DESIGN IMPLEMENTATION OF WEIGHTED GUIDED IMAGE FILTERING FOR IMAGE ENHANCEMENTS

[*]MANDALAPU MANOHAR REDDY [**] P LAXMAN
[*]*MTech student, Dept of ECE, Jagruti Institute of Engineering and Technology, Hyderabad, TS, India.*
[**] *Assistant Professor, Dept of ECE, Jagruti Institute of Engineering and Technology, Hyderabad, TS, India.*

Abstract **-** It is known that local filtering-based edge preserving smoothing techniques suffer from halo artifacts. In this paper, a weighted guided image filter (WGIF) is introduced by incorporating an edge-aware weighting into an existing guided image filter (GIF) to address the problem. The WGIF inherits advantages of both global and local smoothing filters in the sense that: 1) the complexity of the WGIF is O(N) for an image with N pixels, which is same as the GIF and 2) the WGIF can avoid halo artifacts like the existing global smoothing filters. The WGIF is applied for single image detail enhancement, single image haze removal, and fusion of differently exposed images. Experimental results show that the resultant algorithms produce images with better visual quality and at the same time halo artifacts can be reduced/avoided from appearing in the final images with negligible increment on running times.

I. INTRODUCTION

MANY applications in the fields of computational photography and image processing require smoothing techniques that can preserve edge well. Typical examples include image de-noising, fusion of differently exposed images, tone mapping of high dynamic range (HDR) images, detail enhancement via multi-lighting images, texture transfer from a source image to a destination image, single image haze removal, and etc. The smoothing process usually decomposes an image to be filtered into two layers: a base layer formed by homogeneous regions with sharp edges and a detail layer which can be either noise, e.g., a random pattern with zero mean, or texture, such as a repeated pattern with regular structure.

There are two types of edge-preserving image smoothing techniques. One type is global optimization based filters. The optimized performance criterion consists of a data term and a regularization term. The data term measures fidelity of reconstructed image with respect to the image to be filtered while the regularization term provides the smoothness level of the reconstructed image. Even though the global optimization based filters often yield excellent quality, they have high computational cost. The other type is local filters such as bilateral filter (BF), its extension in gradient domain, trilateral filter, and their accelerated versions as well as guided image filter (GIF). Compared with the global optimization based filters, the local filters are generally simpler. However, the local filters cannot preserve sharp edges like the global optimization based filters. As such, halo artifacts are usually produced by the local filters when they are adopted to smooth edges. It was mentioned in that the local filters such as the BF/GIF would concentrate the blurring near these edges and introduce halos while the global optimization based filters such as the weighted least squares (WLS) filter in would distribute such blurring globally. It is worth noting that the Lagrangian factor in the WLS filter is content adaptive whether the Lagrangian factor in the GIF and both spatial similarity parameter and range similarity parameter in the BF are fixed.

1.1 objective

In this paper, an edge-aware weighting is introduced and incorporated into the GIF to form a weighted GIF (WGIF). In human visual perception, edges provide an effective and expressive stimulation that is vital for neural interpretation of a scene. Larger weights are thus assigned to pixels at edges than pixels in flat areas. There are many methods to compute the edge-ware weighting. Local variance in 3×3 window of a pixel in a guidance image is applied to compute the edge-aware weighting. The weighting can be easily computed via the box filter in for all pixels in the guidance image. The local variance of a pixel is normalized by the local variances of all pixels in the guidance image. The normalized weighting is then adopted to design the WGIF. Due to the proposed weighting, the WGIF can preserve sharp edges like the global filters.

As a result, halo artifacts can be reduced/avoided by using the WGIF. Similar to the GIF, the WGIF also avoids gradient reversal. In addition, the complexity of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF. These features allow many applications of the WGIF in the fields of computational photography and image processing. The WGIF is applied for single image detail enhancement, single image haze removal, and fusion of differently exposed images. Experimental results of the three applications show that the resultant algorithms produce images with excellent visual quality as those of global optimization based algorithms, and at the same time the running times of the proposed algorithms are comparable to the GIF based algorithms. It is worth noting that an adaptive GIF (AGIF) was proposed for image sharpening and de-noising by borrowing a shifting technique. It was shown that the complexity of the AGIF in is O(N) for an image with N pixels. On the other hand, both the ABF in and the AGIF are training-based approaches while no training is required by the WGIF.

II. LITERATURE SURVEY

Digital image is defined as "An image is not an image without any object in it". Human visual system has ability to perceive the objects in digital image using edges in efficient manner. Halo artifacts introduces blur in digital image which makes perception of content difficult. Various filtering techniques have designed in literature to preserve the global and local statistics but none can meet the desired requirements and various algorithms yields high complexity which fails them to achieve practical reliability. Digital image processing domain has different research fields and all these research fields have applications ranging from low level to high level. Edge preservation in all these research fields attains attention and implementation of smoothing filters has ability to filter noise content by preserving the edge information. Smoothing algorithms can be classified into two types namely global filters such as bilateral filter , tri-lateral filters , and finally guided image filter .

Global filters attain images with good quality but these filters are highly expensive. Local filters are considered as alternative to global filters which are simple and cost effective but fail to conserve the sharp edges information like global filters. When local filters are forcefully adopts to smooth edges it results halo artifacts. Halo artifacts produced by bi-lateral filter and guided image filter are fixed in equipped way using similarity parameter in terms of range and spatial. Bi-lateral filtering mechanism is considered as adaptive filter and this adaptive mechanism helps to handle the halo artifacts and on negative side it destroys the 3D convolutional form .

An interesting algorithm named weighted guided image filtering scheme is proposed in this paper by combining the edge-based weighting scheme along with guided image filtering. Calculation of edge based weighting scheme is calculated by using 3×3 local variance in a guidance image. This local variance scheme of one individual pixel is normalized by all pixels local variance in guidance image. The acquired normalized weights of all pixels are then adaptively adapted to WGIF. WGIF helps to avoid halo artifacts in accurate manner for excellent visual quality. The intricacy of WGIF is same as GIF. The proposed weighted guide image filtering (WGIF) is applied for multiple purposes as single image mist removal, single image detail enhancement and different exposed images fusion.

III. EXISTING METHOD

3.1 EDGE-PRESERVING SMOOTHING TECHNIQUE

In this section, existing edge-preserving smoothing techniques are summarized with the emphasis on the GIF in [14] and the WLS filter in [4]. The task of edge-preserving smoothing is to decompose an image X into two parts as follows:

$$X(p) = \hat{Z}(p) + e(p), (1)$$

where $\hat{Z}$ is a reconstructed image formed by homogeneous regions with sharp edges, e is noise or texture, and p(= (x, y)) is a position. $\hat{Z}$ and e are called base layer and detail layer, respectively. One type of edge-preserving smoothing techniques is based on local filtering. The BF is widely used due to its simplicity.

However, the BF could suffer from "gradient reversal" artifacts despite its popularity, and the results may exhibit undesired profiles around edges, usually observed in detail enhancement of conventional LDR images or tone mapping of HDR images. The GIF was introduced to overcome this problem. In the GIF, a guidance image G is used which could be identical to the image X to be filtered. It is assumed that $\hat{Z}$ is a linear transform of G in the window ζ1 (p):

$$\hat{Z}(p) = apG(p) + bp, \forall p \in \zeta 1\ (p).$$

where ζ1 (p) is a square window centered at the pixel p of a radius ζ1. ap and bp are two constants in the window ζ1 (p).

To determine the linear coefficients To determine the linear coefficients are then obtained by minimizing a cost function E(ap, bp) which is defined as E = p∈ζ1 (p) [(apG(p) + bp − X(p))2 + λa2 p], (3) where λ is a regularization parameter penalizing large ap . Besides the above local filtering based edge-preserving smoothing techniques, another type of edge-preserving smoothing techniques is based on global optimization. The WLS filter in [4] is a typical example and it is derived by minimizing the following quadratic cost function:

E = N p=1 [(Zˆ(p) − X(p))2 + λ(p)∇ Zˆ(p)2], (4)

It is shown in the linear model (2) that ∇ Zˆ(p) = ap∇G(p). Clearly, the smoothness of $\hat{Z}$ in ζ1 (p) depends on the value of ap . This implies that the data term and the regularization terms in the GIF are similar to those in the WLS filter in the sense that the data term measures the fidelity of $\hat{Z}$ with respect to the filtered image X and the regularization term provides the smoothness level of $\hat{Z}$. There are two major differences between the WLS filter and the GIF. 1) The GIF in [14] is based on local optimization while the WLS filter in [4] on global optimization. As such, the complexity of the GIF is O(N) for an image with N number of pixels and the WLS filter is more complicated than the GIF. 2) The value of λ is fixed in the GIF while it is adaptive to local gradients in the WLS filter.

(a) (b)

Fig. 1. Two tone mapped images. (a) $\lambda = 2$, $\gamma = 1.2$, and $= 0.0001$ as in [4]; and (b) $\lambda = 2$, $\gamma = 0$, and $= 0$.

IV. PROPOSED METHOD

4.1 WEIGHTED GUIDED IMAGE FILTER

In this section, an edge-aware weighting is first proposed and it is incorporated into the GIF in [14] to form the WGIF.

4.1.1 An Edge-Aware Weighting

Let G be a guidance image and σ2 G,1(p) be the variance of G in the 3 × 3 window, 1(p). An edge-aware weighting G(p) is defined by using local variances of 3 × 3 windows of all pixels as follows: G(p) = 1 N N p=1 σ2 G,1(p) + ε σ2 G,1(p) + ε , (5) where ε is a small constant and its value is selected as (0.001×L)2 while L is the dynamic range of the input image. All pixels in the guidance image are used in the computation of G (p). In addition, the weighting G(p) measures the importance of pixel p with respect to the whole guidance image. Due to the box filter in [4], the complexity of G(p) is O(N) for an image with N pixels.

The value of G(p) is usually larger than 1 if p is at an edge and smaller than 1 if p is in a smooth area. Clearly, larger weights are assigned to pixels at edges than those pixels in flat areas by using the weight G(p) in Equation (5). Applying this edge-aware weighting, there might be blocking artifacts in final images. To prevent possible blocking artifacts from appearing in the final image, the value of G(p) is smoothed by a Gaussian filter. The smoothed weights of all pixels in Fig. 2(a) are shown in Fig. 2(b). Clearly, larger weights are assigned to pixels at edges than those pixels in flat areas. The proposed weighting matches one feature of human visual system, i.e., pixels at sharp edges are usually more important than those in flat areas [7].

(a) (b)

Fig. 2. (a) An input image, and (b) its weighting.

It should be pointed out that the proposed weighting G(p) is one edge-aware weighting, and there are many other edge-aware weighting including those derived by the Sobel gradient and the Roberts gradient [4]. The GIF can be improved by incorporating these edge-aware weighting into the GIF. In the following section, the proposed weighting G(p) in Equation (5) is used as an example to illustrate the WGIF.

4.1.2 The Proposed Filter

Same as the GIF, the key assumption of the WGIF is a local linear model between the guidance image G and the filtering output Zˆ as in Equation (2). The model ensures that the output Zˆ has an edge only if the guidance image G has an edge.

The proposed weighting G(p) in Equation (5) is incorporated into the cost function E(ap, bp) in Equation (3). As such, the solution is obtained by minimizing the difference between the image to be filtered X and the filtering output Zˆ while maintaining the linear model (2), i.e., by minimizing a cost function E(ap, bp) which is defined as E = p∈ζ1 (p) [(apG(p) + bp − X(p))2 + λ G(p) a2 p]. (6) The optimal values of ap and bp are computed as ap = μGX,ζ1 (p) − μG,ζ1 (p)μX,ζ1 (p) σ2 G,ζ1 (p) + λ G(p) , (7) bp = μX,ζ1 (p) − apμG,ζ1 (p), (8) where is the element-by-element product of two matrices. μGX,ζ1 (p), μG,ζ1 (p) and μX,ζ1 (p) are the mean values of G X, G and X, respectively.

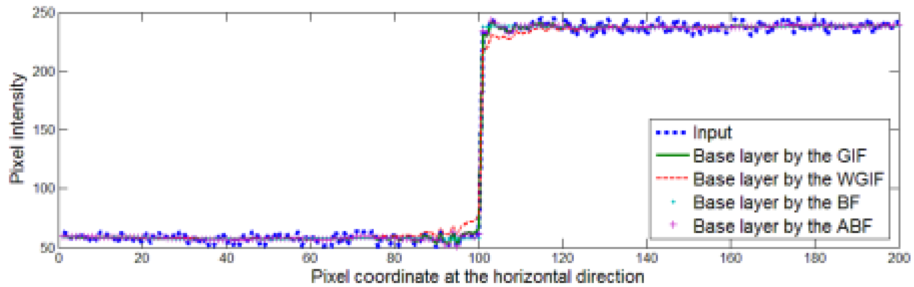

Fig. 3. 1-D illustration of the WGIF, the GIF in [14], the BF in [9], and the ABF in [16]. The values of ζ1 and λ in both the WGIF and the GIF are 15 and 1/64, respectively. The values of σ1 and σ2 in both the BF and the ABF are 15 and 0.2, respectively

For easy analysis, the images X and G are assumed to be the same. Consider the case that the pixel p is at an edge. The value of X (p) is usually much larger than 1. ap in the WGIF is closer to 1 than ap in the GIF [4]. This implies that sharp edges are preserved better by the WGIF than the GIF. As shown in Fig. 3, edges are indeed preserved much better by the WGIF. In addition, the complexity of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF. Edges are also preserved well by the ABF in [3] while the complexity of the ABF is an issue.

V. SIMULATION RESULTS

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

Fig. 4. Comparison of the WGIF with the GIF in [4] by choosing four different values of θ. The values of ζ1 and λ are 15 and 1/128, respectively. (a, c, e) by the GIF in [3] with the value of θ as 1, 4, and 9, respectively, (b, d, f) by the WGIF with the value of θ as 1, 4, and 9, respectively.

Fig. 5. Comparison of enhanced images via different filters. (a, f) images to be enhanced, (b, g) enhanced image by the BF in [4], (c, h) enhanced images by the GIF, (d, i) enhanced images by the global filter in [3], (e, j) enhanced images by the WGIF.

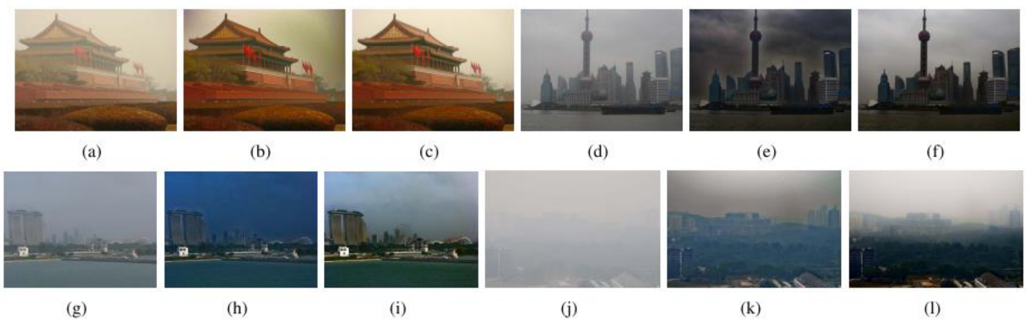

Fig. 8. Comparison of the proposed haze removal algorithm and the haze removal algorithm in [14]. (a, d, g, j) four images with haze; (b, e, h, k) de-hazed images by the algorithm in [14]; (c, f, i, l) de-hazed images by the proposed algorithm.

Fig. 9. Comparison of the proposed haze removal algorithm and the haze removal algorithm in [14] by using two sets of images without haze. (a, d) two images without haze; (b, e) de-hazed images by the algorithm in [14]; (c, f) de-hazed images by the proposed algorithm.

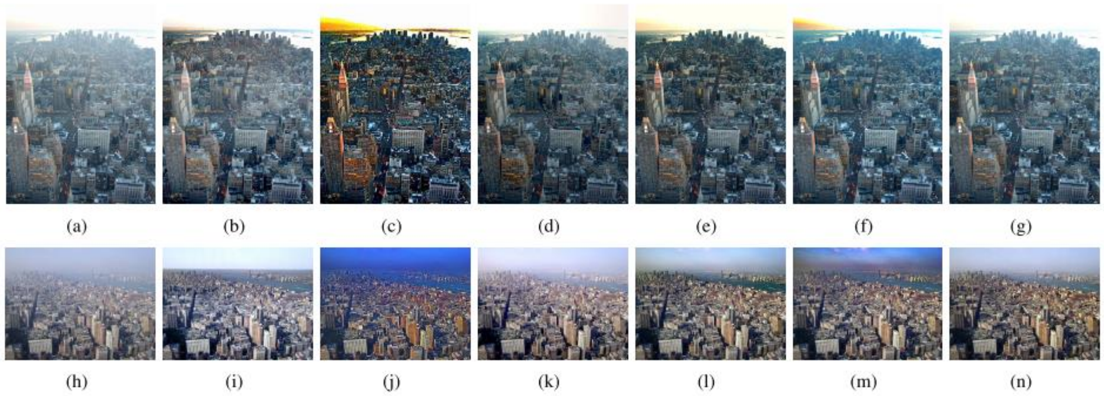

Fig. 10. Haze removal results by the algorithms in [7], [14], [27], [33], and [34] and the proposed algorithm. (a, h) input images; (b, i) de-hazed images by the algorithm in [34]; (c, j) de-hazed images by the algorithm in [27]; (d, k) de-hazed images by the algorithm in [33]; (e, l) de-hazed images by the algorithm in [7]; (f, m) de-hazed images by the algorithm in [14]; and (g, n) de-hazed images by the proposed algorithm.

VI. CONCLUSION

A weighted guided image filter (WGIF) is proposed in this paper by incorporating an edge-aware weighting into the guided image filter (GIF). The WGIF preserves sharp edges as well as existing global filters, and the complexity of the WGIF is O(N) for an image with N pixels which is almost the same as the GIF. Due to the simplicity of the WGIF, it has many applications in the fields of computational photography and image processing. Particularly, it is applied to study single image detail enhancement, single image haze removal, and fusion of differently exposed images. Experimental results show that the resultant algorithms can produce images with excellent visual quality as those of global filters, and at the same time the running times of the proposed algorithms are comparable to the GIF based algorithms. It should be pointed out that the ABFs appear to be similar to the WGIF. Unfortunately, as pointed out, adaptation of the parameters will destroy the 3D convolution form, and the ABFs cannot be accelerated via the approach. While the WGIF preserves the simplicity of the GIF. On the other hand, it was shown in that both the BF and the ABF can be easily extended to gradient domain while it is very challenging to extend the GIF and the WGIF to gradient domain. It is noting that the WGIF can also be adopted to design a fast local tone mapping algorithm for high dynamic range images, joint up sampling, flash/no-flash de-noising, and etc. In addition, similar idea can be used to improve the anisotropic diffusion in [3], Poisson image editing, etc. All these research problems will be studied in our future research.

VII. REFERENCES

[1]. P. Charbonnier, L. Blanc-Feraud, G. Aubert, and M. Barlaud, “Deterministic edge-preserving regularization in computed imaging,” IEEE Trans. Image Process., vol. 6, no. 2, pp. 298–311, Feb. 1997.

[2]. L. I. Rudin, S. Osher, and E. Fatemi, “Nonlinear total variation based noise removal algorithms,” Phys. D, Nonlinear Phenomena, vol. 60, nos. 1–4, pp. 259–268, Nov. 1992.

[3]. Z. G. Li, J. H. Zheng, and S. Rahardja, “Detail-enhanced exposure fusion,” IEEE Trans. Image Process., vol. 21, no. 11, pp. 4672–4676, Nov. 2012.

[4]. Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, “Edge-preserving decompositions for multi-scale tone and detail manipulation,” ACM Trans. Graph., vol. 27, no. 3, pp. 249–256, Aug. 2008.