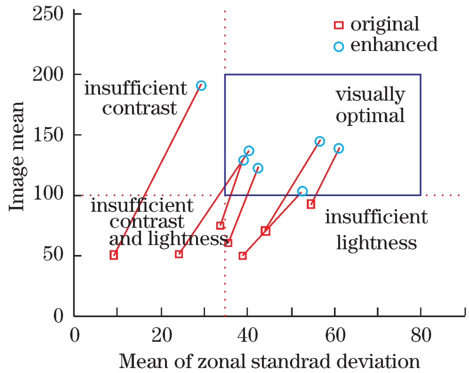

Fig. 5. Statistical characteristics of images before and after enhanced by the proposed algorithm.

Table 1. Corresponding Objective Values

Image	Original		Enhanced	
	Av	MZ_Std	Av	MZ_Std
Girl	61.041	35.6107	123.6454	42.5772
Flower	50.5292	9.1673	192.1964	29.3382
Church	49.4403	38.8197	103.1955	52.4208
Street	51.0054	24.158	137.6584	40.3104
Building	70.5085	43.9874	145.5692	56.7924
Mount	93.0353	54.5569	139.6279	61.3358
Big Ben	74.9878	33.7292	129.6362	38.7518

Further research will give adaptive preset for parameters in the sigmoid function. The more adaptive MF based on property values such as mean and standard deviation etc.[13] for various scenes is the ultimate aim. Although the MF from the tonal correction technique is argued basically neither a general method nor an automatic method[14], but it really works and accomplishes the extra effect known from the traditional one just for the firing process. The parameters for the ICM model is also considered to be set by statistical value or algorithms such as genetic algorithm etc.[15] To combine the local operation, deep analysis for CA's realization should be conducted to enhance the influence of original inter-neuron communications. MFs with different designs of output could be constructed for a wider range of applications, especially the highlight and night scenes. A new mask with anisotropic characteristics will be the solution for CA following the typical and practical convolution operator.

This work was supported by the National "863" Program of China under Grant No. 2007AA701121.

References

1. Z. Wang, Y. Ma, F. Cheng, and L. Yang, Image and Vision Computing **28,** 5 (2010).
2. C. Li, S. Gao, and D. Bi, Chin. Opt. Lett. **7,** 784 (2009).
3. T. Lindblad and J. M. Kinser, *Image Processing Using Pulse-Coupled Neural Networks* (2nd edn.) (Springer, Berlin, 2005).
4. U. Ekblad and J. M. Kinser, Signal Processing **84,** 1131 (2004).

5. J. M. Kinser and C. Nguyen, Pattern Recogn. Lett. **21,** 221 (2000).
6. J. M. Kinser, "Image signatures: ontology and Classification" in *Proceedings of the 4th IASTED Int. Conf. on Computer Graphics and Imaging* (2001).
7. J. Zhang and T. Lu, Computer Engineering and Application (in Chinese) **39,** (19) 93 (2003).
8. Y. Ma, L. Li, K. Zhan, and Z. Wang, *Pulse-Coupled Neural Network and Digital Image Processing* (in Chinese) (Science Press, Beijing, 2008).
9. L. Zhang and L. Huang, J. Optoelectron. Laser (in Chinese) **15,** 877 (2004).
10. D. J. Jobson, Z. Rahman, and G. A. Woodell, Proc. SPIE **4736,** 25 (2002).
11. D. Wang, Y. Hou, and J. Peng, *PDE for Image Processing* (in Chinese) (Science Press, Beijing, 2008).
12. J. Pang, R. Zhang, H. Zhang, X. Huang, and Z. Liu, Chin. Opt. Lett. **6,** 491 (2008).
13. W. Gong, K. Si, X. Ye, and W. Gu, Chin. J. Sensors and Actuators (in Chinese) **20,** 2024 (2007).
14. Z. Chen, B. R. Abidi, D. L. Page, and M. A. Abidi, IEEE Trans. Image Processing **15,** 2290 (2006).
15. J. Yu, H. Chen, W. Wang, and J. Li, Acta Electron. Sin. (in Chinese) **36,** 81 (2008).