

Image Enhancement Using Weighted Guided Image Filtering

G.Nagajyothi, E.Raghuveera

Abstract— Weighted guided image filtering (WGIF) is to enhance filtering and stay away from halo artifacts. We realize that the beforehand utilized local filtering based edge preserving smoothening method experiences halo artifacts furthermore a few disadvantages. To conquer this issue WGIF is presented. This technique is presented by joining an edge-aware weighted into a current guided image filtering (GIF). It has two points of interest of both global and local smoothening filtering in the sense its complexity is $O(N)$ for N pixels and Avoid halo artifacts. The yield of WGIF results in better visual quality and avoids halo artifacts. In future, comparative thoughts can be utilized to enhance the visual nature of an isotropic dissemination and Poisson image altering.

Index Terms— Edge-preserving smoothing, weighted guided image filter, edge aware weighting, image enhancement, haze removal, exposure fusion.

I. INTRODUCTION

In human visual observation, edges give a viable and expressive stimulation which is essential for neural understanding of a scene. In the fields of image handling and computational photography utilize smoothing methods which could save edges better. In smoothing process a image to be filtered is ordinarily decayed into two layers: a base layer created by homogeneous areas with sharp edges and a detail layer framed by either noise or texture, e.g., random pattern with zero mean, a repeated pattern with usual arrangement. There are two sorts of edge-protecting image smoothing systems: global filter, for example, the weighted least square (WLS) filter and local filters for example, bilateral filter (BF) [9], trilateral filter [11], and their acceleration versions [5], [12], [15], as well as Guided image filter (GIF) [13]. Though global optimization filters much of the time yield amazing quality, they have high computational expense. Contrasting to the global optimization filters the local filters are less complex. Be that as it may, the local filters can't monitor sharp edges like the global optimization filters.

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G.Nagajyothi, Department of Electronics and communication engineering, JNTU college of engineering Ananthapuramu, India, Mobile No 9491612004

E.Raghuveera, Department of Electronics and communication engineering, JNTU college of engineering Ananthapuramu, India, Mobile No 9441137327.

Halo artifacts were typically delivered by the local filtering when they were adjusted to smooth edges. Significant reason that the BF/GIF produces halo artifacts was both spatial similarity parameter and range similarity parameter in the BF were fixed.

Be that as it may, both the spatial parameters and the range similarity parameters of the BF could be adaptive to the substance of the image to be filtered. Lamentably as pointed out, issue with adjustment of the parameters will pulverize the 3D convolution structure. To perform better close edges GIF is presented by considering the guidance image for the filtering yield. It is derived from the local linear model here the complexity is $O(N)$ for N pixel image yet is experiencing halo artifacts to stay away from halo artifacts WGIF is presented.

In this WGIF an edge-aware weighting technique incorporated into the GIF to frame a weighted GIF (WGIF). Local variance in the 3×3 window of pixel in a guidance image is connected to figure the edge-aware weighting. The local variance of a pixel is standardized by the local variances of all pixels in guidance image. The normalized weighting is then embraced to plan the WGIF. Thus, halo artifacts can be maintained a strategic distance from by utilizing the WGIF. Like the GIF, the WGIF likewise keeps away from gradient reversal. Likewise, the intricacy of the WGIF is $O(N)$ for a image with N pixels which is the same as that of the GIF. These elements permit numerous utilizations of the WGIF for single image detail enhancement, single image haze removal, and fusion of differently exposed images

II. RELATED WORK

A. Edge preserving smoothing technique

The task of edge-preserving smoothing is to crumble an image X into two parts as follows

$$X(P) = Z(P) + e(P) \quad (1)$$

Where Z is a recreated image shaped by uniform areas with sharp edges, e is commotion or surface, and $p (= (x, y))$ is a position. Z and e are called base layer and detail layer, individually.

One of edge-preserving smoothing technique depends on local filtering. Bilateral filters (BF) is broadly utilized because of its effortlessness yet experience the ill effects of "gradient reversal" artifacts typically saw in point of interest upgrade of traditional LDR images. At that point GIF was acquainted with beat this issue. In this GIF, a guidance image G was used which could be similar to the image X which is to be filtered and Z is a linear transform of G in the window

$$\Omega_{\zeta}(p')$$

$$Z(P) = a_{p'}G(P) + b_{p'} \quad (2)$$

To determine the linear coefficients $(a_{p'}, b_{p'})$ a constraint is added to X and Z as in Equation (1). The values of $a_{p'}$ and $b_{p'}$ are then obtained by minimizing a cost function $E(a_{p'}, b_{p'})$ which is defined as

$$E = \sum_{p \in \Omega_{\zeta}} [(a_{p'}G(p) + b_{p'} - X(p))^2 + \lambda a_{p'}^2] \quad (3)$$

Where λ is a regularization parameter

Another type of edge-preserving smoothing techniques was based on global optimization. The Weighted Least Square filter was a typical example and it was derived by minimizing the following quadratic cost function

$$E = \sum_{p=1}^N [(f(p) - X(p))^2 + \lambda(p) \|\nabla f(p)\|^2] \quad (4)$$

Where N is the total number of pixels in an image

There are two major differences between the WLS filter and the GIF

1) The GIF depends on local optimization while the WLS filtering in view of global optimization. Accordingly, the trouble of the GIF is $O(N)$ for a image with N number of pixels and the Weighted Least Square filtering is more convoluted than the GIF.

2) The estimation of λ is settled in the GIF while it is adaptive to local gradients in the WLS filtering. One conceivable issue for the GIF is halos which could be lessened by the WLS filtering. The spatial fluctuating image slopes aware weighting $\lambda_x(p)$ and $\lambda_y(p)$ are critical for the WLS filtering to stay away from halo artifacts.

III. WEIGHTED GUIDED IMAGE FILTERING

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

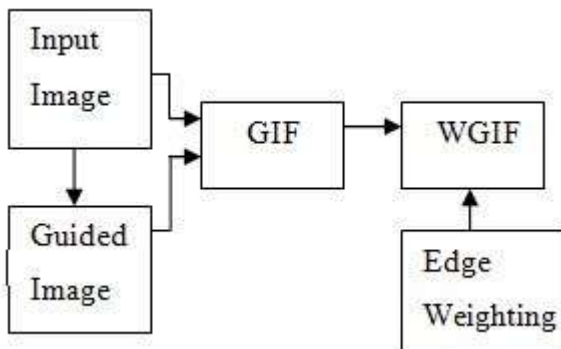


Fig 1: Block diagram

A. An Edge-Aware Weighting

Let G be a guidance image and variance of G calculated in the 3×3 window. An edge-aware weighting is characterized by utilizing local variances of 3×3 windows of all pixels as follows

$$\Gamma_G(p') = \frac{1}{N} \sum_{p=1}^N \frac{\sigma_{G,1}^2(p') + \varepsilon}{\sigma_{G,1}^2(p) + \varepsilon} \quad (5)$$

Where ε is a small constant and its value is selected as $\varepsilon = (0.001 * L)^2$

While L is the dynamic range of the input image

In addition, the weighting $\Gamma_G(p')$ measures the importance of pixel p' with respect to the whole guidance image. Due to the box filter, the complexity of $\Gamma_G(p')$ is $O(N)$ for an image with N pixels. The value of $\Gamma_G(p')$ 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 $\Gamma_G(p')$ in Equation (5).

By applying this edge-aware weighting, there may block artifacts in final images. To keep conceivable blocking artifacts from showing up in the final image, the estimation of $\Gamma_G(p')$ is smoothed by a Gaussian filtering. large weights are allotted to pixels at edges than those pixels in level territories. The proposed weighting matches one element of human visual framework, i.e., pixels at sharp edges are normally more effective than those in level ranges.

B. The WGIF Filter

Same as the GIF, the key suspicion of the WGIF is a local linear model between the guidance image G and the filtering output Z as in Equation (2). This model ensures that the yield Z has an edge just if the guidance image G has an edge. The proposed weighting $G(p)$ in Equation (5) is incorporated into the cost capacity $E(a_{p'}, b_{p'})$ in Equation(3). All things considered, the arrangement is acquired by minimizing the contrast between the image to be sifted X and the separating output Z while keeping up the straight model (2), i.e., by minimizing a cost capacity $E(a_{p'}, b_{p'})$ which is characterized as

$$E = \sum_{p \in \Omega_{\zeta_1}(p')} \left[(a_{p'}G(p) + b_{p'} - X(p))^2 + \frac{\lambda}{\Gamma_G(p')} a_{p'}^2 \right] \quad (6)$$

The optimal values of $a_{p'}$ and $b_{p'}$ are computed as

$$a_{p'} = \frac{\mu_{G \odot X, \zeta_1}(p') - \mu_{G, \zeta_1}(p') \mu_{X, \zeta_1}(p')}{\sigma_{G, \zeta_1}^2(p') + \frac{\lambda}{\Gamma_G(p')}} \quad (7)$$

$$b_{p'} = \mu_{X, \zeta_1}(p') - a_{p'} \mu_{G, \zeta_1}(p') \quad (8)$$

Where \odot is the element-by-element product of two matrices. $\mu_{G \odot X, \zeta_1}(p')$, $\mu_{G, \zeta_1}(p')$ and $\mu_{X, \zeta_1}(p')$ are the mean values of $G \odot X$, G and X, respectively.

The final value of Z (p) is given as follows:

$$Z(p) = \bar{a}_p G(p) + \bar{b}_p \quad (9)$$

Where \bar{a}_p and \bar{b}_p are the mean values of $a_{p'}$ and $b_{p'}$ in the window computed as

$$\bar{a}_p = \frac{1}{|\Omega_{\zeta_1}(p)|} \sum_{p' \in \Omega_{\zeta_1}(p)} a_{p'} \quad (10)$$

$$\bar{b}_p = \frac{1}{|\Omega_{\zeta_1}(p)|} \sum_{p' \in \Omega_{\zeta_1}(p)} b_{p'} \quad (11)$$

And $|\Omega_{\zeta_1}(p)|$ is the cardinality of $\Omega_{\zeta_1}(p)$.

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 $\Gamma_X(p')$ is usually much larger than 1. $a_{p'}$ in the WGIF is closer to 1 than $a_{p'}$ in the GIF. 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 while the complexity of the ABF is an issue.

C. Single Image detail Enhancement

In this single image detail enhancement whole image is enhanced and it is called “full detail enhancement”. With the WGIF, the input image X is decomposed into Z and e as shown in Equation (1) and the details enhancement can be achieved as follows

$$Z(P) = X(P) + \eta(P)\theta e(P) \quad (12)$$

Here θ chosen as 4. $\eta(P)$ is computed by using $\Gamma_C(p')$ in the equation 5. its value is almost 0 if pixel p is in flat region and 1 otherwise.

D. Single image haze removal

Pictures of open air scenes are degraded by fog, haze, and smoke in the climate the corrupted image lose the contrast and colour fidelity. Haze evacuation is fundamental in both computational photography and PC applications. The portrayal of fog image is given by [15]

$$X_C(P) = Z_C(P)t(P) + A_C(1 - t(P)) \quad (13)$$

Where $C \in \{r, g, b\}$ is a colour channel list, X_C is the observed intensity, Z_C is the scene radiance, A_C global atmospheric light and $t(P)$ medium transmission. First term $Z_C(P)t(P)$ is called direct attenuation and second term portrays scene radiance and decay in the medium. Second term portrays is called airlight. Airlight comes about because of past scattered light and prompts the movement of the scene of the colour.

At the point when haze is high the airlight will be more overwhelming so colour fidelity of picture is lost. To maintain a strategic distance from halo artifacts and enhance colour fidelity in a Haze image WGIF is utilized. This single image haze algorithm calculation can be viewed as the spatially varying detail enhancement. Amplification factor is large when the pixel p belongs to sky region .because of this high amplification noise could be opened up and/or halo artifacts could be produced. For this a large lower bound is required, so a non negative compensation term is acquainted with the transition map $t(P)$ in the sky region as indicated by the haze degree. The haze degree is naturally recognized by utilizing the histogram of an image with this halo artifacts and de hazing of a image is done.

E. Fusion of Differently Exposed Images

One of the difficulties in computerized image is the rendering of a HDR regular scene on a routine LDR show. This test can be tended to by catching numerous LDR images at various exposure levels. Each LDR image just records a little portion of the dynamic range and partial scene detail however the entire arrangement of LDR images on the whole contain all scene detail. All the differently exposed images can be fusioned to deliver a LDR image by a exposure fusion algorithm. Similar to detail enhancement of LDR image, halo artifacts, gradient reversal artifacts and amplification of noise

in smooth regions are three major problems to be addressed for the fusion of differently exposed images.

IV. EXPERIMENTAL RESULTS

In this paper input image and guidance image are taken same for easy analysis .Here the edge aware is added to the GIF to form WGIF. The enhancement of an image, haze removal of an image and fusion of directly exposed images by WGIF and their comparison with the GIF shown



Fig 2: Single image detail enhancement



Fig 3: Weighted image



Fig 4: Single image haze removal



Fig 5: Fusion of directly exposed images

Comparison for GIF and WGIF

The reduction of halo artifacts in an image can be physically viewed or by comparing the sharpness parameter values. The sharpness and enhance parameter taken from [16].

The sharpness of the image is given by

$$S = \left\| \sqrt{G_x^2 + G_y^2} \right\| \quad (12)$$

G_X,G_Y indicate horizontal and vertical gradient Values respectively, and S is the average for all the pixels.

The enhancement of the image is calculated as

$$E = \frac{1}{H * V} \sum \sum 20 \ln \frac{I_{max}}{I_{min} + \epsilon} \quad (13)$$

Where the image is broken up into H × V blocks, I_{max} and I_{min} are the maximum and minimum in a given block, and ε is a small constant equal to 0.0001.

The sharpness and enhancement values of GIF and WGIF given by

	GIF	WGIF
Enhancement	10.02	10.39
Sharpness	56.5	87.5

Fig 6: Comparison table

V. CONCLUSION

An optimized framework is proposed in this work by incorporating the edge based weighting scheme with guided image filtering to get proposed weighted guide image filtering (WGIF). WGIF scheme yields low complexity as GIF and preserve the sharp gradient information. WGIF has ability to provide the local and global smoothing filters advantages and successful to avoid the halo artifacts. In practical WGIF is for single image feature enhancement

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G.Nagajyothi studying M.Tech in Department of ECE JNTU College of engineering Ananthapuramu, Completed B.Tech in Shri Vishnu Engineering college for women, Bhimvaram.



E.Raghuvvera completed M.Tech in Department of ECE VNR VJIET Hyderabad, B.Tech in RGM college of Engineering and technology Nandyal.