Design of Unsharp Masking Filter Kernel and Gain using Particle Swarm Optimization

Ngaiming Kwok
School of Mechanical and Manufacturing Engineering
The University of New South Wales
NSW 2052, Australia
email: nmkwok@unsw.edu.au

Haiyan Shi
School of Computer Science and Technology
Shaoxing University
Shaoxing, Zhejiang 312000, China
email: csshy@usx.edu.cn

***Abstract*—The unsharp masking filter is an efficient and effective algorithm frequently applied in image contrast enhancement applications. The principle is based on sharpening object edges by appending a scaled high-pass version of the image to the original. The quality of the processed image is largely dependent on the characteristics of the high-pass signal and the scaling factor. Thus, optimal choices of the high-pass kernel and scaling are needed. In this work, a symmetrical kernel is employed and optimized to extract the edge together with an optimal scale factor to enhance a color image. In particular, the particle swarm optimization algorithm is used to obtain the proper filter kernel settings and the gain with regard to maximizing the information content and minimizing the number of over-ranged pixels. The proposed method is tested with 200 real-world images and the filter performance is assessed by referring to measures in colorfulness, average saturation and entropy. Experimental results have shown that image qualities are improved as compared to results from conventional kernels.**

***Index Terms*—contrast enhancement; unsharp masking filter; kernel optimization; particle swarm optimization.**

I. Introduction

Image based techniques have been widely used in a broad range of engineering, science and medical applications. These applications include, for example, remote sensing of the environment [1], robotic guidance [2], traffic monitoring [3] and medical imaging [4]. It is always a desire and challenge to obtain images of good qualities to satisfy the requirement for a particular task. Due to the fact that images carry a large amount of information, it is not trivial to develop a generic, simple and automatic enhancement algorithm.

In order to improve the image quality, it is often required to correct color fidelity [5] and boost the image contrast [6]. Contrast enhancement methods can be broadly classified as global operation or local operation approaches. In the former category, features and characteristics of the whole image are used to derive an output image of better quality. For instance, histogram equalization and modification are commonly used [7]. On the other hand, local operation based methods make use of local pixel patch features to determine how the enhanced image is obtained. One of the efficient and effective techniques is the unsharp masking filter (UMF) [8].

The principle of UMF is rested on the optical phenomenon that image sharpness is increased when edges of the objects are emphasized. In practice, edges are usually derived from high-passing the input image or obtained from the difference from the input image and its low-passed component. With regard to deriving the emphasizing signal, a number of filtering kernels are available. For example, a quadratic filter was used for imaged fingerprint enhancement [9]. In [10], a hybrid windowed kernel was used for radiographs enhancement. A nonlinear kernel was proposed in [11] for mammogram contrast improvement. In [12], a cubic mask was adopted for general image contrast enhancement.

The focus on the design of the UMF had currently moved towards automating the procedures [13]. In particular, the determination of proper filter parameters was addressed in [14] with a comparison of the filter kernels. Furthermore, the optimality of the parameters was studied in [15] where the importance of filter tuning was revealed. In order to obtain proper filter designs, the feasibility of intelligent computation methodologies were evaluated and adopted. A traditional and popular method used for image enhancement is the genetic algorithms (GA) [16][17][18]. The efficient particle swarm optimization algorithm (PSO) is also a common choice and was used for hue preservation when enhancing color images [19]. Other works employing PSO include image noise removal [20], and contrast improvement [21].

The application of particle swarm optimization, for its implementation simplicity, had been directly applied in UMF designs include the work published in [22] and [23]. In the first report, PSO was used to tune the scale of edge enhancement. In the latter work, the PSO was employed in determining the enhancement profile which is dependent on the original image intensity and the emphases to be augmented. Both approaches had demonstrated satisfactory results.

In the present work, the design of the UMF is focused on the optimization of the filter kernel parameters and the enhancement gain factor such as to maximize the image contrast while keeping over-enhancement artifacts to a minimum. In addition, the PSO algorithm is also applied as the tool to obtain a high performing filter. A symmetric Laplacian-like kernel is designed and used to extract object edges to augment the input image. In order to achieve a generic enhancement process, the kernel is further normalized to unity. With such strategy, kernel parameters as well as the emphasizing gain factor are then determined by applying the PSO. The objective function employed is calculated from the output image entropy. Furthermore, to cater for artifacts produced from over-enhancements, the objective function is penalized by the ratio of the number of pixels falling outside the permitted display range to the total number of pixels in the image. The performance of the proposed approach is evaluated in terms of the output image information, average saturation and colorfulness. Statistics are collected to validate the effectiveness of the proposed approach.

The rest of the paper is arranged as follows. In Section II, the unsharp masking filter operation is reviewed. In Section III, the proposed approach is developed and presented, and the use of the particle swarm optimization to obtain optimal filter parameters is proposed. Experiments are described and results discussed in Section IV. Finally, Section V contains the conclusion.

II. Unsharp Masking Filter

The unsharp masking filter achieves image contrast enhancement by augmenting an edge-like version of the image to the input [8][24]. Edges around object boundaries are emphasized and the quality of the image, in terms of contrast, is therefore enhanced.

Let a color input image be given as

$$\mathcal{I}(u,v) = \{R(u,v), G(u,v), B(u,v)\}, \tag{1}$$

where (u,v) is the pixel coordinate denoting the horizontal and vertical orientations across the image of size $U \times V$; $R,\ G,\ B$ denote the primary red, green and blue color channels. In many reported color image enhancement procedures, the color image is first converted to an alternate color space that is more commensurate to the human visual system. For example, the hue-saturation-value (HSV) space is frequently used. In this color space, hue (H) represents the color, saturation (S) defines the richness of the color and value (V) corresponds to the brightness. In the unsharp masking process, the input color image in RGB space is first converted to the HSV space [23], and the V-channel is used for unsharp masking enhancement, see Fig. 1. The UMF operation can be described as [22]

$$y(u,v) = x(u,v) + \lambda z(u,v), \tag{2}$$

where $y(u,v)$ is the filtered V-channel pixel, $x(u,v)$ is the input V-channel pixel, λ is the scaling factor, and $z(u,v)$ is the high-passed pixel. Here $u \in [1,\cdots,U]$, $v \in [1,\cdots,V]$. It can be seen that a scaled component is added to the input pixel to give the enhanced output, as shown in Fig. 2, where the original gray image has been modified. The set of pixels then replace the original V-channel component and re-converted to the RGB space to give the enhanced image.

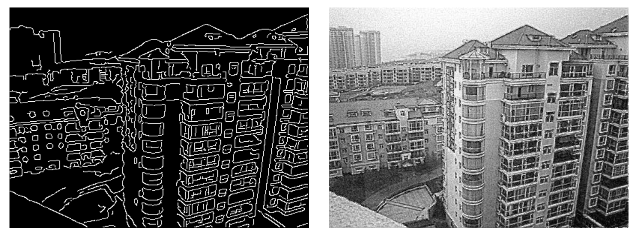
When the UMF is implemented, a high-pass signal has to be extracted from the input image. A direct approach is to use a class of Laplacian kernel to obtain the augmentation. That is,

$$z(u,v) = \mathcal{K}_h(u,v) \otimes x(u,v), \tag{3}$$

where $\mathcal{K}_h(u,v)$ is a high-pass kernel centered at pixel coordinate (u,v), and $\otimes$ is a convolution. On the other hand, it is possible to subtract a low-passed version from the input in order to obtain the high-pass signal. In the latter case, the output can be described as

(a) (b)

Fig. 1. Conversion from color image to the gray image in the HSV space. (a) input color image, (b) converted gray level image in the V-channel.



(a) (b)

Fig. 2. The unsharp masking process. (a) emphasizing signal, (b) emphasizing signal added to the converted gray image.

$$z(u,v) = x(u,v) - \mathcal{K}_l(u,v) \otimes x(u,v), \tag{4}$$

where $\mathcal{K}_l(u,v)$ is the low-pass kernel. However, an additional subtraction operation is required for this procedure and not considered further in this work.

The performance of the filter, with regard to some qualitative measures such as the information content, largely depends on the setting of the gain factor λ and the characteristic of the high-passed signal $z(u,v)$ to be augmented to the original image. On one hand, these two parameters would independently or jointly affect the output image quality. On the other hand, if the gain λ is not set properly, the output would either be under-enhanced or degraded due to over-enhancement. That is, pixel values may become over-ranged resulting in

$$y(u,v) < 0, \text{ or } y(u,v) > 1. \tag{5}$$

The effects of different high-pass kernels and emphasizing scales are illustrated in Fig. 3. These preliminary results are obtained from setting different gain factors, and using two common Laplacian-like kernels given by,

$$\begin{aligned}\mathcal{K}_s(u,v) = [(&4x(u,v) - x(u,v-1) - x(u,v+1) \\ &- x(u-1,v) - x(u+1,v)]/4,\end{aligned} \tag{6}$$

for the sobel-like symmetric kernel $\mathcal{K}_s$. Moreover, a diagonal

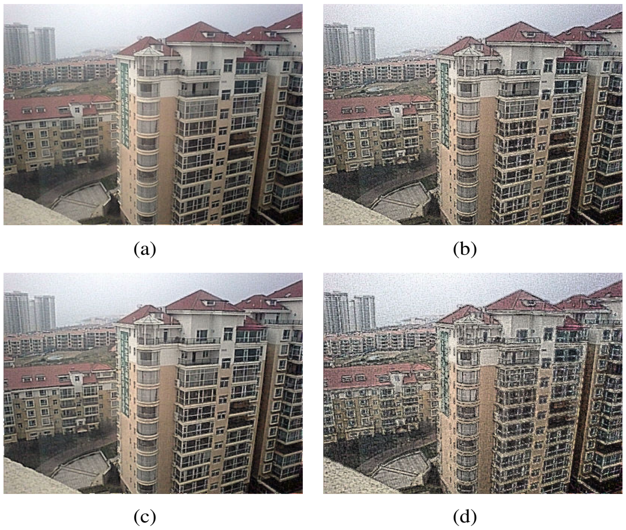


Fig. 3. Outputs from the unsharp masking filter. (a) sobel-like kernel, gain $\lambda = 5$, (b) sobel-like kernel, gain $\lambda = 15$, (c) diagonal kernel, gain $\lambda = 5$, (b) diagonal kernel, gain $\lambda = 15$.

kernel $\mathcal{K}_d$ is determined from,

$$\mathcal{K}_d(u,v) = [4x(u,v) - x(u-1,v-1) - x(u-1,v+1) \\ - x(u+1,v-1) - x(u+1,v+1)]/4. \quad (7)$$

It is observed from Fig. 3 that, when the UMF parameters are determined in ad-hoc manners, satisfactory filter performance cannot be guaranteed. In figures 3(a) and 3(c), with a low gain factor, the output may not receive sufficient enhancement. Whereas in figures 3(b) and 3(d), if the choice of high-pass kernel is not proper, undesirable artifacts would arise. Particularly for color images, intensity distortions as well as color and saturation distortions would also appear.

III. Proposed Approach

Based on the unsharp masking filter structure and the dependence of performance on the choice of parameters, namely, $\mathcal{K}$ and λ, the design of the UMF considered here is tackled as an optimization problem. In the following, the formulation of the high-pass kernel and the emphasizing gain factor are described. Then the use of PSO to obtain optimal filter parameters is presented. The rationale for the construction of the objective function is also given.

A. Filter design

In the proposed optimal unsharp masking filter, a kernel $\mathcal{K}$ of 3×3 size is adopted. The kernel is also constructed as a symmetric matrix. The chosen kernel size provides the most sensitive local edge extraction thus giving thinner edges and contributing to a higher sharpness in the enhanced image. The elements, unlike those in the conventional Laplacian-like kernel, contains no zero values unless there are extreme cases determined as optimal. Similarly, elements of equal magnitudes are also considered as special cases. In the contrary, other element values would constitute a generic kernel that is suitable to be employed in natural images where the appearance of sobel-like or diagonal edges do not always present. The output edge signal from the kernel is then given by

$$\begin{aligned} &z(u,v) = \mathcal{K}(u,v) \otimes \Omega(u,v) \\ &= [-ax(u-1,v-1) - bx(u,v-1) - ax(u+1,v-1) \\ &\qquad - bx(u-1,v) + 4x(u,v) - bx(u+1,v) \\ &- ax(u-1,v+1) - bx(u,v+1) - ax(u+1,v+1)]/4, \end{aligned} \quad (8)$$

where $\Omega(u,v)$ is the 3×3 neighborhood pixels centered around pixel $x(u,v)$. Furthermore, the kernel elements a, b are constrained by

$$a > 0, \ b > 0, \ \text{and} \ a + b = 1. \quad (9)$$

Depending on the numerical values of the parameter a, parameter $b = 1 - a$ can be determined. When $a \neq 0$ or $a \neq 1$, the kernel is neither dominant in the major axes nor diagonally. Hence, edges for the emphasizing purpose can be better extracted from images. In particular, this kernel structure is sufficiently generic to cater for the wide diversity of object shapes that may appear in a natural image.

The output from the convolution of the gray image with the kernel is then scaled with the emphasizing factor λ and finally added to the original gray image to produce a desirable sharpness enhancement. In order to achieve the desired enhancement on the input image, and based on the preliminary test results illustrated in Fig. 3, parameters a and λ are to be optimized by using the particle swarm optimization algorithm.

B. Particle Swarm Optimization

The particle swarm optimization algorithm is a class of meta-heuristic or intelligent computation methods to derive optimal solutions while a model of the problem is not analytically tractable. Unlike the genetic algorithm, the PSO implementation is more simpler as it does not involve selection, crossover, and mutation operations [17][18]. The PSO is motivated by observations from the social and personal behaviors of swarms of living species while searching for food [21][22][23][24]. This metaphor is well suitable for finding optimal solutions in difficult optimization problems where computational resources can be allocated in a distributed manner.

In the optimization problem undertaken in this work, a particle in the PSO is first encoded with the parameters to be optimized. That is, kernel element a, and gain λ as

$$\mathbf{x} = [x_1, \ x_2] = [a, \ \lambda]. \quad (10)$$

In the PSO, there are p particles in the swarm, i.e., $\mathbf{x}_i, \ i = 1, \cdots, p$. Initially, the particles are given their initial positions $\mathbf{x}_{i,0}$ in a random manner within the range of the potential solution space. Then the particles are manipulated according to their evaluated objective function and are guided towards the optimal solution through a number of generations or time steps $t = 1, \cdots, g$. The particles move through the solution space with attractions to the global best solution $\mathbf{x}^g$ found so far. The particle motion is also governed by its own solution experience memorized as $\mathbf{x}_i^p$. The next position that a particle would reach is determined by its original position and a motion velocity. The equations governing the evolution of the particles include a velocity update and a position update given as

$$\mathbf{v}_{i,t+1} = w_i \mathbf{v}_{i,t} + r_g(\mathbf{x}_t^g - \mathbf{x}_{i,t}) + r_p(\mathbf{x}_{i,t}^p - \mathbf{x}_{i,t}), \quad (11)$$

where $\mathbf{v}$ is the velocity vector, ω is the motion inertia commonly set in the range from to 0.6 to 0.8. Coefficients r_g, and r_p are uniform random numbers in $[0,\ r_{max}]$, where r_{max} is the maximum value conventionally adopted between 1.7 and 2.0.

Based on the velocity, a particle moves to its new position according to

$$\mathbf{x}_{i,t+1} = \mathbf{x}_{i,t} + \mathbf{v}_{i,t+1}. \quad (12)$$

In the problem domain considered here, it is required that $a > 0$ and $\lambda > 0$. Hence, a further step is employed to make the particles as potential solutions to satisfy the constraint. That is

$$\mathbf{x}_{i,t} \leftarrow |\mathbf{x}_{i,t}|, \quad (13)$$

for both kernel parameter a and gain λ. In addition, the constraint $a + b = 1$ in the kernel parameter values, requires that $a \leq 1$ has also to be satisfied. Hence,

$$x_1(= a) \leftarrow \min\{a,\ 1\}. \quad (14)$$

The objective function to be maximized is a penalized measure of the image information content determined from

$$f = \mathcal{H} \times (1 - \frac{\eta}{U \times V}), \quad (15)$$

where $\mathcal{H}$ is the entropy, η is the number of over-ranged pixels resulting from the UMF operation.

As seen in the design of the unsharp masking filter given above, a simple procedure with a small number of parameters is established. The design procedure is summarized in Algorithm 1. The number of particles used in the algorithm is 50 while the number of maximum generations is 50. The performance of the proposed filter is tested with a collection of natural images.

Algorithm 1 PSO-based Optimal Design of UMF Procedure

```
Input image in RGB format
Convert to HSV color space
Set PSO iteration count m = 0
Initialize particle (a, λ)
repeat
    Generate kernel from each particle
    Carry out UMF operation
    Calculate entropy penalized by over-range ration
    Update x^g and x_i^p
    Update particle position
until maximum iteration reached
Return optimal solution x^g
```

The contrast of the output image is measured by its entropy $\mathcal{H}$ [25]. Additional attributes including average saturation $\mathcal{S}$ and colorfulness $\mathcal{C}$ [26] are also evaluated. They are

$$\mathcal{H} = -\sum_{i=0}^{L-1} p_i \log(p_i) \quad (17)$$

$$\mathcal{S} = \frac{1}{UV} \sum_{u=1,v=1}^{U,V} \left\{1 - \frac{3\min\{R(u,v), G(u,v), B(u,v)\}}{R(u,v) + G(u,v) + B(u,v)}\right\} \quad (18)$$

$$\mathcal{C} = 0.3\sqrt{\mu_{rg}^2 + \mu_{yb}^2} + \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2}, \quad (19)$$

where p_i is the probability that a pixel has intensity i, $rg = R - G$, $yb = (R + G)/2 - B$, and μ, σ are the mean and standard deviation corresponding to the color channel differences rg and yb given in the subscript. The amount of potential artifacts produced is given by the ratio of the number of over-ranged to the total number of pixels in the image

$$\eta = \sum\{y(u,v) < 0, \text{ or } y(u,v) > 1\}, \quad (20)$$

where $y(u,v)$ is the intermediate gray pixel magnitude before converting back to the final RGB color space.

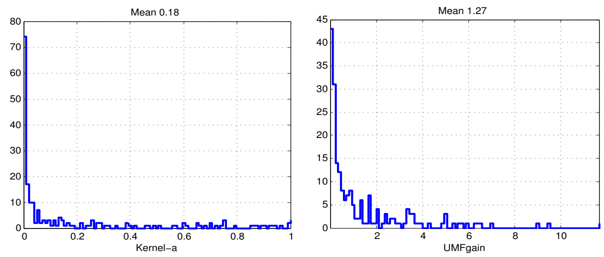
Figure 4 shows the distribution of the kernel parameter and gain factor of the PSO tuned filter. It can be seen that in order to obtain a high information content in the output image, the settings of the parameters cannot be fixed for all images. The average value of the kernel parameter is 0.18, indicating a kernel that is not a sobel-like or a Laplacian kernel. The mean value of the gain factor is 1.27, but it is also observed that a fixed gain is not suitable for all images.

The performances of the PSO tuned UMF are depicted in Fig. 5 illustrating the improvements in entropy while there are no degradations on the average saturation and colorfulness. It is evident that the distribution of entropies of the enhanced images had shifted to a higher value from 7.33 to 7.52 as compared to the input images. The proposed UMF is further examined in terms of the over-ranged pixels giving rise to artifacts in the output image. Figure 6 shows the distribution of the over-range ratios for different UMF approaches included in the test. It is observed that the PSO tuned UMF is able to confine the ratio to 1% averaged over the set of test images.

IV. Experiments

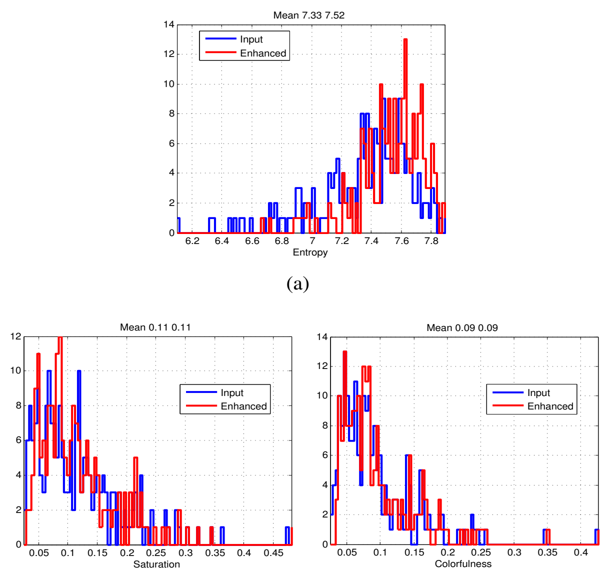
Experiments were conducted to verify the effectiveness of the proposed PSO-based UMF kernel and gain tuning strategy. A data set of 200 images of natural scenery, size 400×300, were used and statistics of the enhancement results collected for evaluation. The sobel-like, diagonal and a full element kernel were used in the tests. The full element kernel is

$$\begin{aligned}\mathcal{K}_f(u,v) = [&-x(u-1,v-1) - x(u,v-1) - x(u+1,v-1) \\ &- x(u-1,v) + 8x(u,v) - x(u+1,v) \\ &- x(u-1,v+1) - x(u,v+1) - x(u+1,v+1)]/8. \quad (16)\end{aligned}$$



(a) (b)

Fig. 4. Distributions of high-pass kernel parameters, (a) kernel parameter a, (b) UMF gain λ.



(a)

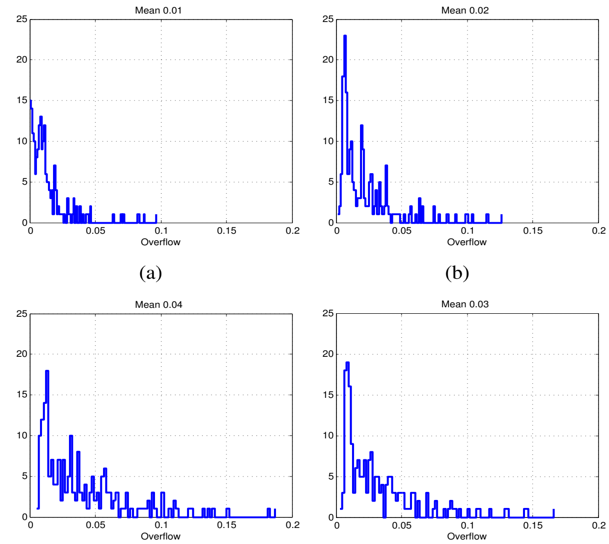
(b) (c)

Fig. 5. Performance evaluation of the proposed UMF based on distributions. (a) entropy $\mathcal{H}$, (b) average saturation $\mathcal{S}$, (c) colorfulness $\mathcal{C}$.

On the other hand, the UMF using diagonal kernel produces the highest ratio of over-range up to 4% while the sobel-like kernels and full kernel give ratios at 2% and 3% respectively. Fig. 7 shows several selected test images and results.

V. Conclusion

An unsharp masking filter design strategy had been presented. The approach, adopting the particle swarm optimization algorithm as the optimizer, tuned the edge extraction kernel and the augmentation gain factor to produce an output image of increased contrast with minimum over-range artifacts. The study, based on a set of 200 test images of natural scenery, had revealed that using a fixed kernel and a fixed gain is not able to produce high quality images by the filter. On the other hand, a varying set of filter parameters has to be obtained for each individual image.



(a) (b)

(c) (d)

Fig. 6. Performance comparison with respect to over-range pixel ratios. (a) PSO tuned kernel and gain, (b) sobel-like kernel fixed gain, (c) diagonal kernel fixed gain, (d) full kernel fixed gain.

References

[1] G. Zhang, X. Jia, and N. M. Kwok, "Super pixel based remote sensing image classification with histogram descriptors on spectral and spatial data," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2012, pp. 4335–4338.

[2] F. Su, G. Fang, and N. M. Kwok, "Adaptive colour feature identification in image for object tracking," *Mathematical Problems in Engineering*, vol. 2012, 2012, article ID 509597, 18 pages, http://dx.doi.org/10.1155/2012/509597.

[3] J. T. Xue, L. Y. Hui, and S. F. Xing, "Research on shadow elimination in intelligent traffic monitoring," in *Proc. 2012 International Conference on Machine Learning and Cybernetics*, 2012, pp. 1350–1355.

[4] F. L. Yi and W. H. Xu, "Segmentation of blood vessels in color fundus images based on optimal multi-threshold method," in *Proc. 2012 International Conference on Machine Learning and Cybernetics*, 2012, pp. 725–728.

[5] N. M. Kwok, H. Y. Shi, Q. P. Ha, G. Fang, S. Y. Chen, and X. Jia, "Simultaneous image color correction and enhancement using particle swarm optimization," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 10, pp. 2356–2371, 2013.

[6] L. Lu, Y. Zhou, K. Panetta, and S. Agaian, "Comparative study of histogram equalization algorithms for image enhancement," in *SPIE Defense, Security, and Sensing*, 2010, pp. 770 811–770 811.

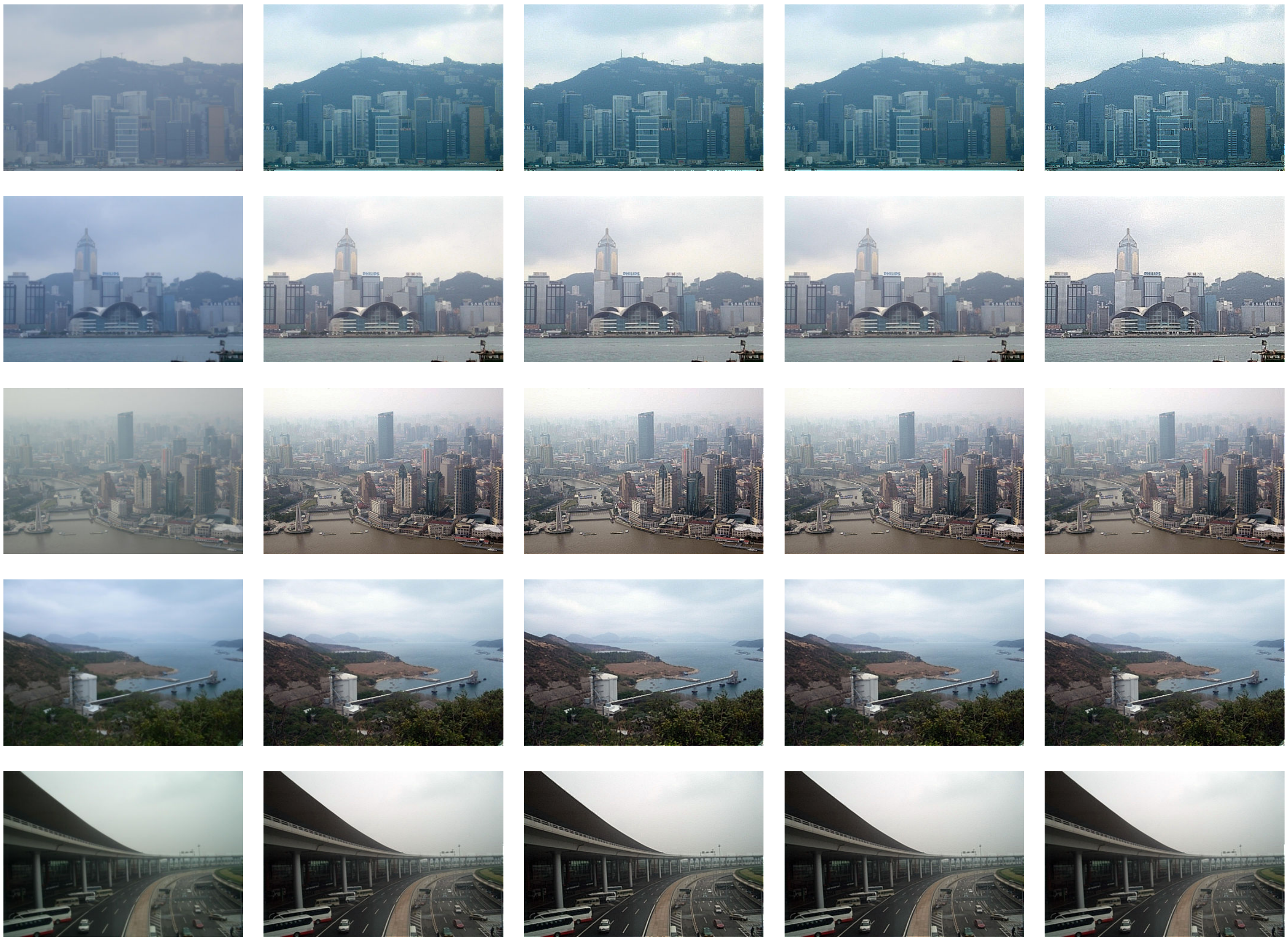
[7] N. M. Kwok, X. Jia, D. Wang, S. Y. Chen, G. Fang, and Q. P. Ha, "Visual impact enhancement via image histogram smoothing and continuous intensity relocation," *Computers and Electrical Engineering*, vol. 37, no. 5, pp. 681–694, 2011.

[8] J. A. Ferrari, J. L. Flores, C. D. Perciante, and E. Frins, "Edge enhancement and image equalization by unsharp masking using self-adaptive photochromic filters," *Applied optics*, vol. 48, no. 19, pp. 3570–3579, 2009.

[9] V. S. Hari, V. P. Jagathy Raj, and R. Gopikakumari, "Unsharp masking using quadratic filter for the enhancement of fingerprints in noisy background," *Pattern Recognition*, vol. 46, no. 12, pp. 3198–3207, 2013.

[10] L. Wang, D. Wang, L. Shi, and W. C. Chu, "Radiographs enhancement based on unsharp masking and gray-level grouping," in *Biomedical and Health Informatics (BHI), 2012 IEEE-EMBS International Conference on*, 2012, pp. 350–353.

[11] K. Panetta, Y. Zhou, S. Agaian, and H. Jia, "Nonlinear unsharp masking for mammogram enhancement," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 15, no. 6, pp. 918–928, 2011.



(a) (b) (c) (d) (e)

Fig. 7. Results from sample test images. (a) input, (b) sobel-like kernel, (c) diagonal kernel, (d) full kernel, (e) PSO tuned kernel and gain.

[12] G. Ramponi, "A cubic unsharp masking technique for contrast enhancement," *Signal Processing*, vol. 67, no. 2, pp. 211–222, 1998.

[13] H. G. İlk, O. Jane, and Ö. İlk, "The effect of laplacian filter in adaptive unsharp masking for infrared image enhancement," *Infrared Physics & Technology*, vol. 54, no. 5, pp. 427–438, 2011.

[14] J. Onur and H. G. Ilk, "A quantitative study on optimum parameters selection in adaptive unsharp masking technique for infrared images," *Radioengineering*, vol. 18, no. 4, p. 611, 2009.

[15] S. H. Kim and J. P. Allebach, "Optimal unsharp mask for image sharpening and noise removal," *Journal of Electronic Imaging*, vol. 14, no. 2, pp. 023 005–023 005, 2005.

[16] C. Munteanu and A. Rosa, "Towards automatic image enhancement using genetic algorithms," in *Evolutionary Computation, 2000. Proceedings of the 2000 Congress on*, vol. 2, 2000, pp. 1535–1542.

[17] R. Lukac, K. N. Plataniotis, B. Smolka, and A. N. Venetsanopoulos, "Color image filtering and enhancement based genetic algorithms," in *Circuits and Systems, 2004. ISCAS '04. Proceedings of the 2004 International Symposium on*, vol. 3, May 2004, pp. III–913–16.

[18] M.-S. Shyu and J.-J. Leou, "A genetic algorithm approach to color image enhancement," *Pattern Recognition*, vol. 31, no. 7, pp. 871–880, 1998.

[19] A. Gorai and A. Ghosh, "Hue-preserving color image enhancement using particle swarm optimization," in *Recent Advances in Intelligent Computational Systems (RAICS), 2011 IEEE*, 2011, pp. 563–568.

[20] S. Roomi, P. L. Karuppi, P. Rajesh, and B. G. Revathi, "A particle swarm optimization based edge preserving impulse noise filter," *Journal of Computer Science*, vol. 6, no. 9, 2010.

[21] M. Braik, A. Sheta, and A. Ayesh, "Particle swarm optimisation enhancement approach for improving image quality," *International Journal of Innovative Computing and Applications*, vol. 1, no. 2, pp. 138–145, 2007.

[22] S. Mohamed, R. J. Priya, S. Rojan, and S. Y. Arafath, "Particle swarm based unsharp masking," in *Proceedings of the Seventh Indian Conference on Computer Vision, Graphics and Image Processing*, 2010, pp. 498–505.

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

[24] C. L. D. A. Mai, M. T. T. Nguyen, and N. M. Kwok, "A modified unsharp masking method using particle swarm optimization," in *Proceedings - 4th International Congress on Image and Signal Processing, CISP 2011*, vol. 2, 2011, pp. 646–650.

[25] A. Santos, C. Ortiz de Solorzano, J. J. Vaquero, J. M. Pena, N. Malpica, and F. Del Pozo, "Evaluation of autofocus functions in molecular cytogenetic analysis," *Journal of Microscopy*, vol. 188, no. 3, pp. 264–272, 1997.

[26] H. Palus, "Colorfulness of the image: definition, computation, and properties," in *Lightmetry and Light and Optics in Biomedicine 2004*, 2006, pp. 615 805–615 805.