Image Detail Enhancement via Constant-Time Unsharp Masking

Dat Ngo and Bongsoon Kang *
Department of Electronic Engineering, Dong-A University
Busan, Korea
* Correspondence: bongsoon@dau.ac.kr

Abstract

Image degradation due to weather phenomena and poor lighting conditions is inevitable in photography and computer vision applications. For example, fine details like distant objects or traffic signs are easily obscured by haze, mist, or dust in the atmosphere. Thus, the proposed algorithm is designed to address this issue by means of unsharp masking technique. Our approach differs from other unsharp masking methods in: i) the ability to control the contribution of sharpness enhancement according to the local variance of the image, and ii) the constant-time algorithmic complexity by virtue of the constant-time O(1) box filter. The use of the image's local statistics allows the proposed method to add more details in the heavily-degraded areas and little or no details in the smooth areas. In addition, the advantage of speed facilitates the integration into real-time processing applications. A comparative study and quantitative evaluation are conducted with a state-of-the-art algorithm to demonstrate the performance and efficiency of the proposed approach.

Keywords: image enhancement, unsharp masking, image statistics, constant-time, real-time processing.

Introduction

Digital image acquisition is affected by a variety of external factors such as weather/lighting conditions and artificial aerosols in the atmosphere. Such external degradation sources absorb and scatter the incoming light, fading away minute details in the image and then giving rise to a steep fall in performance of algorithms designed for ideal environmental conditions. A good example of this is the adverse influence of weather phenomena like haze, rain, and snow over the accuracy of deep learning-based recognition system integrated into self-driving vehicles. Thus, image enhancement approaches that focus on low-level features like sharpness and contrast hold many practical applications.

The visual perception of an image may be significantly improved by enhancing its high frequency contents extracted by a linear high pass filter. However, since the high frequency information also contains noises, the classic linear unsharp masking (UM) technique is noise-sensitive. Various algorithms have been developed to overcome this shortcoming. Adaptive UM and homomorphic filtering (HF) are cases in point [1-4]. Weighting the high pass filter output according to the local activity level and utilizing an adaptation algorithm to produce an output image with desired local dynamics are presented in [1]. The main drawback of this scheme is the high algorithmic complexity owing the iterative procedure for finding optimal weighting factors at each image pixel. To lower the complexity, Lin et al. weighted the high frequency contents by two hyperbolic tangent functions and a global gain determined by minimizing the entropy of the image [2]. Since Lin et al. employed the iterative golden search to find only one optimal parameter, this method is clearly simpler than the first one. Tanaka et al. developed a non-iterative scheme according to the local variances of the image background and the image itself, respectively [3]. This scheme depends largely on the edge preserving filter employed to extract the image background. If the filter mistakenly smooths the image edges, the weighting scheme will fail. HF is a well-known image enhancement method carried out in the frequency domain [4]. This technique assumes a multiplicative noise model and is widely used in medical image processing to correct the non-uniform illumination as well as amplifying the high frequency components. The use of Fast Fourier Transform in HF results in the complexity of O(N×logN), where N is the number of image pixels, nevertheless. Therefore, a fast and robust sharpness enhancement algorithm is in demand.

In this paper, we propose an algorithm weighting the high frequency contents using the local statistics and possessing constant-time algorithmic complexity. In the next section, we discuss the fundamentals of sharpness enhancement. Then, the proposed algorithm is described in more detail. A comparative study is also conducted with an approach proposed by Tanaka et al. to validate the performance of the proposed algorithm.

Sharpness Enhancement

Equation (1) describes the general linear unsharp masking algorithm, where (m,n) denotes the spatial coordinate of the input image x, the enhanced image z, and the high frequency contents f. The scaling factor λ is used to control the level of enhancement achieved at the output.

$$z(m,n) = x(m,n) + \lambda f(m,n) \qquad (1)$$

The high pass filter is commonly employed to extract the detailed contents from the input image [2, 3]. In this work, we exploit the Laplacian operator horizontally and vertically to obtain the image details in these directions, respectively. Equations (2) and (3) show the input-output relationships of Laplacian operators and Eq. (4) is the modified form of Eq. (1).

$$f_x(m,n) = 2x(m,n) - x(m,n-1) - x(m,n+1) \qquad (2)$$
$$f_y(m,n) = 2x(m,n) - x(m-1,n) - x(m+1,n) \qquad (3)$$
$$z(m,n) = x(m,n) + \lambda\left[f_x(m,n) + f_y(m,n)\right] \qquad (4)$$

In order to achieve the desired enhancement effect, the scaling factor λ plays an important role. For example, Lin et al. realized λ as a hyperbolic tangent function of the image background and the image detail explicitly. This function assigned minimum gains to pixels with values lying at two extremes (e.g., 0 and 255 for 8-bit image data) and gradually-increasing gains to pixels whose values approach the middle (e.g., 128 for 8-bit image data). Therefore, this scheme is lack of generality. Our objective is to scale each pixel in the image according to its local variance calculated by concerning its neighbors in a square window. As a result, maximum enhancement is applied in heavily-degraded areas of the image, moderate enhancement is applied in moderately-degraded areas, and little or no enhancement is applied in smooth areas.

Proposed Algorithm

As mentioned in the preceding section, the novelty of this paper is to derive a weighting scheme according to the local variance of the image, which is calculated according to Eq. (5). $\Omega(m,n)$ is the square window centered at the (m,n)th pixel, $|\Omega|$ denotes the total number of pixels within the window, and $\bar{x}(m,n)$ refers to the average pixel value over the same window.

$$v(m,n) = \frac{1}{|\Omega|} \sum_{h,k\in\Omega(m,n)} [x(h,k) - \bar{x}(m,n)]^2 \qquad (5)$$

The variance of smooth areas of the image is extremely low and may approach zero. Similar observation is made in areas obscured by dense haze or very dark areas owing to too short exposure time. The sharpness enhancement does not bring about any visual effects in these cases, whereas haze removal or light stretch is highly appropriate [5, 6]. Nonetheless, when the haze or mist obscuring the image becomes thinner, the local variance begins to increase and it is now possible to obtain the image details and perform sharpness enhancement. The variance is largest in areas containing detailed and colorful objects. Based on this observation, two positive threshold values v_1 and v_2 are employed to classify the (m,n)th pixel as belonging to a smooth area if $v(m,n) < v_1$, a medium-contrast area if $v_1 \le v(m,n) < v_2$, and a high-contrast area otherwise. The smooth areas may belong to either clear objects (e.g., a plain wall or gate) or objects faded by thin haze or lack of incoming light (e.g., a distant car or traffic sign). In the latter case, assigning a large scaling factor to the smooth areas helps recover the faded details. Even in the former case, a large scaling factor does not cause any side effects, since there is no details to enhance in flat and plain areas. The medium-contrast areas require moderate enhancement, while little enhancement is adequate for the high-contrast areas. The proposed staircase scaling factor $\lambda(m,n)$ is depicted in Fig. 1 and its mathematic expression is shown in Eq. (6).

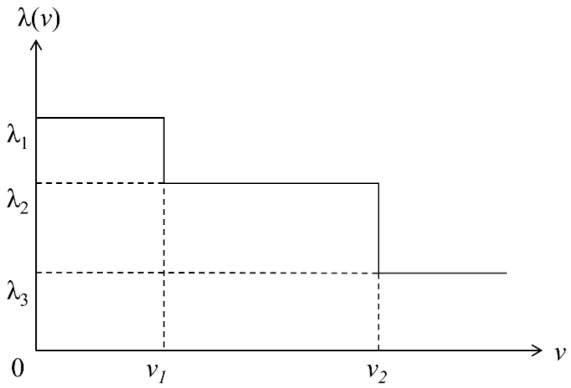

Fig. 1. The proposed staircase scaling factor

$$\lambda(m,n) = \begin{cases} \lambda_1, & v(m,n) < v_1 \\ \lambda_2, & v_1 \le v(m,n) < v_2 \\ \lambda_3, & v(m,n) \ge v_2 \end{cases} \qquad (6)$$

The values that v_1, v_2, λ_1, λ_2, and λ_3 take depend on the desired enhancement level at the output image. Through various experiments on Image and Vision Computing Laboratory (IVC) image dataset, we have empirically found that the values of (v_1, v_2) = (0.002, 0.01) and $(\lambda_1, \lambda_2, \lambda_3)$ = (3, 2, 1) are effective in providing visually-pleasing results [7].

For an input image of H×W and a square window of $S_v \times S_v$, direct realization of the proposed unsharp masking algorithm results in the algorithmic complexity of O(H×W×S_v×S_v). Following the idea presented by He et al., nonetheless, the approximate formula expressed by Eq. (7) can be employed to calculate the local variance, where average values are all calculated over the same window $\Omega(m,n)$ [8]. The mean filter required to obtain $\bar{x}(m,n)$ and $\overline{x^2}(m,n)$ can be implemented in constant-time by virtue of the O(1) box filter [9]. In this context, the filter's O(1) complexity means that filtering operation is independent of the window size. Accordingly, the fast realization of the proposed algorithm now solely results in O(H×W) complexity. This will be verified the next section.

$$v(m,n) \approx \overline{x^2}(m,n) - \bar{x}(m,n)\bar{x}(m,n) \qquad (7)$$

The entire block diagram of our system is illustrated in Fig. 2. The input RGB image is first converted to YCbCr color space. While sharpness enhancement is applied to the luminance channel, the chrominance channels are sub-sampled using YCbCr422 format for efficient transmission. Finally, the enhanced luminance and the sub-sampled chrominance are converted back to RGB color space.

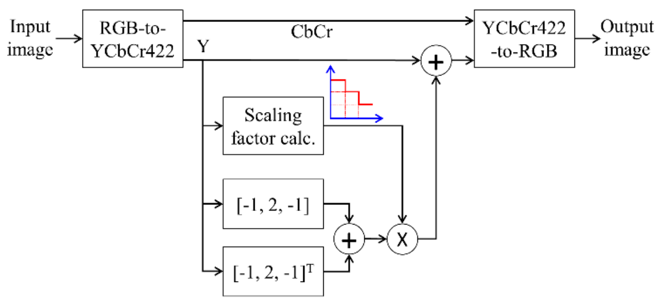

Fig. 2. The proposed unsharp masking system

Evaluation

The IVC image dataset is used in this section to assess the enhancing performance of the proposed algorithm and Tanaka et al.'s approach. Two referenceless evaluation metrics involving the rate of new visible edges (e) and the quality of the contrast restoration (r) are used in the quantitative assessment [10]. The values of e and r are determined by the Eqs. (8) and (9), where n_r and n_o refer to the numbers of the set of visible edges in the enhanced image and the original image, respectively. Therefore, e is the metric assessing the ability of an algorithm to restore or enhance edges that are faded in the original image. Ψ in Eq. (9) denotes the set of visible edges in the enhanced image, and r_i is the ratio determining the improvement of visibility level. Hence, higher values of e and r are desired in image enhancement.

$$e = \frac{n_r - n_o}{n_o}, \tag{8}$$

$$r = exp\left[\frac{1}{n_r}\sum\nolimits_{i\in\Psi} log(r_i)\right] \tag{9}$$

Table 1 shows the average evaluation metric results on the tested image dataset. The best results are marked bold. It is evident that the proposed method outperforms the benchmarking approach in terms of e and r metrics. It is attributed to the staircase weighting scheme that scales the high frequency contents based on the local variance of the image. In Tanaka et al.'s algorithm, the gain was assigned to each pixel according to the ratio between local variances of the input image's background and detail signals. However, since the filter employed to extract the background may mistakenly smooth the image edges, resulting in poorer performance in comparison to ours.

Table 1. Quantitative evaluation results on IVC dataset.

Image No.	Tanaka et al.'s method		Proposed method	
	e	*r*	*e*	*r*
1	0.1027	1.1982	0.1175	2.0102
2	0.2132	1.1617	0.5343	1.8552
3	0.1379	1.1471	0.7119	2.0004
4	0.2401	1.2324	0.5436	1.9992
5	0.0510	1.2082	0.0305	1.7704
6	0.2418	1.1675	0.7504	1.9479
7	0.4252	1.1762	1.1962	1.8817
8	0.2119	1.0841	1.2102	1.6292
9	0.1305	1.1699	0.5292	1.7392
10	0.5878	1.2061	1.9306	2.1514
11	0.1960	1.2047	1.2831	2.0492
12	0.3063	1.1705	0.7137	2.0033
13	0.1193	1.1519	0.4658	1.8151
14	0.1375	1.2466	0.0070	2.1726
15	0.0786	1.1888	0.9032	2.2164
16	0.1510	1.1150	0.9097	1.7954
17	0.0739	1.2661	0.0663	2.0391
18	0.1735	1.1943	0.4274	1.9793
19	0.1347	1.1817	0.2815	1.9930
20	1.1823	1.2434	3.9721	2.2344
21	0.8521	1.2415	1.7914	2.2286
22	0.2539	1.0762	1.8666	1.7461
23	0.3690	1.1802	1.4227	1.9798
24	0.1829	1.1303	0.5717	1.6224
25	0.0556	1.0532	0.8839	1.6161
Avg.	0.2643	1.1758	**0.9243**	**1.9390**

Figure 3 presents an outdoor scene obscured by thin haze in order to visually evaluate the performance of two algorithms. We selectively pick out three image areas that are slightly, moderately, and heavily affected by haze. As mentioned in previous paragraph, the use of a low pass filter to extract the image's background may smooth the image edges, resulting in an unimpressive performance of Tanaka et al.'s method. In contrast, the proposed algorithm exhibits better detail enhancing power in all three different areas. It is attributed to the good use of the staircase scaling factor according to the image's local variance.

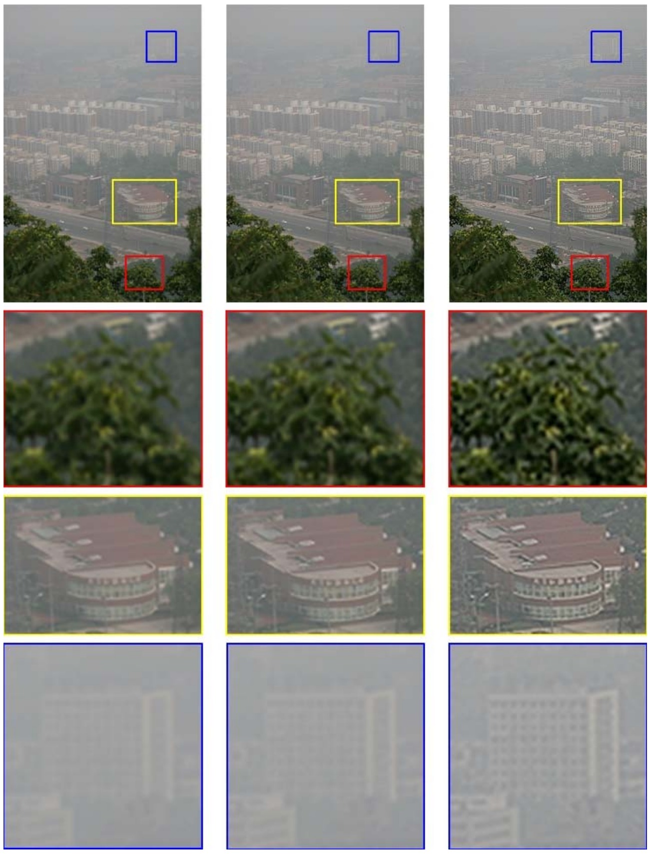

Fig. 3. Qualitative evaluation on a real faint scene. From left to right: input image, result of Tanaka et al.'s method, and result of the proposed algorithm

In order to validate the constant-time characteristics, the proposed algorithm is tested on the input image of size 1920×1080 for various filtering window sizes ranging from 3×3 to 31×31. The experiment was conducted in MATLAB R2019a on a Core i7-6700 CPU (3.4 GHz) with 32GB RAM. It is evident from Fig. 4 that the processing time is virtually constant and the average value is 0.63 seconds.

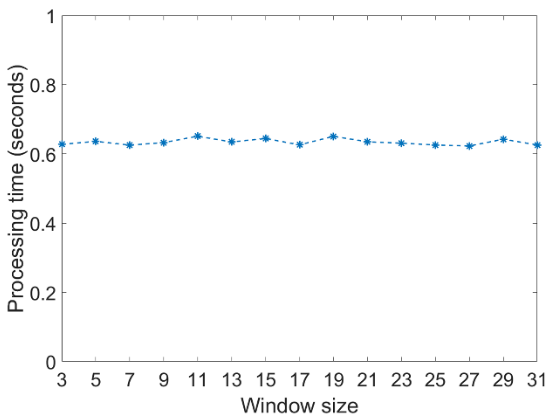

Fig. 4. Constant-time characteristics validation

Conclusions

In this paper, a fast and efficient unsharp masking algorithm is presented. To effectively enhance the image areas with varied degradation levels, a staircase scaling factor based on the image's local variance has been proposed. Furthermore, an approximate formula for fast calculation has been also adopted, therein lies the proposed algorithm's constant-time complexity. Experimental results shown that the proposed unsharp masking technique is superior the benchmarking method both quantitatively and visually. Moreover, experiments on various filtering window sizes verified the constant-time characteristics.

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