An UM-based silhouette-crease edge enhancement for noisy images

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Abstract: This paper presents an improved unsharp masking (UM) technique that enhances the quality and suppresses noises for the images acquired from a noisy environment such as taken during night time. Our approach employs noise smoothing and the idea that important edges should be enhanced more than minor edges. Edges are classified as silhouette and crease edges (major and minor edges) according to their lengths. An adaptive weighting method is used to enhance the edges. In this way, the major edges (silhouette) are sharpened more than minor edges (crease). The proposed method is examined on night images as well as noisy images. It is also compared to existing UM-based methods with satisfying results.

Keywords: unsharp masking; UM; silhouette; crease; enhancement; detail variance; background variance.

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1 Introduction

Image enhancement is an important issue to many subsequent images processing tasks. There are many methods for image enhancement. Some focus on noise removal, e.g., median filtering, others may focus on contrast enhancement, e.g., adaptive histogram equalisation. The median filtering is a common approach to reduce speckle noise. Different variations of the median filter have been proposed (Premchaiswadi et al., 2010; Hsieh et al., 2009; Ng and Ma, 2006; Manikandan et al., 2004). In Premchaiswadi et al. (2010), authors used a window and a core – a smaller window inside it. Depending on the number of black (or white) pixels inside the core, the median filtering is applied on the window or on the core. Despite the simplicity of the median filter, it does not work well when images are highly corrupted. Hsieh et al. (2009) proposed an improved boundary-based approach originated from Ng and Ma (2006). The method first detects noise and is followed by noise replacement. They suggested using the smallest window median filtering to have better quality of the restored images. On the other hand, Manikandan et al. (2004) proposed an adaptive window length recursive weighted median filtering in order to retain the edges and fine details.

Unsharp masking (UM) technique is also a popular approach in image enhancement (Ramponi, 1998; Polesel et al., 2000; Nakashizuka and Aokii, 2005; Kim and Cho, 2008; Badamchizadeh and Aghagolzadeh, 2004). The UM concept is adopted in many digital-imaging software packages, such as Adobe Photoshop and GIMP (*Wikipedia*). The 'unsharp' of the name derives from the fact that the UM technique uses a blurred (unsharp) image of the original image as a mask. Subtracting the 'unsharp' from the original image produces the high frequency portion of the image. Thus, magnifying the high frequency of the original image enhances the visual quality of the image. Equivalently, UM method uses a high-pass filter to produce the high frequency portion of the image and enhance the image by adding back a scaled high frequency, as given in the equation (1).

$$Y(n,m) = I(n,m) + \lambda \times Z(n,m), \tag{1}$$

where $I(n, m)$ is the original image, $Z(n, m)$ is the high-frequency portion of the original image produced by a high-pass filter, λ is a (global) scaling factor, and $Y(n, m)$ is the enhanced image.

There are many ways for generating $Z(n, m)$. One of the most basic linear methods is Laplacian filter, but there are two drawbacks. It increases the sensitivity of the noise. And it may cause overshooting problem in the high-frequency part and under shooting problem in the low-frequency part of the enhanced image. To suppress noises, nonlinear polynomial operator is often used as in Ramponi (1998), Polesel et al. (2000) and Nakashizuka and Aokii (2005). Cubic unsharp masking (CUM) is one of the most representative method (Ramponi, 1998). CUM effectively suppresses noises when the image is moderately damaged, but it enhances the noises when the image is seriously damaged. In addition, it tends to have the over/under shooting along the borders of edges. To solve the over/under shooting problem, adaptive UM (Polesel, et al., 2000) was proposed such that they used different scaling factors for high-, medium-, and low-frequency parts of the image. But the price is the complicated algorithm with many parameters. It may not be easy to choose suitable parameters for a given image. In Nakashizuka and Aokii (2005), improved from the method of Ramponi (1998), it used a cascaded configuration of cubic unsharp masking (CS-CUM) to simultaneously remove image noises and improve image quality. Authors especially emphasised on the continuity of the 'edge'. According to Nakashizuka and Aokii (2005), their method can effectively reduce the noise amplification value about one-third along edges comparing to that in Ramponi (1998). However, in smooth area, it not only fails to suppress the noises but also amplifies the noise. Kim and Cho (2008) probed the relationship between textures and noises. They classified four kinds of textures that all share the same property of large local variances just like noises do. The proposed method helps to clear out texture and noise somehow, but it did not suppress noises and cannot distinguish all possible textures from noises. In Russo (2002), a sharpening method combining fuzzy theory and UM was proposed. They used fuzzy theory to locate and smooth noises. The experimental result in Russo (2002) is good with the cost of computation due to iteration of the method.

Recently, the research in image rendering of computer graphics has a progressive development owing to the popularity of video games, simulators, movie or TV special effects, etc. To have a better visual effect, the contours of interested objects are usually enhanced. Particularly, edges are classified as silhouettes and creases according to whether they are major edges or minor edges. A silhouette will be enhanced more and a crease will only be enhanced moderately (Winkenbach and Salesin, 1994; Chen, 2003; Yang and Yang, 2006).

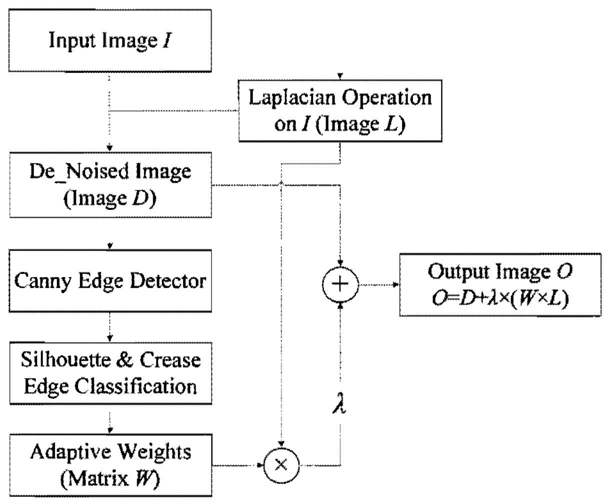
When taking digital photos in low light conditions, charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) sensor chips take a longer exposure time to acquire the necessary light. However, a longer exposure time causes camera shake if a tripod is not used. A solution commonly adopted by automatic digital camera is to use a higher ISO. ISO means the amount of sensitivity of light falling on sensor. However, a high digital photography ISO causes noise. The noise occurs because of the physical properties of light-sensitive components, for example, read noise, dark current noise, fixed pattern noise, etc. These noises in the mathematics can be divided into uniform noise, Gaussian noise, impulse noise, etc., and they greatly reduce the image quality.

How to sharpen and de-noise images taken in low light conditions is examined in this study. The proposed method is combining UM technique and the concept of major-minor edges. The method first identifies and smoothes noises, then detects and classifies edges into silhouettes and creases. In this way, proper weights can be assigned and, therefore, edges are enhanced appropriately.

2 Proposed method

The outline of the proposed algorithm is given in Figure 1.

Figure 1 Flow diagram of the proposed method (see online version for colours)



For a given greyscale image I, it generates a de-noised image D and a high-frequency image L by Laplacian operator. Contrary to the traditional UM method, we only enhance the important portion of L by assigning weights. Importance depends on whether they are major or minor edges. Canny operator is applied on D to detect edges (Canny, 1986). Silhouette and crease are classified, and the weighting matrix is determined such that the major edges (silhouette) deserve more weights. By multiplying the weighting matrix W and the Laplacian image L position-wise, the true edges of I can be more appropriately represented. Finally, the enhanced image is obtained as in equation (2).

$$O = D + \lambda \times (W \times L), \tag{2}$$

where O is the output image, λ is the scaling factor, image L is the image after implementation of the Laplacian filter on I, W is the weighting matrix (its size is the same as the image I's), and image D is the image after noise removal. The details are given in the following.

2.1 Noise detection and suppression

Laplacian operator can be used to detect pixels where intensity changes. Figure 2(a) is a night view of Tamsui River in New Taipei City, Taiwan. A point (x, y) on the original image I is a noise candidate if $|L(x, y)| \geq th_{Noise}$. The magnitude of Laplacian value, $|L(x, y)|$, reflects how large the intensity changes at this point, and th_{Noise} is a threshold.

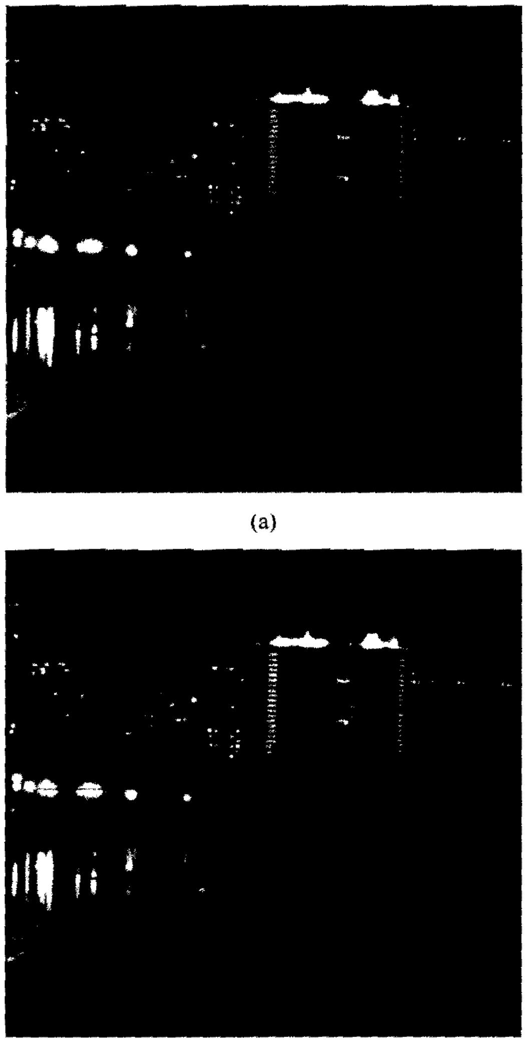
Noise candidates include both noises and edge points. By observing many images taken in low light conditions, the noises from high ISO have blobs with size not larger than 3×3, whereas the edges points usually form blobs larger than that. Therefore, by connected component (CC) analysis on those noise candidates, we label those candidates to be noises if the CC has the size not larger than 3×3. To smooth noises, the intensity of every noise point P is replaced by the average intensity value taken from non-noise points of a 5×5 window on I (centred at P). Figure 2(b) shows the smoothed result D.

2.2 Edge detection and classification

Canny edge detector is applied on the smoothed image D to find edges. Canny edge detector has three parameters, Gaussian blur of σ, double thresholds T_1 and T_2 ($T_2 > T_1$). A larger σ is more suitable when the image noise is severe. When T_1 is fixed, the smaller T_2 the more edge points are detected; when T_2 is fixed, the smaller T_1 the more edge points are detected. Figure 3(a) is the result of edge detection from Figure 2(b) with $\sigma = 0.6$, $T_1 = 150$ and $T_2 = 200$.

Improving the contrast of contour and details is critical for an image to have a good visual quality. However, the principal contours deserve more enhancement than fine details do. Therefore, we adopt the concept of silhouette and crease, and assign them different enhancement weights. To distinguish between silhouettes, principal contours or major edges, and creases, fine details or minor edges, we take the lengths of curves into consideration. Since Canny edge detector produces one-pixel width edges, the length of a curve can be defined as the number of edge pixels. Taking two thresholds, T_{L1} and T_{L2} ($T_{L1} \leq T_{L2}$), a continuous curve is a silhouette if it is long enough, length $\geq T_{L2}$, and it is a crease if its length is between T_{L1} and T_{L2}. Finally, the rest of edges which from continuous curves with length less than T_{L1} are not important and they are eliminated. Figure 3(b) illustrates the classification of silhouette and crease. Comparing (a) and (b), noises are eliminated further in (b).

Figure 2 The night view of Tamsui River, New Taipei City, Taiwan, (a) original image I (b) image after noise removal D



(a)

(b)

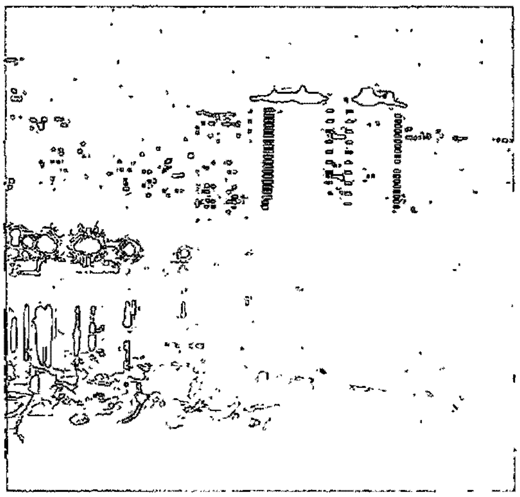
2.3 The assignment of adaptive weights

To assign weights to silhouette/crease, two binary images are created. One is having ones on those points belonging to silhouettes (image S) and the other is having ones on those points belong to creases (image C). To S, a morphological dilation with a structuring element of 3×3 is applied, and a Gaussian blurring is applied next. To C, a Gaussian blurring is applied. Now combine these two images into a weighting matrix W as in equation (3).

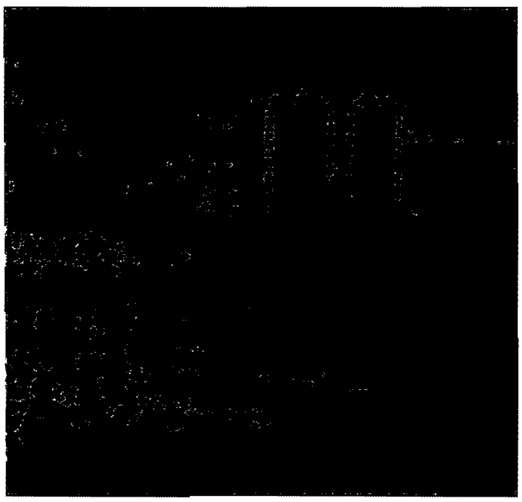
$$w(i,j) = \begin{cases} s(i,j) & \text{if } c(i,j) = 0 \text{ and } s(i,j) \neq 0, \\ c(i,j) & \text{if } c(i,j) \neq 0 \text{ and } s(i,j) = 0, \\ \max(s(i,j), c(i,j)) & \text{if } c(i,j) \neq 0 \text{ and } s(i,j) \neq 0, \\ 0 & \text{others.} \end{cases} \tag{3}$$

where $w(i, j)$ is the weight assigned to point on (i, j) position, $s(i, j)$ and $c(i, j)$ are the values on point (i, j) in images S and C respectively. To have a vision of the weighting matrix W, Figure 4 shows W in terms of a greyscale image with intensities proportional to the weights. Note that, a 3×3 dilation is to emphasise more on silhouette edges, and a Gaussian blurring (standard deviation = 1) makes weights diminished gradually as points departed away from those edge points (silhouette or crease).

Figure 3 Edge detection and classification of D in Figure 2(b), (a) result of canny edge detector (b) edges are classified as silhouettes (in yellow) and creases (in white) (see online version for colours)



(a)

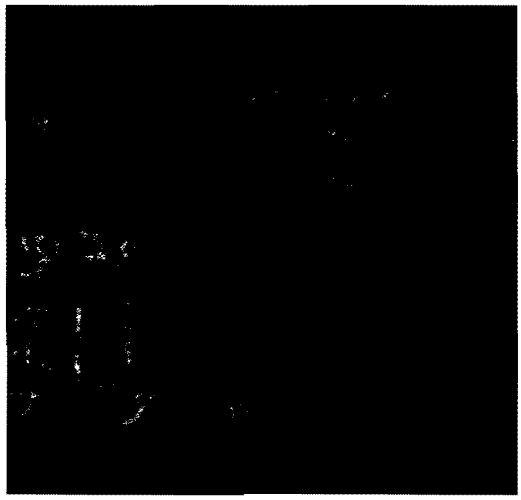


(b)

2.4 Image enhancement

Finally, UM technology for image enhancement is implemented as in equation (2). Comparing to the traditional UM method, our method smoothes noises first to avoid noises erroneously magnified, and it soothes the over/under shooting problem and gives a natural look on edges on the enhanced image since weights are smoothed by Gaussian blurring. Figure 4(b) shows the final result of the image on Figure 2(a).

Figure 4 The adaptive weight and the result, (a) the weighting matrix W (b) the final enhanced result



(a)

(b)

3 Experimental results and analysis

To verify the proposed algorithm, we use night images and noisy (synthetic and natural) images as sample images. Partial results are shown in here. Three existing methods are compared: CUM (Ramponi, 1998), CS-CUM (Nakashizuka and Aokii, 2005), and Kim's feature and noise adaptive UM (Kim's) (Kim and Cho, 2008). Parameter settings are adopted from their papers.

3.1 Parameter setting

Our method has several parameters: the enhancement scaling factor λ in equation (2), th_{Noise} in determining the noise candidates, σ, T_1, T_2 in Canny edge detector, T_{L1}, T_{L2} in determining silhouette and crease. Table 1 gives the experimental values that they give satisfactory results in general.

Table 1 Parameter default values

λ	th_{Noise}	σ	T_1	T_2	TL_1	TL_2
0.35	25	0.6	150	200	20	70

Although the parameters setting in Table 1 is applicable to images in general, however, it may not be suitable when the image is severely damaged. For example, when Gaussian noise of variance 50 is added, there are many noise candidates and it is possible that some noises link up to be large blobs. Then these noises will be mistaken to be edge points and magnified in later process. Thus, in a fixed T_1, T_2, T_{L1}, T_{L2} consideration, we take a small rectangular area from smooth background to serve as an estimate of noise for the image. Observing from many experiments we have done, the parameters σ and th_{Noise} can be adjusted accordingly as in equations (4) and (5) where v is the intensity variance from this area. In equation (4), logarithm is applied on v, so small variations on v do not affect the results. For example, in Figure 5, *Lena* with Gaussian noise of variance 50 added, three different smooth rectangular areas (in blue, from top to bottom, left to right) have variances (v) 160, 175, 158, respectively. After evaluation from equations (4) and (5), the values for σ and th_{Noise} are 0.81, 0.83, 0.81, and 21, 22, 21, respectively.

$$\sigma = \begin{cases} 0.6 & \text{if } v \le 60, \\ 0.5231 \times \log_{10} v - 0.3416 & \text{if } v > 60, \end{cases} \tag{4}$$

$$th_{Noise} = \begin{cases} 15 & \text{if } v \le 60, \\ 25 & \text{if } v \ge 300, \\ \lfloor 30.385 \times \sigma - 3.4231 \rfloor & \text{if } 60 < v \le 300. \end{cases} \tag{5}$$

As for the scaling factor λ, it gives good results for values between 0.35 and 0.5 (0.35 is used throughout the tests).

3.2 Experiments and data

Three tests are implemented. One is referring to high ISO problem. The second test is applied on the synthetic grey image. Finally, the terms detail variance (DV) and background variance (BV) as in (Ramponi, 1998) are adopted for evaluating the performance of algorithms.

Test 1 Night image (ISO 800) Olympus E-510.

Figure 6 shows the enhanced results by different methods. Noises are erroneously magnified in all (b) to (d). We further examine the enhanced results in two areas, smooth and textured as indicated in Figure 6(a). The enlarged corresponding areas with variances are shown in Table 2. As we know, after enhancement, the variance in smooth area is smaller the better, and the texture area is larger the better. The figures in Table 2 do confirm that the proposed method effectively suppressed the noise (with variance 13.56, smaller than the original's) and properly enhanced edges (with variance 4,779.59, larger than the original's).

Test 2 Synthetic image with Gaussian noise (variance = 50) added.

Figure 5 Lena with Gaussian noise (variance = 50) added where blue boxes are used in illustrating equations (4) and (5) (see online version for colours)

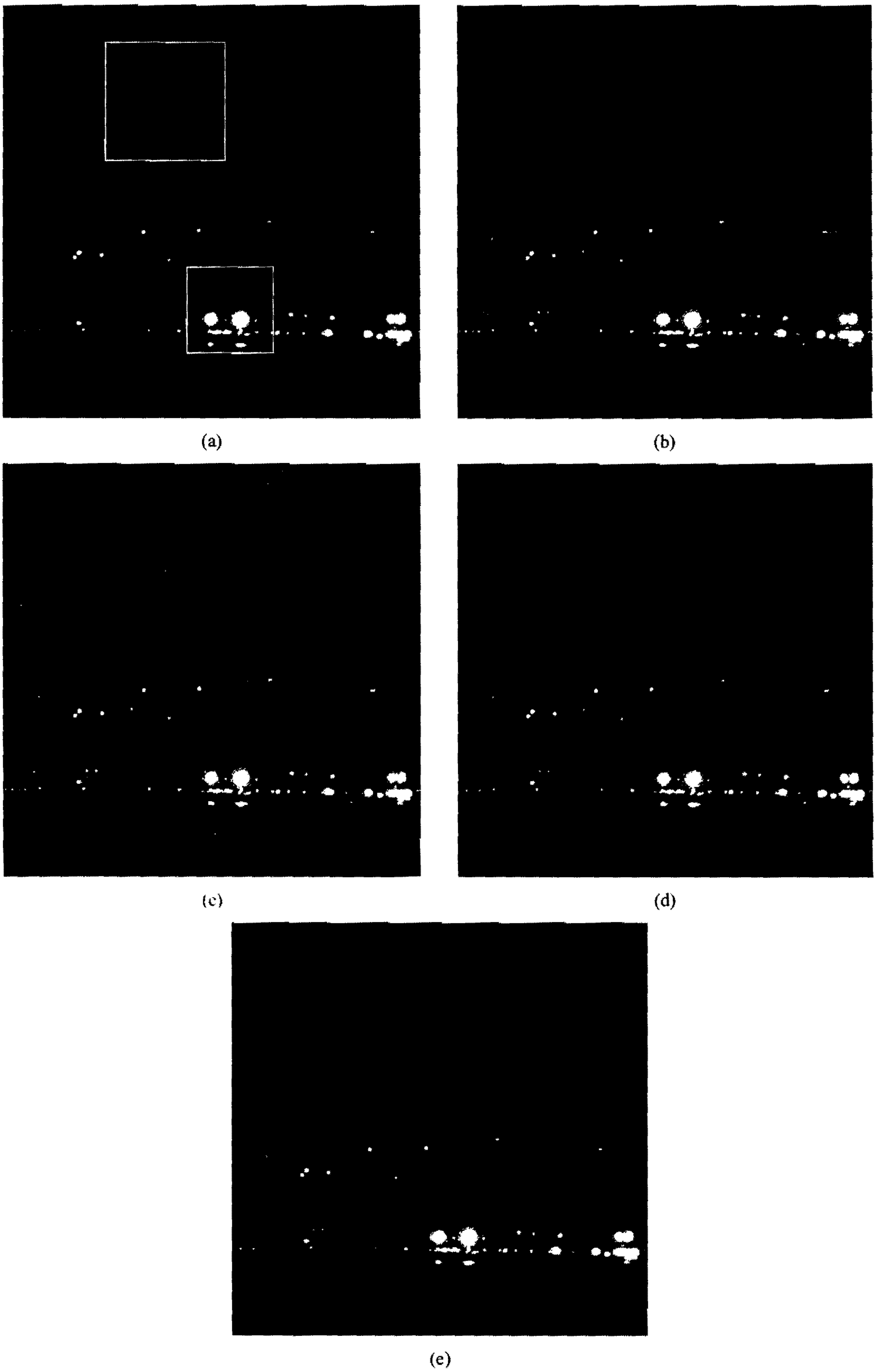
Note: Results are summarised in Table 4, referring to Test 3.

Figure 7 shows the enhanced results by different methods. In (b) to (d), not only noises are erroneously magnified, there are black/white ghost lines along the true line segments. We also examine the enhanced results in two areas, smooth and textured as indicated in Figure 7(a). The enlarged corresponding areas with variances are shown in Table 3. Again, the figures in Table 3 do confirm that the proposed method effectively suppresses the noise and properly enhanced edges.

Test 3 Objective evaluation on *Lena* with noises.

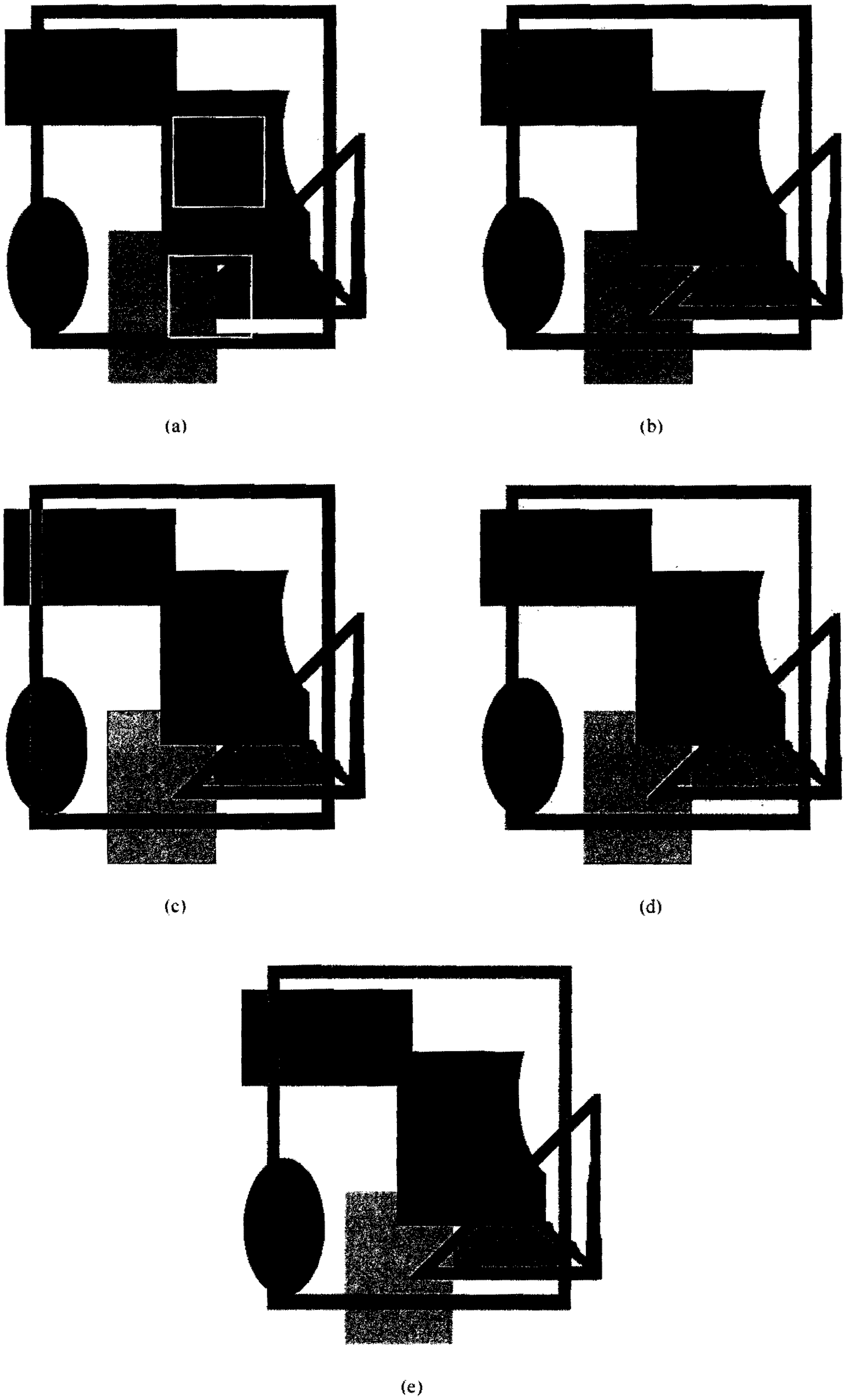
As different algorithms use various parameters, the overall image quality sometimes is difficult to judge. Thus, the terms DV and BV as in Ramponi (1998) are adopted for evaluating the performance of algorithms. Take a noise-free image and classify each point to be a background pixel or detail pixel according to its local variance. Then, apply enhancement algorithms to the test image with noise added. The DV (BV) is the average variance from those detail (background) pixels in the enhanced image. By tuning the scaling factors λ in different enhancement methods to make the enhanced images having the same DV, we compare BV for different methods. Now these enhanced images are under the same degree of enhancement, then the result with small BV would be desired. *Lena* with Gaussian noise of variance 50 added is tested as shown in Figure 5. The results of BV and DV (fixed to be close to 953) are shown in Table 4. We can see that our method reduces BV to less than a half of Kim's and CS-CUM's, and about three quarters of the CUM's. Comparing to their methods, the proposed method significantly reduces noises that appear in the homogeneous regions of the input image while raising the contrast of the detail regions.

Figure 6 The enhanced results on high ISO night image where two yellow boxes in (a) indicates the areas for later comparison, (a) original (b) Kim's (c) CUM (d) CS CUM (e) ours (see online version for colours)



Note: Results are summarised in Table 2, referring to Test 1.

Figure 7 The enhanced results of different methods on the synthetic image with noise added where two yellow boxes in (a) indicates the areas for later comparison, (a) original (b) Kim's (c) CUM (d) CS CUM (e) ours (see online version for colours)



Note: Results are summarised in Table 3, referring to Test 2.

Table 2 Regional comparison as indicated in Figure 6(a)

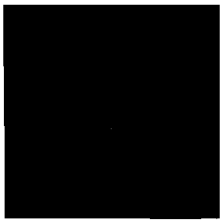
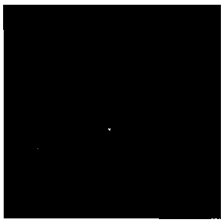
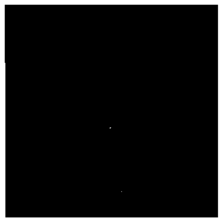
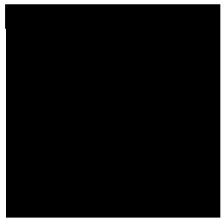
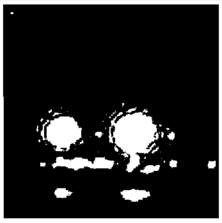
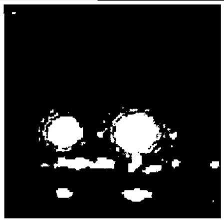
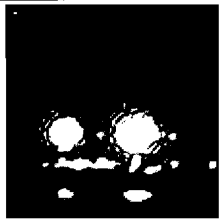
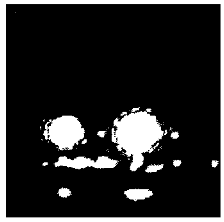
Method	*Original*	*Kim's*	*CUM*	*CS-CUM*	*Ours*
Smooth area					
Variance	22.57	60.91	68.51	40.11	13.56
Texture area					
Variance	4406.97	5018.87	5019.01	4889.52	4779.59

Table 3 Regional comparison as indicated in Figure 7(a)

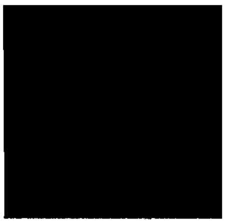
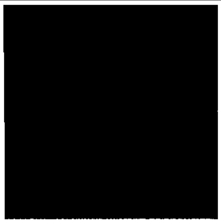
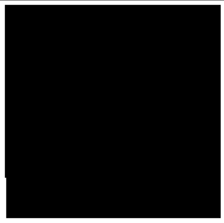
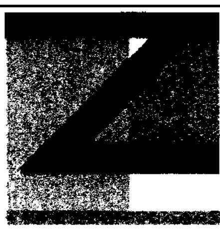
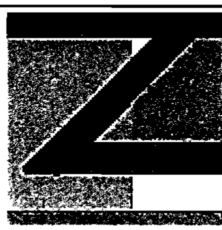
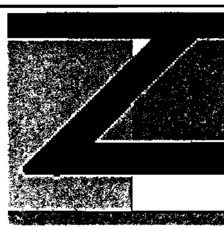
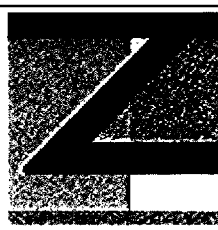
Method	*Original*	*Kim's*	*CUM*	*CS-CUM*	*Ours*
Smooth area					
Variance	134.63	363.68	286.98	645.75	107.17
Texture area					
Variance	2,834.99	4,028.75	3,974.85	4,055.44	3,075.92

Table 4 *Lena* (with Gaussian noise of variance = 50) of BV value comparison (DV ≈ 953)

Method	*None (noise-free)*	*Kim's*	*CUM*	*CS-CUM*	*Ours*
BV	22.61	271.41	167.08	290.56	127.04
DV	457.60	953.03	953.49	953.54	953.30

4 Conclusions

This paper presented a UM-based image enhancement method. Unlike traditional UM, our method first detects and suppresses noises before magnifying the high frequency portion of the image. Also, to have a more natural enhancement visual effect along edges, silhouette and crease edges are classified and different weights are assigned. By this way, the problem of noises caused by high ISO for images taken in low light conditions is solved. The parameters in our method are provided in the paper which is applicable to most images. Users can also specify a smooth rectangular area to reflect the noisy degree of the input image. In this way, the parameters can be adjusted accordingly. To evaluate the proposed method, visual qualities and quantitative evaluations are both presented. The method outperformed existing methods.

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