Parametric Rational Unsharp Masking for Image Enhancement

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ABSTRACT

Unsharp masking is an effective enhancement tool to improve the visual quality of fine details in images. However, it also amplifies noisy and over-enhances steep edges. To address this problem, this paper proposes a parametric rational unsharp masking. It utilizes the horizontal and vertical gain factors to enhance image details in two directions independently. Experiments and comparisons are provided to demonstrate its excellent enhancement performance.

Keywords: parametric rational unsharp masking, image enhancement, nonlinear filtering

1. INTRODUCTION

Digital images have great effects to many important fields such as medical diagnosis, military, meteorology, security, and entertainments. Many applications require images with more details and demand high visual quality of images. However, the visual quality of images may not be always desired because of many factors such as out of focus and various environment conditions (i.e. frog, water, and windstorm). Image enhancement is an effective tool to improve the visual quality of image. It acts as a pre-processing in a large amount of applications like face recognition and vehicles tracking.

Image enhancement is usually to improve image contrast. Many effects have been done in different prospectives such as the logarithmic image processing (LIP)[1] and parameterized LIP (PLIP).[2,3] Technologies of local contrast enhancement can be divided into two groups: adaptive histogram equalization (AHE) and adaptive contrast enhancement (ACE).[4] The contrast-limited adaptive histogram equalization (CLAHE)[5,6] is a well-known AHE that operates in small regions to improve image details while avoiding amplifying noise. Agaian et al. proposed transform histogram equalization. It combines AHE with the logarithmic transform for image enhancement.[7,8] Although these improvements of AHE has good effects to image quality, they still have some artificial effects to images.

Unsharp masking (UM) is a taditional technology of ACE. It enhances an image by subtracting a lowpass filtered image from its original, or by adding a scaled high-frequency part of the image to its original. It can enhance edges and fine details in images. However, UM suffers some critical drawbacks including noise sensitivity, out-of-range, and halo effects. To reduce the noise sensitivity, Strobel and Mitra proposed an improved UM using quadratic filters,[9] and Ramponi developed the cubic UM and Rational UM techniques by replacing the linear highpass filter in the traditional UM with nonlinear filters.[10,11] Kim and Cho introduced a feature and noise adaptive UM to separate image feature and noises.[12] It requires the searching window size to be at least 5×5 and at least 4 directions to be concerned. This leads a high computation cost. Deng proposed a generalized UM algorithm.[13] It intends to solve halo effects using exploratory data model, log-ratio operations and new generalized linear system. To reduce the halo effects of UM, Kwok developed an intensity-based gain adaptive UM.[14] However, they often introduce the background noise.

This paper proposes a new UM scheme called the parametric rational unsharp masking. It uses a nonlinear filtering with two independent gain factors at the horizontal and vertical directions It intends to improve the

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visual quality of fine details in images while minimizing side effects of UM. The simulation and analysis are also given.

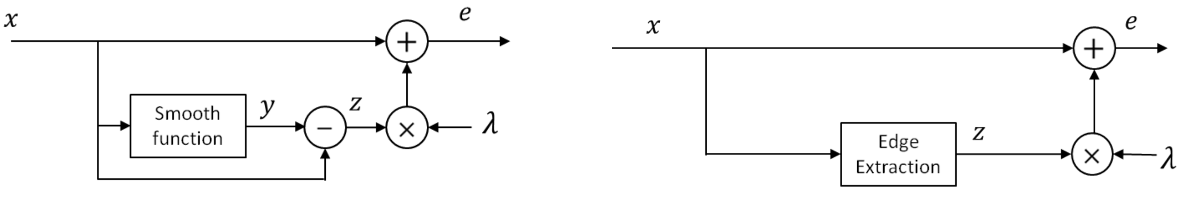
This paper is organized as follows. Section 2 will review the background of the traditional UM and four improved UM methods. Our proposed approach will be introduced in Section 3. The experimental and comparison results are provided in Section 4. A short conclusion will be drawn in Section 5.

2. BACKGROUND

This section briefly reviews several existing unsharp masking algorithms. They will be used for the performance comparison with the proposed algorithm in Section 3.

2.1 Unsharp masking

As one of simple and well-known methods of image enhancement, unsharp masking (UM) is an effective tool to improve the visual quality of fine details in images. It extracts and amplifies high frequency components of a target image, then adds them back to the target image. According to different extraction methods, UM can be classified as the low pass filter model and high pass filter model. The block diagram and definition of the low pass filter model are shown in Figure 1(a) and Equation (1), respectively.



(a) (b)

Figure 1. Two UM models. Block diagrams of the (a) low pass filter model and (b) high pass filter model.

$$e = x + \lambda(x - y) \tag{1}$$

where x is the input image, y is the smoothed image by a low pass filter, and λ is the gain factor.

Similarly, the block diagram of the high pass filter model are shown in Figure 1(a). The model is defined in Equation (2),

$$e = x + \lambda z \tag{2}$$

where z is the high frequency component of the input image x, and λ is the gain factor.

Because of its simple structure and efficiency, UM became the classical method for image enhancement. However, it also has side effects, including (1) high sensitivity to noise, (2) out of range problem, and (3) halo effect.

2.2 Cubic UM

The cubic UM[10] (CUM) replaces the linear filter in Equation (2) with the quadratic nonlinear filter. There are two types of the CUM filters: the ”separable” CUM (S-CUM) and ”nonseparable” CUM (NS-CUM). They are defined in Equations (3) and (4).

$$\begin{aligned} z(m,n)_{S-CUM} = {} & [x(m-1,n) - x(m+1,n)]^2 \, [2x(m,n) - x(m-1,n) - x(m+1,n)] \\ & + [x(m,n-1) - x(m,n+1)]^2 \, [2x(m,n) - x(m,n-1) - x(m,n+1)] \end{aligned} \tag{3}$$

$$\begin{aligned} z(m,n)_{NS-CUM} = {} & [x(m-1,n) + x(m+1,n) - x(m,n-1) - x(m,n+1)]^2 \\ & [4x(m,n) - x(m-1,n) - x(m+1,n) - x(m,n-1) - x(m,n+1)] \end{aligned} \tag{4}$$

The CUM filters amplify the high gradient areas and reduce sensitivity to low variations. The goal is to distinguish noise from true image details.

2.3 Rational UM

Rational UM[11] substitutes the rational operator for the linear filter. The model is based on Equation (2). The high frequency component z in Equation (2) is defined by Equation (5),

$$z(m,n) = F_x(m,n)C_x(m,n) + F_y(m,n)C_y(m,n) \tag{5}$$

where

$$\begin{aligned} F_x(m,n) &= 2x(m,n) - x(m,n-1) - x(m,n+1) \\ F_y(m,n) &= 2x(m,n) - x(m-1,n) - x(m+1,n) \\ C_x(m,n) &= \frac{2\omega[x(m,n+1) - x(m,n-1)]^2}{2[x(m,n+1) - x(m,n-1)]^4 + \omega^2} \\ C_y(m,n) &= \frac{2\omega[x(m+1,n) - x(m-1,n)]^2}{2[x(m+1,n) - x(m-1,n)]^4 + \omega^2} \end{aligned} \tag{6}$$

where ω is a parameter and $x(m,n)$ is the pixel intensity value at location (m,n) in the input image. The rational operations are able to amplify low and medium intensity gradient details. Steep edges and noise will generate a low value in the detail map. This may avoid the undesired overshoots and noise amplification.

2.4 Generalized UM Algorithm

The generalized UM[13] Algorithm uses an exploratory data model, log-ratio operations and new generalized linear system to overcome the side effects of UM. By using the interpolation median filter (IMF) and log-ratio operations, this algorithm intends to solve the halo effects and out of range problems. The adaptive histogram equalization process is added for contrast enhancement. The log-ratio operations are defined as follows:[13]

$$\begin{aligned} x \oplus y &= \frac{1}{1+\frac{(1-x)(1-y)}{xy}} \\ x \ominus y &= \frac{1}{\frac{1-x}{x}\left(\frac{1-y}{y}\right)^{-1}+1} \\ \alpha \otimes x &= \frac{1}{1+\left(\frac{1-x}{x}\right)^{\alpha}} \qquad (\alpha \text{ is a real number}) \end{aligned} \tag{7}$$

The structure of generalized UM algorithm is shown in Figure 2.

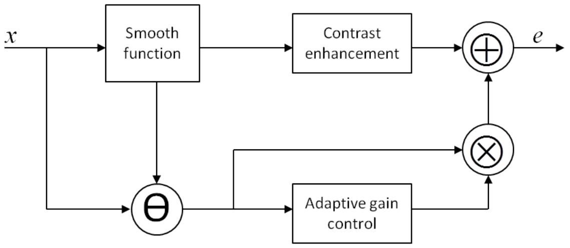


Figure 2. Block diagram of the generalized UM algorithm

2.5 Gain-adjusted Adaptive UM

The gain-adjusted adaptive UM[14] modulates the gain factor based on the original intensity. The gain factor λ in UM is no longer a constant, instead, one adaptive and normalized matrix is generated using the intensity based Gaussian kernel function $g(m,n)$ as shown in Figure 3. It can be expressed by,[14]

$$\tilde{g}(m,n) = \exp\left(-\frac{(x(m,n) - 0.5)^2}{2\sigma^2}\right). \tag{8}$$

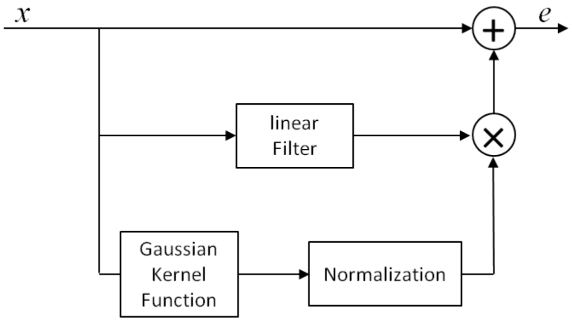


Figure 3. Block diagram of the gain-adjusted adaptive UM.

The purpose of this method is to eliminate the our of range problem in the traditional UM.

3. PARAMETERIZED RATIONAL UNSHARP MASKING

Rational unsharp masking (RUM)[11] is able to reduce the side effects of the traditional UM in the noise sensitivity and the halo effect. Here, we propose the parametric rational unsharp masking (PRUM) to further improve the performance of RUM. Figure 4 shows the block diagram of PRUM.

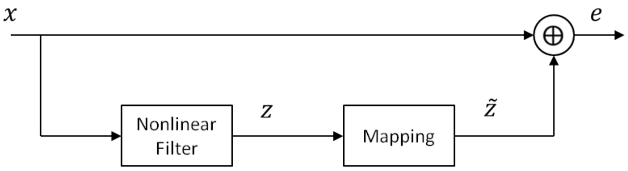


Figure 4. block diagram of the parametric rational unsharp masking

PRUM first applies a nonlinear filter to the original image x to obtain its high frequency part z, uses a mapping processing to transform z into $\tilde{z}$, generates the enhanced image by adding $\tilde{z}$ back to the original image x by the conditional sum defined in Equation (11). The enhanced image can be written as

$$e = x \oplus \tilde{z} \tag{9}$$

where e and x are the enhanced and original images, $\tilde{z}$ is the mapped high-frequency component of x and $\bigoplus$ is the conditional sum defined in Equation (11).

Next, we will present each step of PRUM in detail.

3.1 Nonlinear Filter

The nonlinear filter in PRUM uses two weighted nonlinear filtering operations to extract the image details (the high-frequency components) at the horizontal and vertical directions independently. It is defined in Equation (10).

$$z(m,n) = \alpha F_x(m,n)C_x(m,n) + \beta F_y(m,n)C_y(m,n) \tag{10}$$

where α and β are scaling factors, and other terms are defined in Equation (6)

3.2 Mapping

To further reduce the background noise, a nonlinear mapping is applied to the high frequency portion z to remove its small values. The mapping function was proposed by Sanjit K. Mitra et al.[15] The mapping structure is shown in Fig.5.

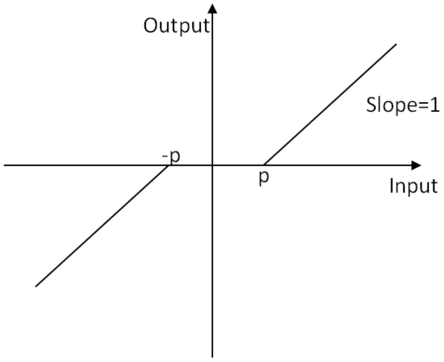


Figure 5. The pixel mapping of PRUM

After mapping process, small pixel values are eliminated and other values are decreased linearly at the same time to avoid bring artifacts.

3.3 Conditional Sum

The classical UM enhances the image details by adding the extracted high frequency components back to the original image. This linear addition may easily introduce the out-of-range problem. To overcome this, instead of using linear addition, PRUM uses the conditional sum defined in Equation (11).

$$e = \begin{cases} I + \dfrac{\tilde{z}(L-I)}{\tilde{z}+(L-I)} & \tilde{z} > 0 \\ I & \tilde{z} = 0 \\ I + \dfrac{\tilde{z}I}{\tilde{z}+I} & \tilde{z} < 0 \end{cases} \tag{11}$$

where I e are the input and output images, L denote the maximum value of I.

In Figure 6, the enhanced result $e - I$ is shown as a function of $\tilde{z}$ for a specific $I = 220$, $\tilde{z} \geq 0$. When $\tilde{z}$ increases, the output $(e - I)$ nonlinearly increases too. Thus, $(e - I)$ is less than or equal to $(L - I)$, or $e \leq L$.

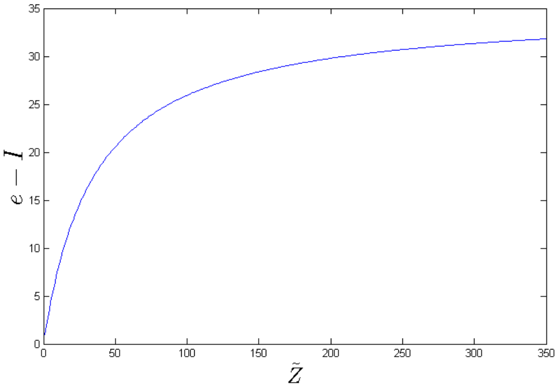


Figure 6. The conditional sum with $I = 220$.

4. EXPERIMENTAL RESULTS

This section provides several simulation and comparison results to show the enhancement performance of the proposed PRUM. The test images are retrieved from the web page[*] and USC-SIPI image database[†]

4.1 Gray image enhancement

A grayscale boat image with size of 512×512 is used as an example to show the enhancement performance of the proposed PRUM. First, we study the effects of the scaling factors α and β. The enhanced results are shown in Fig.7. As can be seen, the vertical and horizontal details are not equally enhanced. The halo effects occur around around cables in the boat in Figure 7(b), but not in Figure 7(c). Therefore, The horizontal and vertical parameters are able to work independently to adapt different situations in images.

(a) (b) (c)

Figure 7. Image enhancement using PRUM with different parameter settings. (a) The original boat image; the enhanced images using PRUM with (b) $\alpha = 1.4$, $\beta = 0.5$; and (c) $\alpha = 0.5$, $\beta = 1.4$.

We also compare the proposed PRUM with several existing UM techniques for image enhancement. These techniques include the cubic UM,[10] generalized UM,[13] gain-adjusted adaptive UM[14] and rational UM,.[11] Fig.8 shows the comparison results. The background noise in the sky and boat body is amplified by the cubic UM, generalized UM and gain-adjusted adaptive UM. see Figures 8(b)-(d). In Figures 8(d) and (e), halo effects appear around cables in the boat. As shown in Figure 8(f), the proposed PRUM shows better enhancement performance. It ensures the sharping the edges and details in images while minimizing the background noise and halo effects.

4.2 Color image enhancement

The propsoed PRUM can be used for color image enhancement and show excellent enhancement performance. For color images enhancement, images are first converted from the RGB (red, green, blue) color space into the HSI (hue, saturation, intensity) color space. The prosed PRUM is used to enhance the intensity component while keeping the hue and saturation components unchanged. The enhancement results of color images are shown in Figure 9. The visual quality of the image details are greatly improved without any artifact or background noise involved.

5. CONCLUSION

This paper has introduced an improved version of unsharp masking called the parametric rational unsharp masking. It uses a parametric nonlinear filter with two gain parameters to enhance image details in the horizontal and vertical directions independently. To overcome the shortcomings of unsharp masking in out of range and halo effects, the proposed PRUM utilizes the nonlinear mapping and conditional sum. Experiments and comparisons shown that PRUM show excellent enhancement performance and outperforms several existing UM methods.

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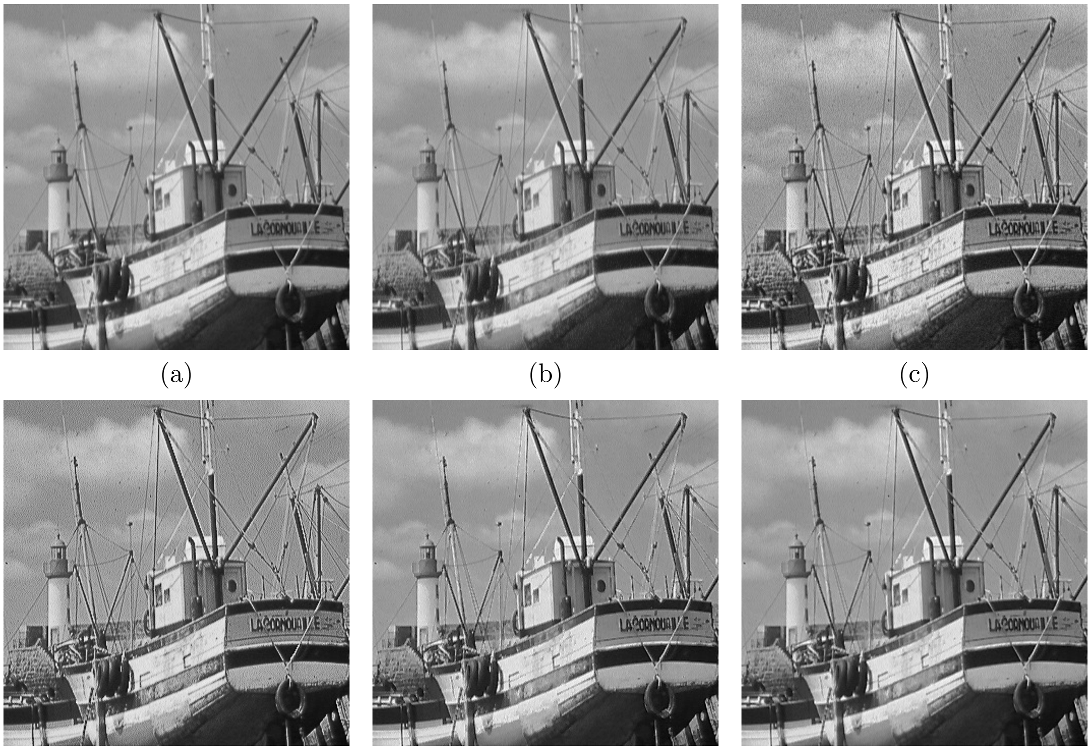
[*] `http://www.imageprocessingplace.com/root_files_V3/image_databases.htm`

[†] `http://sipi.usc.edu/database/database.php`



(a) (b) (c)

(d) (e) (f)

Figure 8. Image enhancement using different UM techniques. (a) the original boat image and the enhanced images using the (b) cubic UM, (c) generalized UM, (d) gain-adjusted adaptive UM, (e) rational UM, and (f) PRUM.

(a) (b) (c)

Figure 9. Color image enhancement using PRUM. The top and bottom rows show the original and enhanced images respectively.

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REFERENCES

[1] Jourlin, M. and Pinoli, J., "Logarithmic image processing: The mathematical and physical framework for the representation and processing of transmitted images," *Advances in Imaging and Electron Physics* **115**, 129 – 196, Elsevier (2001).

[2] Panetta, K., Agaian, S., Zhou, Y., and Wharton, E., "Parameterized logarithmic framework for image enhancement," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* **41**(2), 460–473 (2011).

[3] Panetta, K., Wharton, E., and Agaian, S., "Parameterization of logarithmic image processing models," *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans* (2007).

[4] Arici, T., Dikbas, S., and Altunbasak, Y., "Local contrast enhancement using 2-dimensional recursive filters," in [*IEEE 8th Workshop on Multimedia Signal Processing*], 329–333.

[5] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., ter Haar Romeny, B., Zimmerman, J. B., and Zuiderveld, K., "Adaptive histogram equalization and its variations," *Computer Vision, Graphics, and Image Processing* **39**(3), 355–368 (1987).

[6] Panetta, K., Zhou, Y., Agaian, S., and Jia, H., "Nonlinear unsharp masking for mammogram enhancement," *IEEE Transactions on Information Technology in Biomedicine* **15**(6), 918–928 (2011).

[7] Agaian, S. S., Silver, B., and Panetta, K. A., "Transform coefficient histogram-based image enhancement algorithms using contrast entropy," *IEEE Transactions on Image Processing* **16**(3), 741–758 (2007).

[8] Silver, B., Agaian, S., and Panetta, K., "Logarithmic transform coefficient histogram matching with spatial equalization," in [*Defense and Security*], 237–249 (2005).

[9] Strobel, N. and Mitra, S. K., "Quadratic filters for image contrast enhancement," in [*Conference Record of the Twenty-Eighth Asilomar Conference on Signals, Systems and Computers.*], **1**, 208–212 vol.1.

[10] Ramponi, G., "A cubic unsharp masking technique for contrast enhancement," *Signal Processing* **67** (1998).

[11] Ramponi, G. and Polesel, A., "Rational unsharp masking technique," *Journal of Electronic Imaging* **7**(2), 333–338 (1998).

[12] Kim, Y.-H. and Cho, Y., "Feature and noise adaptive unsharp masking based on statistical hypotheses test," *IEEE Transactions on Consumer Electronics* **54**(2), 823–830 (2008).

[13] Deng, G., "A generalized unsharp masking algorithm," *IEEE Transactions on Image Processing* **20**(5), 1249–1261 (2011).

[14] Kwok, N. M., Shi, H. Y., Fang, G., and Ha, Q. P., "Intensity-based gain adaptive unsharp masking for image contrast enhancement," in [*2012 5th International Congress on Image and Signal Processing*], 529–533 (2012).

[15] Mitra, S. K., Li, H., Lin, I.-S., and Yu, T.-H., "A new class of nonlinear filters for image enhancement," in [*1991 International Conference on Acoustics, Speech, and Signal Processing*], **4**, 2525–2528 (1991).