Advances in 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 guide image filter (WGIF) is introduced by incorporating an edge aware weighting in to an existing guided image filter (GIF) to solve the problem. Here in this paper weighted guided image filter is used for single image enhancement, single image haze removal, fusion of differently exposed images, and also for videos enhancement.**

Keywords: edge preserving smoothing, WGIF, edge aware weighting, detail enhancement, haze removal, exposure fusion.

1. INTRODUCTION

Many applications in the field of computational photography and image processing require smoothing techniques that can preserve edges well .The smoothing process usually decomposes an image to be filtered in to two layers. A base layer formed by homogeneous region with sharp edges, and a detail layer which can be either noise or texture, such as a repeated pattern with regular structure. There are two types of edge preserving smoothing techniques; one type is global optimization based filters. The optimization performance criterion consists of a data term and a regularization tern. The data term Measures the 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 global optimization filters often yields excellent quality, they are having high computational cost. The other type is local filters such as bilateral filters (BF), guided image filer (GIF), compared with global optimization filters local filters are simpler. However the local filters cannot preserve sharp edges like the global optimization filters. As mentioned in [12] that local filters such as the BF/GIF would concentrate blurring near these edges and introduce halo artifacts, while global optimization filters such as weighted lest squares(WLS) filter in [4] would distribute such blurring globally. It is worth nothing that the Lagrangian factor in the WLS filter in [4] is content adaptive and whether the Lagrangian factor in the GIF and both spatial similarity parameters and range similarity parameters in the BF are fixed. This is the major reason that the BF/GIF produces halo artifacts. In human visual perception edges provide an effective and expressive stimulation that is vital to neural interpretation of a scene. To obtain these requirements an edge- aware weighting is introduced and incorporated in to GIF to form a weighted guided image.

2. EDGE PRESEVING SMOOTHING TECHNIQUES

In this section we summarize the edge preserving-smoothing techniques on GIF [12] and WLS filter [4]. The task of edge- preserving smoothing is to decompose an image X in to two parts as follows

$$X(p)=\hat{U}(p)+e(p) \qquad (1)$$

Where Û is a reconstructed image formed by homogeneous regions with sharp edges, e is noise texture and p (= (x, y)) is a position. Û and e are called base layer and detail layer respectively. The local filter which is suffering from gradient reversal so we are introducing the GIF [12] .In GIF, a guidance image G is used which can be identical to image to be filtered. It is assumed that Û is a linear transform of G in the window $\Omega_{\zeta_1}(p')$

$$\hat{U}(p) = a_{p'}G(p) + b_{p'} \;\; \forall\, p \in \Omega_{\zeta_1}(p') \qquad (2)$$

Where $\Omega_{\zeta_1}(p')$ is a square window centered at the pixel p' of radius ζ_1 , a$p'$and bp' are two constants in the window $\Omega_{\zeta_1}(p')$

To determine the linear coefficients (a_p', b_p') a constraint is added to X and Û as in equation (1).the values of the, a_p' and b_p' are then obtained by minimizing a cost function E (a_p', b_p') which is defined as

$$E = \sum_{P\epsilon\Omega\varsigma}\left[(a_{p'}G(p) + b_{p'} - X(p))^2 + \lambda {ap'}^2\right]$$
(3)

Where λ is a regularization parameter penalizing large a_p'. Beside all these there is another edge preserving smoothing technique which is based on global optimization, the WLS filter in [4] is derived by minimizing the quadratic cost function

$$E = \sum_{P=1}^{N}\left[\left(\hat{U}(p) - X(p)\right)^2 + \lambda(p)\left\|\nabla\hat{U}(p)\right\|^2\right] \qquad (4)$$

Where N is the total number of pixels in an image

The main difference between the GIF and WLS are first one the complexity of GIF is O (N), for N number of pixels where as for WLS is complicated, second one is the value of ‘λ’ is fixed in GIF where as it is adaptive to local gradients in WLS.

3. WEIGHTED GUIDED IMAGE FILTER

In this section an edge aware weighting is first proposed and it is in corporate into the GIF in [12] to form the WGIF.

A. An Edge-Aware Weighting

Let G be a guided image and $\sigma^2_{G,1}(p')$ be the variance of G in the 3 × 3 window $\Omega_{\zeta_1}(p')$. An edge aware weighting $\Gamma_{G(p')}$ is defined b using local variances of 3 × 3 windows of all pixels as follows

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

Where ε is a small constant and its value is selected as $(0.001\times L)^2$ while L is the dynamic range of the input image. The weighting $\Gamma_{G(p')}$ measures the importance of pixel p' with respect to whole guidance image. The value of the $\Gamma_{G(p')}$ is larger than 1 if p' is at an edge and smaller than 1 if p' is in smooth area. By 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 $\Gamma_G(p')$ is smoothed by a Gaussian filter. The smoothed weights of all pixels in Fig. 1(a) are shown in Fig. 1(b). Clearly larger weights are assigned to pixels at edges than the pixels at flat areas.

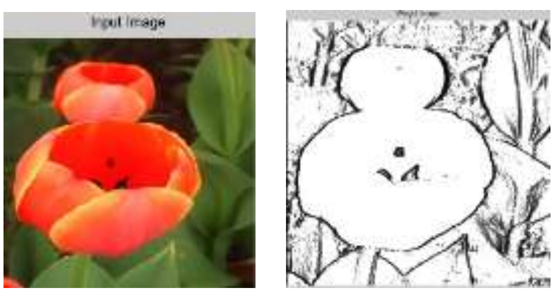


Figure 1(a): An input image (b): Its weighted image

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 Û in equation (2). The proposed weighting $\Gamma_{G(p')}$ in equation (5) is incorporated in to the cost function E (a_p', b_p') in equation (3).the solution is obtained by minimizing the difference between the image to be filtered X and the filtering output Û, while maintaining the linear model (2) that is by minimizing a cost function E(a_p^1, b_p^1) which is define as

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

The optimal values of a_p^1 and b_p^1 are computed as

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

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

Where ⊙ 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 ⊙ X, G and X, respectively.

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

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

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

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

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

4. APPLICATIONS OF THE WGIF

A. Single Image Detail Enhancement

We first consider the case that the whole image is enhanced and it is called "full detailed enhancement" with the WGIF, the input image X is decomposed in to Û and e as shown in equation (1) and detail enhancement can be achieved as follows

$$U_{enh} = X(p) + \theta\, e(p) \quad (11)$$

Where θ (>0) is a positive constant and is called an amplification factor. Its value is fixed as '4' in our experiment.

However there is a fundamental limitation for all detailed enhancement that is noise is also amplified when fine details are enhanced. The human visual system can tolerate amplified noise in complex regions but is particularly sensitive to amplified noise in flat areas. Separating the noise from the fine detail is known to be very challenging. To overcome the full detail enhancement algorithm a selective detail enhancement algorithm is introduced as follows

$$U_{enh}(p) = X(p) + \eta(p)\,\theta\, e(p) \quad (12)$$

Where the values of Ƞ (p) is computed by using $\Gamma_{G(p')}$ in equation (5) .the value is almost 0 if the pixel is in a flat region and 1 other wise.


(a) (b)


(c) (d)

(e)

Fig. 2. (a) An input image (b) its weighting (c) weighted image (d) enhanced image by GIF (e) enhanced image by WGIF

B. Single Image Haze Removal

Images of outdoor scenes could be degraded by haze, fog, and smoke in the atmosphere. The degraded image loss the contrast and color fidelity, thus haze removal is highly desired in both computational photography and computer vision applications. The model adopted for haze image is given as

$$X_c(p) = \hat{U}c\,(p)t(p) + A_c\big(1f - t(p)\big) \qquad (13)$$

Where c ε{r, g, b} is a color channel index, $X_{c\ is}$ observed intensity, $\hat{U}_c$ is scene radiance, A_c global atmospheric light, t is the medium transmission describing the portion of the light that is not scattered and reaches the camera. The first term $\hat{U}_c$ (p) t (p) is called direct attenuation and it describes the scene radiance and its decay in the medium. The second term A_c (1-t (p)) is called air light. When the atmosphere is homogeneous, the transmission t (p) can be expressed as

$$t(p) = e^{-ad(p)} \qquad (14)$$

Where α is the scattering coefficient of the atmosphere.

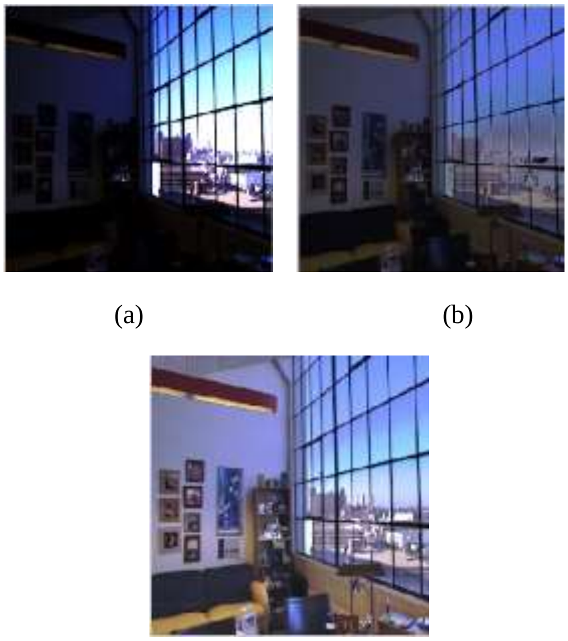

(a) (b)


(C) (d)

Fig. 3. (a) An input image (b) guided image (c) de-hazed image by GIF (d) de-hazed image by WGIF

C. Fusion of Differently Exposed Images

One of the challenges in digital image processing research is the rendering of a HDR natural scene on a conventional LDR display. This challenge can be addressed by capturing multiple LDR images at different exposure levels. Each LDR image only records a small portion of the dynamic range and partial scene details but the whole set of LDR images collectively contain all scene details. All the differently exposed images can be fused together to produce a LDR image by an exposure fusion algorithm. Similar to the detail enhancement of a 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.



(a) (b)

(c)

Fig. 4. (a) an input image (b) enhanced image by GIF
(b) enhanced image by WGIF

D. Enhancement of Videos

In this section we will discuss how effectively the WGIF work on the different videos. In previous sections we have seen that how an image enhancement will takes on different filters in the same way in videos enhancement first the image is divided to number of frames, then operate on each pixels with frame wise. Same as of image enhancement there are some problems like haze removal, fusion of differently exposed images on videos and halo artifacts and quality of the video. All these are accurately obtained by WGIF

6. CONCLUSION

A weighted guided image filter (WGIF) is proposed in this paper by incorporating an edge-aware weighting in to 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 same as the GIF. It is nothing that WGIF can also be adopted to design a fast tone mapping algorithm for high dynamic range (HDR) images. Experimental results show the resultant algorithm can produce images and videos with excellent visual quality as those of global filters. All research problems will be studied in future research.

7. REFERENCES

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