A pilot study on a new image enhancement method using spatial statistics

Tzong-Jer Chen[1, a*], Xiu-Juan Deng[1, b], Yue-Ran Lu[1, c], Wei He[1, d], Gaofeng Che[1, e], Sixian Niu[1, f] and Ronghui Lu[2, g]

[1]School of Information Engineering, Baise University, Baise, Guangxi, 533000 China.

[2]Section of Laboratory Management Center, Wuyi University, Wuyishan, Fujian, 354300 China.

[a*]d838502@qq.com, [b]269720761@qq.com, [c]yr.lu@hotmail.com, [d]350977176@qq.com, [e]chexuping@163.com, [f]1752348119@qq.com, [g]lrh-mail@163.com

* corresponding author

Keywords: image enhancement, unsharp masking, spatial autocorrelation, adaptive filter.

Abstract. The unsharp masking method is a well-known approach for image enhancement but is very sensitive to noise. Low pass filters are usually employed to suppress the noise, but often lead to the blurred edge. To overcome these problems a sharping algorithm for digital images based on spatial autocorrelation is proposed. The new method can smooth images and simultaneously produce good detail structure maintenance performance. Spatial statistical calculation be used as a threshhold for adaptive filtering. A synthetic image with various pixel values and added Gaussian noise was produced. To verify this, a high-boost filter was used to take a comparison with the adaptive average filter results. This new method successfully accomplishes the dual objectives of decreasing noise and not amplifying the detailed areas. The experimental results demonstrate the effectiveness of the proposed method.

1 Introduction

Significant growth in digital image technology development in a wild range of fields has led to rapid expansion in its use. In many applications, its behavior depends on the input image quality [1]. Digital images may be contaminated by a variety of noise sources during acquisition, processing, transmission and reconstruction. Image filtering or reproduction may result in visual quality degradation [2], requiring image enhancement in these processes.

High frequency content enhancement, such as edge and detail information may significantly improve the visual appearance of an image [3]. The simplest algorithm, unsharp masking (UM), is often employed for this purpose. The UM method is computationally and conceptually simple [4]. This method works well in many applications producing a sharpening effect. However, the presence of the linear high-pass filter makes the system extremely sensitive to noise. In addition, it enhances high-contrast areas to a great degree but does not present a high dynamic image [3, 4].

The UM adaptive unsharp masking and nonlinear module were recently proposed [3-5]. These algorithms enhance images while effectively decreasing the noise. These methods can also be used to sharpen images with good noise reduction performance. The development of adaptive, nonlinear modules for image enhancement may be a good scheme.

A nonlinear module named the Moran statistic, suggested by Chen *et al.* and Shiao *et al.*, proved to be a good index for determining the smoothness or sharpness of an image [6-9]. These statistics were also shown to be very sensitive to image blurring and consistent with the NMSE (Normalized Mean Square Error) results [8]. The Moran test was introduced by Chuang and Huang. They found that this calculation correlated with the noise level in medical images [10]. A higher Moran Z value means that there is more structured information and less random noise in the image and vise versa [10]. These statistics showed the ability to distinguish image noise, burring, and edges.

A new image enhancement method using Moran statistics as an adapting priori on image filtering was proposed. This statistical method is applied to determine if an image area belongs in the edge, noise or smooth areas. In this pilot study a synthetic image with various pixel levels was used to verify the proposal. Gaussian noise (μ=100, σ=20) was added to this image first. Following that, the average filters with or without Moran statistics calculations as an adaptive filter were then applied to this noisy image. The proposed method result was also compared with the enhanced image using a high-boost filter.

2 Methods

The Moran Statistics

The Moran statistics are used to evaluate the randomness of mapped data by measuring the spatial autocorrelation [11]. The Moran parameter measurement M in a window (a window is part of an image) was calculated as:

$$M = \frac{N \sum_{j=1}^{rxc} \sum_{i=1}^{rxc} \delta_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{rxc} (x_i - \bar{x})^2} \tag{1}$$

where x_i is the gray level for pixel *i*, $\bar{x}$ is the mean gray level of the window, $S_0 = 2(2mn - m - n)$, m and n are the number of rows and columns in the window, N is the total number of pixels in the window, and $\delta_{ij} = 1$ if pixel i and j are adjacent and 0 otherwise. The numerator and denominator are measures the covariance and variance among the pixels, respectively. When the size of N is large enough, the variable M approximately follows a normal distribution with the mean and variance given by

$$a = -1/(N-1) \tag{2}$$

and

$$\sigma^2 = \frac{N[(N^2 - 3N + 3)S_1 - NS_2 + 3S_0^2] - K[N(N-1)S_1 - 2NS_2 + 6S_0^2]}{(N-1)(N-2)(N-3)S_0^2} - a^2 \tag{3}$$

where $K = N\sum(x_i - \bar{x})^4 / [\sum(x_i - \bar{x})^2]^2$, $S_1 = 2S_0$, and $S_2 = 8(8mn - 7m - 7n + 4)$. We can use the standardized normal statistic

$$Z = \frac{M - a}{\sigma} \tag{4}$$

to determine noise, burring and edge on image.

The Average Filter

The average filter is well known and commonly used for image enhancement [12]. The average filter is the linear module windowed filter used to smooth the image. The filter works as a low-pass filter. The basic idea behind the filter is to take an average across the neighborhood for any element of the image.

High-Boost Filter

In X-ray imaging and Radiography the High-Boost filter is used for image sharpening. A high frequency part of an image can be obtained by subtracting the low-pass filtered part from the original image. i.e.

high-pass = (original)–(low-pass). (5)

The High-Boost filter modifies the above formula using the original image multiplied by an amplification factor *A*. i.e.

high-boost = (A)(original) – (low-pass)

= (A-1)(original)+ (original) – (low-pass)

= (A-1)(original)+ (high-pass) (6)

When $A = 1$, a standard high-pass filter was used. As $A > 1$, part of the original has been added back into the high-pass result, which partially restores the low frequency components lost in the high-pass filtering operation. The image becomes more blurred when increasing A. The mask used for high-boost spatial filtering is shown as below [12]

$\frac{1}{9}\times$

-1	-1	-1
-1	*w*	-1
-1	-1	-1

where $w = 9A\text{-}1$, and $A \geqq 1$.

Images

A synthetic noise free image with various pixel values was produced in this study. The image size is 512×512 and 12 bits in depth, as shown in Figure 1. The most outside background gray levels were 37 and inner 100. Sixteen different circles with gray levels from 300 (upper left) to 783 (bottom right). The Gaussian noise (μ=100,σ=20) is added to this image, as indicate in Figure 2. So, we can have

$$I(x,y)=f(x,y)+\eta(x,y), \quad (7)$$

where f is the synthetic image, I is the synthetic noisy image, and η is the noise components.

3 Results

The noisy image was filtered using an average filter with a 5×5 window size first. The image was smoothed and the noise effectively decreased, as indicated in Figure 3. However, the circle edges are obviously blurred. Figure 4 shows the high-boost filter result as A=1.6. This UM filter enhanced the edge but concurrently increased the noise, as shown in this figure. The image enhancement result using the adaptive method proposed in this paper is shown in Figure 5. In this figure an average filter with 5×5 window size was slid onto the whole image as before but proceeded adaptively. This filtering process depends on the Moran statistic calculations. Because of the fact that “A higher Moran Z value means that there is more structured information and less random noise in the image and vise versa”. After examining the histogram of Z values, image areas belong in edge if Z >= 3.4 and then skip the filtering process at those points. The noise was decreased and the edge was not excessively overshot, as noted in Figure 5. This new method accomplishes the dual objectives of successfully decreasing noise as well as not amplifying the detail areas.

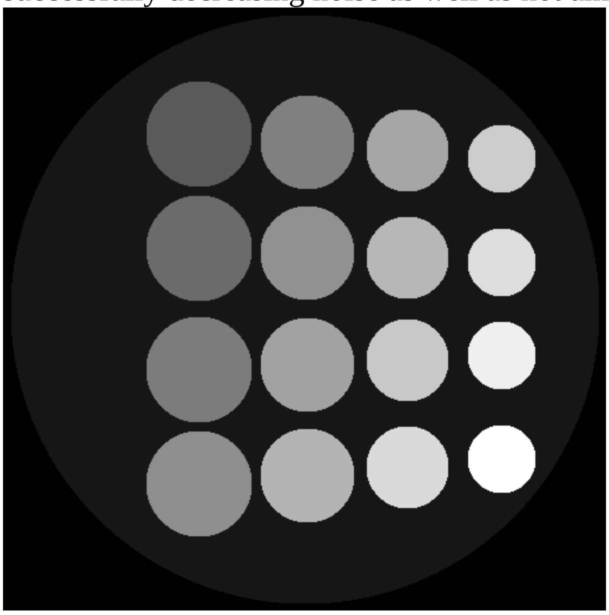

Figure 1. The synthtic ideal image

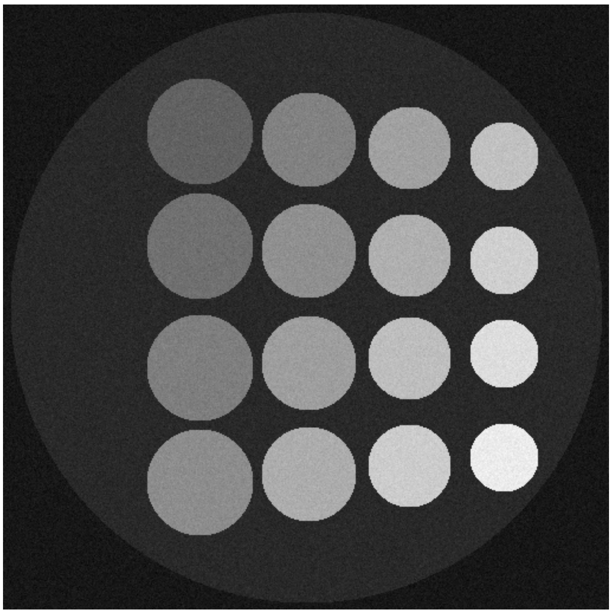
Figure 2. The synthetic image with Gaussian noise added

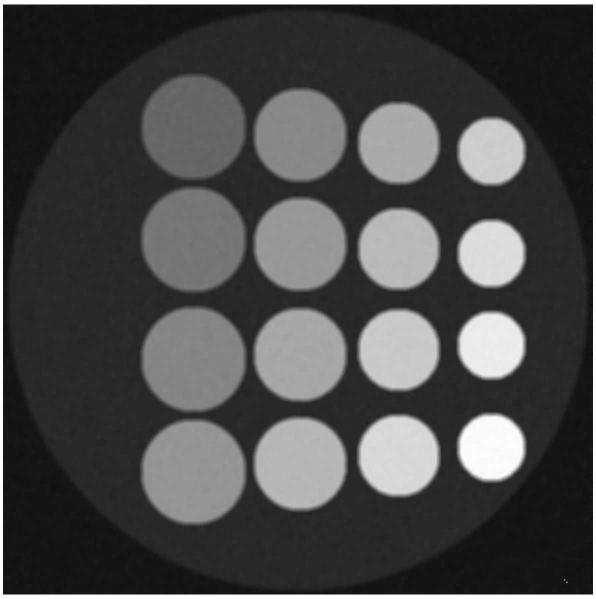
Figure 3. Denoised image using the average filter with 5x5 window size

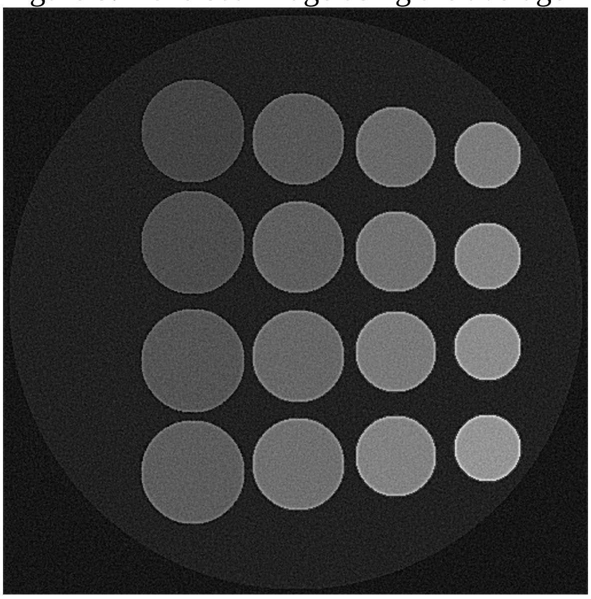
Figure 4. Enhanced image using high-boost filter with A= 1.6.

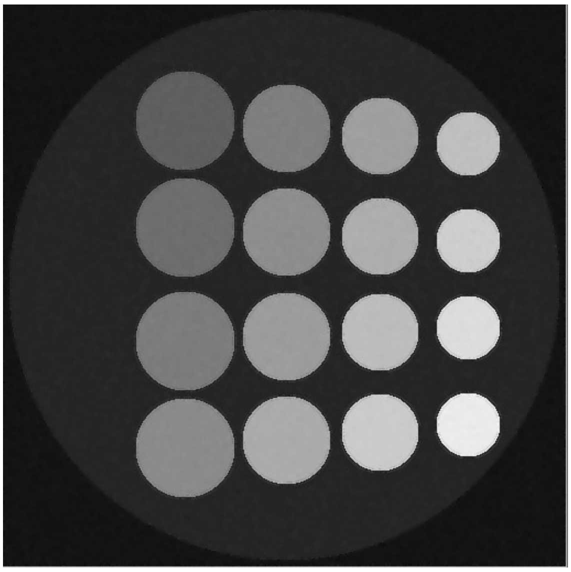

Figure 5. Enhanced image using 5×5 average filter with Moran statistics.

4 Discussion

A new image enhancement method has been presented. The proposed algorithm uses spatial statistic calculations as a threshold to adaptively proceed with filtering. A noisy synthetic image is significantly improved by effectively maintaining the edge structure and decreasing the noise. However, the synthetic image is not a real scene image. Only Gaussian noise is assumed in this image. The areas set belong in the edge when the Moran Z value is higher than 3.4, which is too rough. The algorithm visual processing is good but more forward research is required. Test images of actual scenes will be used in the future, examining the Z value corresponding to various image structures. A noise model such as the Poisson distribution will be considered to simulate medical imaging systems.

Acknowledgements

This work was supported in part by a research grants from Baise University: Scientific Research Booting Grants for Doctors, Baise University, Baise, Guangxi, China.

References

[1] S.B. Javier, Structure similarity image quality reliability determining parameters and window size, Signal Processing 91 (2011) 1012-1020.
[2] J.D. Ruikar, A.K. Sinha and S. Chaudhury, Review of image enhancement techniques, International Conference on Information Technology in Signal and Image Processing-ITSIP 20/3, Oct (2013) 18-19.
[3] A. Polesel, G. Ramponi, and V. John Mathews, Image Enhancement via Adaptive Unsharp Masking, IEEE Transactions on image processing 9 (2000) 505-510.
[4] Z.G. Gui, P.C. Zhanga, J.H. Zhang and Y.J. Zeng, A X-ray image sharpening algorithm using nonlinear module, The Imaging Science Journal 60 (2012) 3-8.
[5] S.J. Fu, Q.Q. Ruan, W.Q. Wang, F.Z. Gao and H.D. Chen, A feature dependent fuzzy bidirectional flow for adaptive image sharpening, Neurocomputing 70 (2007) 883-895.
[6] T.J. Chen, K.S. Chuang, J. Wu, S.C. Chen, I.M. Hwang and M.L. Jan, A novel image quality index using Moran I statistics, Phys. Med. Biol. 48(2003) N131-N137.
[7] T.J. Chen, K.S. Chuang, Y.C. Chiang, J.H. Chang, R.S. Liu, A statistical method for evaluation quality of medical images: case study in bit discarding and image compression, Comput. Med. Imaging Graphics 28 (2004) 167-175.

[8] T.J. Chen, K.S. Chuang, J.H. Chang, Y.H. Shiao and C.C. Chuang, A blurring index for medical images, J Digital Imaging, 19 (2006)118-125.
[9] Y.H. Shiao, T.J. Chen, K.S. Chuang, C.H. Lin, and C.C. Chuang, Quality of Compressed Medical Images, Journal of Digital Imaging 20 (2007) 149-159.
[10] K.S. Chuang, H.K. Huang, Assessment of noise in a digital image using the join-count statistic and Moran test, Phys. Med. Biol. 37 (1992) 357-369.
[11] A.D. Cliff and J.K. Ord, Spatial process: models and applications Pion, London, UK, 1981.
[12] R. C. Gonzalez and R.E. Woods, Digital Image Processing, Addison-Wesley, New York, 1992.