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Weighted Guided Image Filtering

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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 computation 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.

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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. This could be another major reason that the BF/GIF produces halo artifacts. It is worth noting that the reason was also noticed in and. The range similarity parameter of the BF in is adaptive to the content of the image to be filtered while both the spatial similarity and the range similarity parameters of the BF in are adaptive to the content of the image to be filtered. Unfortunately, as pointed out in adaptation of the parameters will destroy the 3D convolution form, and the adaptive BF (ABF) cannot be accelerated via the approach in [13]. It is thus desired to design a new local filter which is as fast as the GIF and preserves edges as well as the WLS filter

In this paper, an edge-aware weighting is introduced and incorporated into the GIF [14] 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 scen Larger weights are thus assigned to pixels at edges than pixels

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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 [14] 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 in [14], 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 in. 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 in [18] for image sharpening and de-noising by borrowing a shifting technique in [15]. It was shown in [

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 in are training-based approaches while no training is required by the WGIF. The rest of this paper is organized as follows. Existing edge-preserving smoothing techniques are summarized

II. RELATED WORKS ON EDGE-PRESERVING SMOOTHING TECHNIQUES

In this section, existing edge-preserving smoothing techniques are summarized with the emphasis on the GIF in and the WLS filter in 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 in 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 ˆZ is a linear transform of G in the window

_ζ1 (p_) ˆZ (p) = ap_G(p) + bp_ , ∀p ∈ _ζ1 (p_), (2)

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 (ap_ , bp_), a constraint is added to X and ˆZ as in Equation (1). The values of ap_ and bp_

Fig. 1. Two tone mapped images.

(a) λ = 2, γ = 1.2, and _ = 0.0001 as in and (b) λ = 2, γ = 0, and _ = 0. are then obtained by minimizing a cost function E(ap_ , bp_) which is defined as

E = _ p∈ _ζ1 (p_) [(ap_G(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 is a typical example and it is derived by minimizing the following quadratic cost function:

E = N _ p=1 [(ˆZ (p) − X(p))2 + λ(p)_∇ ˆZ (p)_2], (4)

where N is the total number of pixels in an image, ∇ ˆZ (p) = [∂ ˆZ (p) ∂x , ∂ ˆZ(p) ∂y]T, and λ(p) = [λx (p), λy (p)]T is defined as

λx (p) = λ | ∂ X(p) ∂x |γ + _ ; λy (p) = λ | ∂ X(p) ∂y |γ + _ λ, γ and _1 are three constants. The values of λ, γ and are 2, 1.2 and 10−4, respectively.

It is shown in the linear model (2) that ∇ ˆZ (p) = ap_∇G(p). Clearly, the smoothness of ˆZ 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 ˆZ with respect to the filtered image X and the regularization term provides the smoothness level of ˆZ . There are two major differences between the

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WLS filter and the GIF. 1) The GIF in [14] is based on local optimization while the WLS filter in 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. One possible problem for the GIF is halos which can be avoided by the WLS filter. As indicated in the GIF would concentrate blurring near edges and introduce halos while the WLS filter would distribute the blurring globally.

Here, we would argue that the latter is another possibly major reason that halo artifacts can be avoided by the WLS filter. To support our argument, the WLS filter is applied to design a tone mapping algorithm for HDR images. Two tone mapped images are shown in Fig. 1. With the values of λ, γ and _ halo artifacts are avoided from appearing in the final.

However, halo artifacts appear in the final image when the values of λx (p) and λy (p) are fixed as λ_s. This implies that the spatially varying image gradients aware weighting λx (p) and λy(p) are crucial for the WLS filter in to avoid halo artifacts. Unfortunately, the value of λ in the GIF [is fixed rather than being spatially varying as in As such, halos are unavoidable for the GIF in when it is forced to smooth edges.

III. WEIGHTED GUIDED IMAGE FILTER

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

A. An Edge-Aware Weighting

Let G be a guidance image and σ2G ,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 σ2G 1(p_) + ε σ2G ,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 [14], 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

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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 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 . 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 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. Sobel gradient and the Roberts gradient [24]. 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.

B. 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 ˆZ as in Equation (2). The model ensures that the output ˆZ 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 ˆZ while maintaining the linear model (2), i.e., by minimizing a cost function E(ap_ , bp_) which is defined as

E = _ p∈_ζ1 (p_) [(ap_G(p) + bp_ − X(p))2 + λ G(p_) a2 p_]. (6)

The optimal values of ap_ and bp_ are computed as

ap_ = μG_X,ζ1 (p_) − μG,ζ1 (p_)μX,ζ1 (p_) σ2G ,ζ1 (p_) + λ G(p_) , (7)

bp_ = μX,ζ1 (p_) − ap_μG,ζ1 (p_), (8)

where _ is the element-by-element product of two matrices. μG_X,ζ1 (p_), μG,ζ1(p_) and μX,ζ1 (p_) are the mean values of G _ X, G and X, respectively. The final value of ˆZ (p) is given as follows: ˆZ (p) = ¯¯ apG(p) + ¯¯ b p, (9)

where ¯¯ ap and ¯¯ b p are the mean values of ap_ and bp_ in the window computed as ¯ap = 1 |_ζ1(p)| _ p_∈ _ζ1 (p) ap_ ;

¯b p = 1 |_ζ1 (p)| _ p_∈ _ζ1 (p) bp_ , (10)

and |_ζ1(p_)| is the cardinality of _ζ1 (p_). 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 [14]. This implies that sharp edges are preserved better by the WGIF than the GIF values of ζ1 and λ are 15 and 1/32, respectively. 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 while the complexity of the ABF is an issue.

IV. CONCLUSION AND DISCUSSION

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 in 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 upsampling, flash/no-flash de-noising, and etc. In addition, similar idea can be used to improve the anisotropic diffusion in Poisson image editing etc. All these research problems will be studied in our future research.

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