Nonlinear Unsharp Masking Algorithm

Dat Ngo, Seungmin Lee and Bongsoon Kang
Department of Electronics Engineering
Dong-A University
Busan, Korea
bongsoon@dau.ac.kr

***Abstract*—Image properties such as contrast, brightness, sharpness, and colorfulness exert a great influence on human perception of image quality. Thus, image enhancement has been assumed an important role in image analysis and computer vision. We propose an efficient algorithm for improving the image sharpness that automatically resolves the well-known out-of-range problem by the means of nonlinear transformation. Adding to that, an optional contrast enhancement step could be applied concurrently to further enhance the image. The proposed algorithm also reduces the halo effect by utilizing the modified hybrid median filter in an iterative manner. A comparative study against other benchmarking methods and experimental results validate the performance of the proposed method.**

Keywords—image enhancement; unsharp masking; contrast enhancement; nonlinear transformation; modified hybrid median filter

I. Introduction

Image degradation rooted in a variety of external factors like weather phenomena, poor lighting conditions, and man-made aerosols (e.g. dust from industrialization) is inevitable in computer vision applications. For instance, a lack of incoming light to image sensors or the attenuation of light by transmission medium is a common source of minute details fading. This kind of image degradation is highly likely to make an adverse impact on image processing algorithms designed for ideal environmental conditions. A prime example of this is the sharp decrease of recognition rate of deep learning systems due to weather conditions such as fog, snow, and rain. Hence, image enhancement algorithms focusing on the sharpness and contrast of images have many practical applications. There has been unceasing scientific effort put into the development of new algorithms.

Image enhancement algorithms are generally classified into three main categories: nonlinear transfer function-based, histogram-based, and frequency domain methods [1]. Due to their low computational complexity and easy adjustment, nonlinear transfer functions are widely used for image contrast enhancement. Low-light image enhancement and gamma correction are cases in point. The simple light stretch algorithm [2] solely invokes simple arithmetic operations, giving rise to the compact and fast hardware implementation [3] that is highly appropriate to real-time surveillance systems. However, this algorithm requires to be manually parameterized according to the input image, therein lies the cause of its lack of generality. Histogram equalization (HE) could be considered as an implicit image enhancement method, since the desired effect is achieved through rearranging the histogram of image luminance. Even though HE exhibits good performance with low computational complexity, it suffers from one noticeable shortcoming that large smooth image areas are usually over-enhanced. Several refinement approaches have been proposed, e.g. adaptive gamma correction with weighting distribution [4] and contrast-limited adaptive histogram equalization with dual gamma correction [5]. Regarding the image enhancement method carried out in the frequency domain, homomorphic filtering (HF) [6] is a good example. Unlike conventional denoising/enhancement techniques that assume an additive noise model, HF works with the multiplicative model, also known as the illumination-reflectance model of image formation. Then, by simply applying the normalized high-pass filter, the high-frequency noise could be easily removed. Additionally, by further linearly transforming the high-pass filter, the detail enhancement effect could also be achieved. However, all the above-mentioned image processing methods share a common out-of-range problem. They must be either carefully parameterized or truncated to keep image values in the proper range, leading to the lack of generality and possibly unwanted color artifacts.

In this paper, we propose an algorithm that automatically prevents the out-of-range problem by making the clever use of the logarithm function. In addition, an optional contrast enhancement technique could be applied in a concurrent manner to improve both sharpness and contrast of images. We also reduce the possible halo artifact by using the iterative modified hybrid median filter. The rest of the paper is organized as follows. Section II describes the theories of sharpness enhancement and nonlinear approach to unsharp masking. Section III details the proposed algorithm. Section IV provides a thorough evaluation, while Section V concludes the paper.

II. Fundamentals

A. Sharpness enhancement

Equation (1) describes the equation for unsharp masking algorithm, where z is the enhanced image, y refers to the background of the input image x, and d denotes the detail information. In general, the background y is obtained using a low-pass filter, and then detail information d is calculated as the subtraction of the background from the input image, $d = x - y$. The positive gain α is employed as a scaling factor to control the amplitude of detail information. As the signal d may contain noise together with high frequency information, α must be carefully adjusted so that unsharp masking techniques only enhance the desired image details.

$$z = y + \alpha d \tag{1}$$

Another problem possibly arising in unsharp masking techniques is the occurrence of visually unpleasant halo artifacts. This is traced back to the background extraction from input images. The use of a low-pass filter may create an unwanted by-product of smoothing image edges, resulting in over-shoots and under-shoots in areas of sharp edges in the signal d. Thus, the enhancement of over-shoots and under-shoots creates halo artifacts. To resolve these two shortcomings of unsharp masking techniques, edge-preserving filters and adaptive gain control have been taken into consideration.

B. Nonlinear approach to unsharp masking

Following the idea presented in [7], usual operations like addition and multiplication could be generalized to tackle the out-of-range problem. Fig. 1 shows this kind of generalized system, where Φ denotes a nonlinear function. The generalized addition and scalar multiplication operations denoted by $\oplus$ and $\otimes$ are defined in (2) and (3), where x and y are signal samples, and α is a real scalar.

$$x \oplus y = \Phi^{-1}[\Phi(x) + \Phi(y)] \tag{2}$$

$$\alpha \otimes x = \Phi^{-1}[\alpha\Phi(x)] \tag{3}$$

The above-mentioned sharpness enhancement could also be expressed in terms of generalized operations, as shown in (4). To maintain a high level of generality, the function $h(y)$ could be either linear or nonlinear, indicating that it is possible to perform an optional operation on the background signal y. The adaptive gain $\alpha(d)$ is a function of the detail signal d for selectively enhancing the image edges.

$$z = h(y) \oplus [\alpha(d) \otimes d] \tag{4}$$

Deng discovered a connection between the Bregman divergence and the generalized system, providing useful insights into the development of such a system [7]. Therefore, a general rule for selecting the nonlinear function Φ was presented in [8], which stated that Φ must be strictly convex and differentiable.

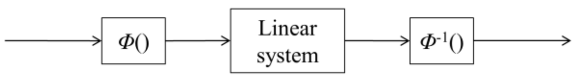

Fig. 1. Block diagram of a generalized system.

III. Proposed Algorithm

We consider an N-bit image x, where the pixel gray scale value is within $[0, 2^N\text{-}1]$. The input image must be normalized to the range (-1, 1) of the proposed nonlinear function shown in (5). This is achieved by first scale the image by $1/(2^N\text{-}1)$ such that it is in the range [0, 1]. Then the two extreme values are replaced by their rightmost and leftmost values to change the range to (0, 1). Finally, the linear transformation ($x \coloneqq 2x - 1$) is applied so that input image x is now in the desired range (-1, 1).

$$\Phi(x) = log[(1 + x)/(1 - x)], x \in (\text{-}1, 1) \tag{5}$$

The proposed unsharp masking algorithm follows (4) to adaptively enhance the image details. The block diagram of the entire proposed approach is depicted in Fig. 2, and each step is thoroughly described in following subsections.

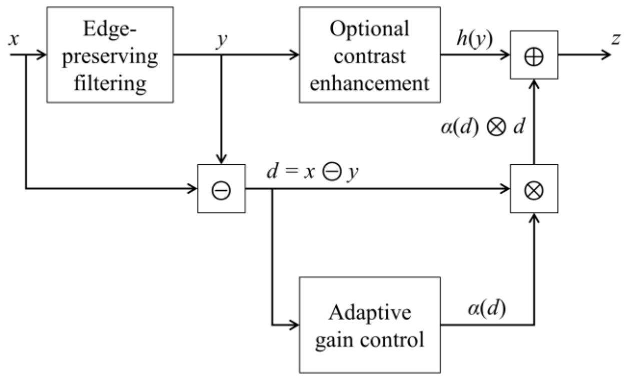

Fig. 2. Block diagram of the proposed nonlinear unsharp masking algorithm.

A. Background signal extraction

Deng utilized the standard median filter (SMF) in an iterative manner to extract the background signal [7]. This process terminates when the mean squared difference of images between two successive iterations falls below a pre-determined threshold. SMF functions properly in the smooth image areas but it may smooth down the sharp edges in image areas containing abrupt changes like objects' outline. Applying SMF iteratively could result in halo artifacts as discussed in Section II-A. Hence, we proposed using the modified hybrid median filter (mHMF) in place of SMF. mHMF was proposed in [9] for the accuracy estimation of haze distribution in the hazy image. mHMF first computes the medians of three windows: square, cross, and diagonal. Then, the median of these three is selected as the final result that would replace the center pixel of filtering window. Accordingly, in the smooth image areas, mHMF behaves in a similar manner to SMF, but in the abrupt image areas, the information from cross and diagonal windows helps mHMF to better preserve image edges.

In order to assess the performance of mHMF and SMF, we apply these filters to the same input image 20 times. The window size and threshold are set to 5×5 and 1.5×10^{-4}, respectively. The experiment was conducted in MATLAB

R2019a on a Core i7-6300 CPU (3.4GHz) with 32GB RAM. The result in Fig. 3 shows that using mHMF makes the mean squared difference fall below the threshold more quickly. Adding to that, image data at line 185 of the input image were also plotted in Fig. 4 to prove that the mHMF preserves edges better than SMF. Thus, the iterative mHMF is used in the proposed algorithm to extract the background information from the input image.

B. Adaptive gain control

To develop an adaptive gain function, it is necessary to understand which component in the image details d must be enhanced. As mentioned in Section II-A, the detail signal d contains: 1) image edges, 2) noise, and 3) over-shoots and under-shoots. The use of the iterative mHMF presented in the preceding section reduces the number of over-shoots and under-shoots. Additionally, since out-of-range problem is automatically resolved by the means of nonlinear transformation, the effect of high-frequency noise is insignificant. Hence, a simple form of adaptive gain function could be adopted. In this paper, we utilize an exponential function that gradually decrease from its maximum value α_{MAX} to its minimum value α_{MIN}. The mathematical equation of adaptive gain $\alpha(d)$ is shown in (6), where β and γ are two parameters obtained by solving the equations: $\alpha(0) = \alpha_{MAX}$ and $\alpha(1) = \alpha(-1) = \alpha_{MIN}$, and η is a parameter controlling the decreasing rate of $\alpha(d)$.

$$\alpha(d) = \beta + \gamma \times \exp(-|d|^{\eta}) \qquad (6)$$

To enhance the image details, the gain must be greater than or equal to one. Accordingly, α_{MIN} is set to one. Regarding the values of α_{MAX}, we show the mapping function $\alpha_{MAX} \otimes d$ by setting $\alpha_{MIN} = 1$ in Fig. 5. It can be seen that the large value of α_{MAX} leads to over-enhancement of small details and saturation of sharp edges. Thus, α_{MAX} is set to five in this paper. By setting $\alpha_{MIN} = 1$ and $\alpha_{MAX} = 5$, we plot the mapping function $\alpha(d) \otimes d$ with η varies from 0 to 3. In order to avoid saturation, η could be set to 0.5 or 1.

C. Optional contrast enhancement

In traditional image processing algorithms, sharpness and contrast enhancements could not achieved simultaneously. In generalized schemes, since the input image is separated into detail and background signals, unsharp masking and contrast enhancement algorithms can be applied to corresponding components concurrently. This is motivated by Deng's work in [7]. In this paper, we utilize the well-known contrast-limited adaptive histogram equalization (CLAHE).

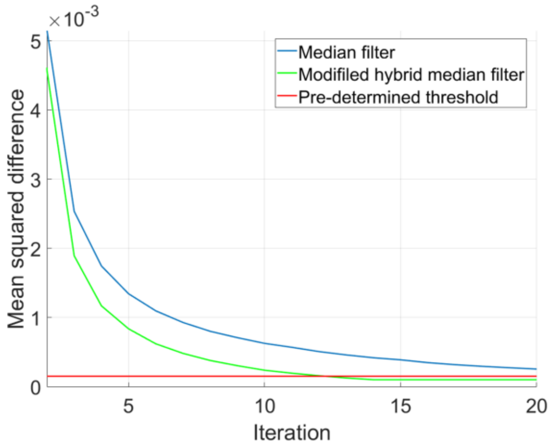

Fig. 3. Mean squared difference of images between two consecutive iterations for two cases: using SMF and using mHMF.

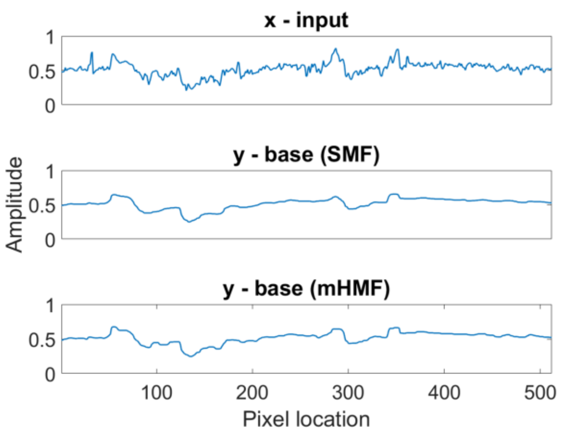

Fig. 4. Plot of image line 185 data to compare edge-preserving characteristics of SMF and mHMF.

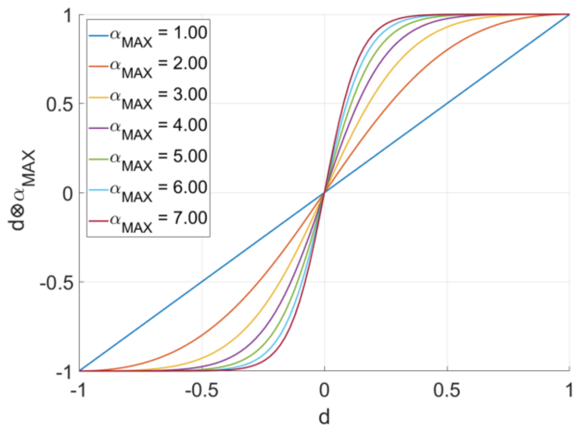

Fig. 5. Illustrations of mapping function $\alpha_{MAX} \otimes d$ for different values of α_{MAX}.

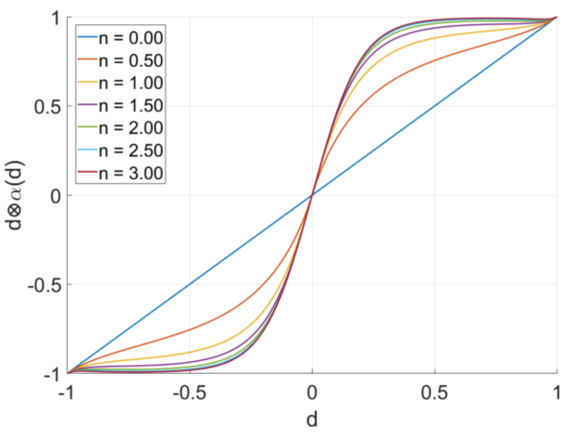

Fig. 6. Illustrations of mapping function $\alpha(d) \otimes d$ for different values of η.

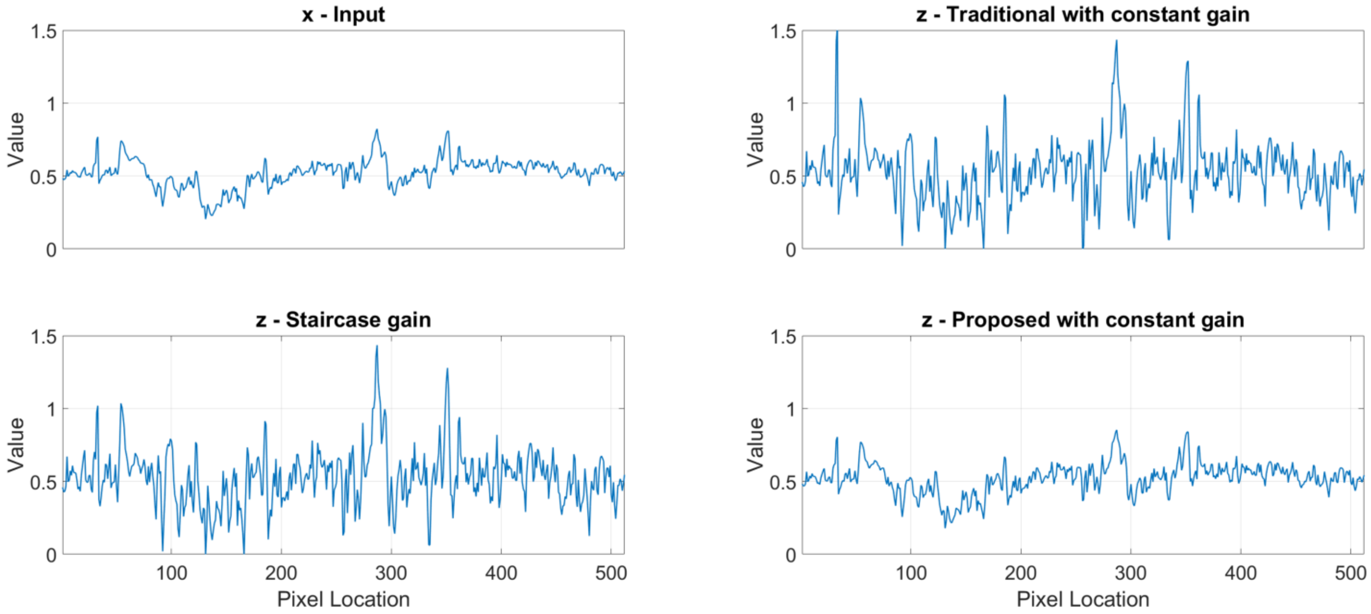

Fig. 7. Illustration of the proposed algorithm's automatic out-of-range prevention characteristic. Top left: input image line data, top right: result of traditional unsharp masking with constant gain, bottom left: result of recently-proposed algorithm using staircase gain, and bottom right: result of the proposed method with simple constant gain.

IV. EVALUATION

A. Automatic out-of-range prevention

To illustrate that the proposed algorithm is capable of automatically preventing out-of-range problem, Fig. 7 shows an input image line data and its corresponding enhanced results of the traditional unsharp masking with constant gain, the recently-proposed algorithm with staircase gain [10], and the proposed method with simple constant gain in lieu of adaptive gain. For fair assessment, the gain is set to 3 for methods with constant gain. In case of the recent method with staircase gain, three values of gain are set to 1, 2, and 3. It can be seen that the out-of-range problem is most severe in the top right result of Fig. 7, since a constant gain is applied equally to all image details. In the bottom left result, this problem is alleviated to a certain extent, since three values of gain are assigned according to the local variance of image. In the bottom right result, the proposed algorithm effectively enhances the input data while preventing it varying outside the normalized range.

B. Quantitative assessment

The rate of new visible edges (e) and the quality of the contrast restoration (r) [11] are used to evaluate the performance of three methods mentioned in the previous section, where the proposed algorithm now utilizes the adaptive gain instead of simple constant gain. In both subsections, we do not apply the optional CLAHE. Metric e assesses the ability of an algorithm to recover edges that are invisible in the original image, but that are visible in the restored image. In addition, metric r denotes the ratio determining the improvement of visibility level. Thus, higher values of e and r are desired in image enhancement approaches.

TABLE I. AVERAGE QUANTITATIVE SCORES ON IVC IMAGE DATASET

Image No.	Constant gain		Staircase gain		Proposed method	
	e	r	e	r	e	r
1	0.026	1.926	0.053	2.232	0.569	2.556
2	0.427	1.738	0.539	2.046	0.899	2.546
3	0.639	1.819	0.749	2.214	1.005	3.515
4	0.467	1.872	0.553	2.230	0.675	2.648
5	0.078	1.851	0.027	1.970	0.283	2.041
6	0.672	1.765	0.791	2.163	1.266	3.100
7	1.045	1.742	1.302	2.071	1.318	2.724
8	0.984	1.495	1.446	1.794	2.686	2.959
9	0.408	1.695	0.600	1.904	1.017	3.043
10	1.718	1.941	2.083	2.394	2.464	3.098
11	0.926	1.851	1.649	2.290	2.512	3.790
12	0.676	1.825	0.726	2.222	1.001	2.150
13	0.345	1.760	0.482	2.020	0.630	2.664
14	0.022	2.009	0.075	2.354	0.953	2.591
15	0.690	2.029	0.928	2.483	1.527	4.329
16	0.759	1.663	1.073	1.979	1.430	2.790
17	0.038	2.039	0.006	2.287	0.512	2.622
18	0.356	1.862	0.451	2.201	0.638	2.464
19	0.237	1.857	0.258	2.215	0.539	3.066
20	3.586	1.985	4.249	2.480	5.263	2.879
21	1.635	2.037	1.893	2.485	1.920	2.630
22	1.541	1.600	2.185	1.916	2.159	2.796
23	1.162	1.826	1.694	2.227	1.420	2.726
24	0.486	1.564	0.658	1.770	0.728	2.190
25	0.635	1.495	1.170	1.791	2.954	3.817
Avg.	0.771	1.810	1.023	2.150	**1.455**	**2.870**

Fig. 8. Visual assessment of the proposed algorithm with benchmarking methods. From left to right: input image, results and their corresponding zoomed-up regions of the traditional unsharp masking with constant gain, the recent-proposed method with staircase gain, and the proposed nonlinear approach.

Table I shows these two metrics for 25 images in the IVC image dataset [12]. The best result is marked bold. It is evident that the proposed algorithm possesses the best enhancement power under *e* and *r* metrics. Fig. 8 presents a scene faded by thin haze to visually assess the performance of three algorithms. The red cropped regions show that the proposed nonlinear unsharp masking method produces the most visually-satisfactory result in comparison to the other two benchmarking algorithms.

V. Conclusions

In this paper, a nonlinear unsharp masking algorithm is presented. Image enhancement approaches that operate directly on image gray scale value may suffer from out-of-range problem and produce visually unpleasant halo artifacts. The proposed algorithm automatically gets rid of out-of-range issue by the means of nonlinear transformation. Adding to that, halo artifacts are also reduced by clever use of modified hybrid median filter in an iterative manner to decompose the input image into detail and background signals. Experimental results shown that the proposed method is superior to benchmarking algorithms in terms of both visual quality and quantitative metrics.

Acknowledgment

This research was supported by the BK21 Plus Program (Future-oriented innovative brain raising type, 22A20130000047) funded by the Ministry of Education (MOE, Korea) and National Research Foundation of Korea (NRF).

References

[1] L. Artur, R. B. David, R. H. Paul, and M. A. Alin, "Automatic contrast enhancement of low-light images based on local statistics of wavelet coefficients," Digital Signal Processing, vol. 23, no. 6, pp. 1856–1866, Dec. 2013.

[2] D. Ngo, S. Lee, and B. Kang, "Light Stretch Algorithm for Image Quality Enhancement," ICVR 2018 Proceedings of the 4th International Conference on Virtual Reality, pp. 56–60.

[3] D. Ngo and B. Kang, "Preprocessing for High Quality Real-time Imaging Systems by Low-light Stretch Algorithm," j.inst.korean.electr.electron.eng., vol. 22, no. 3, pp. 585–589, Sep. 2018.

[4] S.-C. Huang, F.-C. Cheng, and Y.-S. Chiu, "Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution," IEEE Trans. on Image Process., vol. 22, no. 3, pp. 1032–1041, Mar. 2013.

[5] Y. Chang, C. Jung, P. Ke, H. Song, and J. Hwang, "Automatic Contrast-Limited Adaptive Histogram Equalization With Dual Gamma Correction," IEEE Access, vol. 6, pp. 11782–11792, 2018.

[6] W. A. Mustafa, W. Khairunizam, H. Yazid, Z. Ibrahim, A. Shahriman, and Z. M. Razlan, "Image Correction Based on Homomorphic Filtering Approaches: A Study," in 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA), Kuching, 2018, pp. 1–5.

[7] Guang Deng, "A Generalized Unsharp Masking Algorithm," IEEE Trans. on Image Process., vol. 20, no. 5, pp. 1249–1261, May 2011.

[8] F. Nielsen and R. Nock, "Sided and Symmetrized Bregman Centroids," IEEE Trans. Inform. Theory, vol. 55, no. 6, pp. 2882–2904, Jun. 2009.

[9] G. Kim, S. Lee, and B. Kang, "Single Image Haze Removal using Hazy Particle Maps," IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, vol. E101-A, no. 11, pp. 1999–2002, Nov. 2018.

[10] D. Ngo and B. Kang, "Image Detail Enhancement via Constant-Time Unsharp Masking," unpublished.

[11] N. Hautière, J.-P. Tarel, D. Aubert, and É. Dumont, "BLIND CONTRAST ENHANCEMENT ASSESSMENT BY GRADIENT RATIOING AT VISIBLE EDGES," Image Analysis & Stereology, vol. 27, no. 2, pp. 87–95, May 2011.

[12] K. Ma, W. Liu, and Z. Wang, "Perceptual evaluation of single image dehazing algorithms," in 2015 IEEE International Conference on Image Processing (ICIP), 2015, pp. 3600–3604.