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A Novel Specific Approach of Smooth Global Image Decomposition

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Abstract: *As a key problem in image handling, image smoothing has still pulled in a great deal of research consideration. Because of the huge computational cost, particularly for high-determination images, it ends up testing to take care of the smoothing minimization problem and the hidden incomplete differential conditions. The space disintegration strategy (DD), as a standout amongst the most proficient calculations for taking care of expansive scale problems, had not been connected straightforwardly to image smoothing in light of the worldwide normal for the obscure administrator. In this paper, keeping in mind the end goal to abstain from isolating the obscure administrator, we propose a calculation for specifically understanding the aggregate variational based minimization problems with DD. Different numerical trials and examinations exhibit that the bigger the image size is, the more effective the proposed technique is in sparing running time. The parallelization has additionally been acknowledged by utilizing the parallel computing tool stash of MATLAB.*

1. INTRODUCTION

Numerous applications in image handling and PC illustrations regularly require decaying an image into a piecewise smooth base layer and a detail layer. The base layer catches the primary auxiliary data, while the detail layer contains the leftover littler scale subtle elements in the image. These layered signs can be controlled or potentially recombined in different approaches to coordinate diverse application objectives. In the course of the most recent decades, a few edge-protecting smoothing (EPS) strategies have been proposed.

At an abnormal state, EPS strategies can be characterized into two gatherings. The main gathering comprises of the edge-safeguarding (EP) channels that expressly register a separating yield as a weighted normal, in some cases in an iterative way. The early work in this class incorporates the anisotropic dispersion [1] and the two-sided channel [2]. Late serious endeavors have prompted a few productive strategies [3] [7] to quicken the respective channel, and furthermore a significant number quick separating approaches in light of various speculations and computational models [8]– [12]. Despite the fact that with shifting smoothing execution and application requirements, these EP channels are ordinarily effective, frequently giving a direct time many-sided quality reliant on the quantity of image pixels as it were. Notwithstanding, as will be explained later, a typical confinement of these basically nearby channels is that they can't totally resolve the vagueness in regards to regardless of whether to smooth certain edges. Also, the vast majority of them are not straightforwardly pertinent to a few propelled image altering undertakings.

The inferior of existing EPS strategies depend on worldwide streamlining definitions [13] [17]. They look to discover an all around ideal answer for a target work for the most part including an information limitation term and an earlier smoothness term. On account of settling such target works internationally in a principled way, the advancement based methodologies frequently accomplish the best in class brings about a scope of image preparing and PC designs undertakings, defeating the restriction (e.g. corona antiquities) of the unequivocal EP channels. In any case, this outperformance is accomplished at a much expanded cost of computational cost, primarily emerging from illuminating a huge straight framework. Indeed, even with the ongoing undertaking in creating speeding up systems [18], [19], the enhancement based strategies are ordinarily still a request of size slower than the effective EP channels.

In this paper, we show a quick system that performs spatially inhomogeneous edge-safeguarding smoothing, called quick worldwide smoother (FGS). Like [14], [15], our approach intends to upgrade a worldwide target work characterized with an information limitation and a smoothness earlier, yet we propose a proficient contrasting option to the past tedious huge straight framework solvers [19]. In particular, we surmised the arrangement of a unique straight framework with an inhomogeneous Laplacian lattice, characterized over a d-dimensional spatial space, by understanding a grouping of 1D worldwide advancement based direct sub-frameworks. Such a disintegration plot enables one to use a very productive tridiagonal network calculation [20] in a fell design iteratively. Accordingly, our calculation has a runtime many-sided quality direct to the quantity of image pixels as it were

Table I contrasts our technique and the best in class EPS approaches, with respect to smoothing properties. We picked two EP channels, the guided channel (GF) [8] and the area change (DT) [9], and one enhancement based smoothing procedure, the weighted slightest squares (WLS) strategy [15]. We measure the runtime for sifting a 1M pixel RGB image on a solitary CPU center. In DT, the recursive channel (RF) is utilized, which is the quickest neighborhood channel. Our technique has an equivalent runtime to the proficient EP channels, yet the advancement definition of our approach defeats the restrictions of past channels as far as smoothing quality, i.e. delivering no coronas (see Figure 1). It accomplishes excellent outcomes as the condition of-theart advancement based systems, however keeps running around 30 times speedier. All the more particularly, our strategy utilizes just a little (settled) number of math tasks (5 duplications and 1 division) at each pixel for 1D flag smoothing. Additionally, thinking about the adaptability in characterizing a goal work, we additionally propose summed up quick calculations that perform Lγ standard smoothing and support an accumulated (powerful) information term for dealing with loose information limitations. Note that such capacities are unattainable for nearby EP channels.

We exhibit the adequacy and effectiveness of our methods in a scope of utilizations, where the scanty Laplacian network is characterized e.g. utilizing a four-or eight-neighbor smoothness term on a 2D image, including image smoothing, multi-scale detail control [15], structure extraction from surface [17], scanty information introduction [13], uncertain alter engendering [21], and profundity upsampling.

We show the viability and productivity of our procedures in a scope of uses, where the scanty Laplacian framework is characterized e.g. utilizing a four-or eight-neighbor smoothness term on a 2D image, including image smoothing, multi-scale detail control [15], structure extraction from surface [17], scanty information introduction [13], loose alter engendering [21], and profundity upsampling.

The primary commitments of this work are abridged in the accompanying.

• We show a quick O(N) edge-safeguarding image smoothing technique, where N speaks to an image size, by approximating the arrangement of a unique direct framework with a progression of 1D worldwide straight sub-frameworks.

• We propose new computational devices for effectively performing Lγ standard smoothing and supporting a collected (vigorous) information term, which are not practical in existing separating approaches.

2. RELATED WORK

Among numerous edge-saving channels, the respective channel (BF) [2] is the most prevalent one. The BF figures a separated yield with a weighted normal of neighboring pixels, by considering spatial and run (shading) removes in the two-sided part. It is, in any case, computationally costly because of its nonlinearity, when a substantial bit is utilized. As of late, a few techniques have been proposed for quickening the BF [3] [6]. These strategies have a straight time many-sided quality with the image size just, called O(N) channels where N is the quantity of image pixels, yet regularly trade off the smoothing quality by utilizing quantization or downsampling on a reciprocal framework. Adams et al. proposed a quick BF strategy on a permutohedral cross section [7], however it is as yet a request of extent slower than other quick calculations due to an entangle information get to design. Fattal [12] presented another sort of quick channel in view of edgeavoiding wavelets (EAW). This multiscale system empowers a quick calculation, however compels the size of the sifting portion to forces of two. All the more as of late, a few exceptional O(N) edge-saving channels have been proposed, e.g. with a nearby straight model [8], [11], an area change [9], or a recursive information proliferation [10]. Numerous scientists have exhibited the viability of these techniques in such applications as detail/tone control, high unique range (HDR) pressure, colorization, and intelligent division.

TABLE I COMPARISON WITH OTHER APPROACHES; TWO LOCAL FILTERS, THE GUIDED FILTER (GF) [8] AND THE DOMAIN TRANSFORM (DT) [9], AND ONE OPTIMIZATION BASED SMOOTHING APPROACH, THE WEIGHTED LEAST SQUARES (WLS) METHOD [15]. FOR MORE DETAILS, PLEASE REFER TO THE TEXT IN SECTION I. (N.A.: NOT AVAILABLE)

Properties	GF [8]	DT [9]	WLS [15]	Ours
Runtime efficiency [Sec. V.C]	0.15s	0.05s	3.3s	0.10s
Smoothing quality [Sec. V.A]	halo	halo	no halo	no halo
L_γ norm smoothing $(0 < \gamma < 2)$ [Sec. IV.D]	N.A.	N.A	N.A.	Yes
Using aggregated data [Sec. IV.E]	N.A.	N.A.	N.A.	Yes

As an elective approach of image smoothing, Farbman et al. proposed to play out the edge-safeguarding smoothing utilizing the WLS system [15], comprising of an information term and an earlier term that depends on a weighted L2 standard. The sifted yield is gotten by understanding a substantial straight

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framework with a meager Laplacian lattice, speaking to a proclivity work characterized by the given information image. It was demonstrated that this enhancement based approach accomplishes a superb smoothing quality with no corona ancient rarity, which ordinarily seems even in the state-ofthe-craftsmanship nearby channels [9], [25]. It is important that notwithstanding their frail smoothing quality, BF-like neighborhood channels [2], [26] can be more attractive in a few applications, e.g. recoloring between disjoint components. The WLS-based streamlining has likewise been connected into image colorization [13] and tone mapping [14] utilizing scanty client writes on a grayscale image. Not at all like the neighborhood sifting approaches [2], [8], [9], the optimizationbased strategies are specifically material to numerous undertakings past image smoothing, which can be displayed as a direct framework with an inhomogeneous Laplacian grid, including structure extraction [17], inclination area handling [16], and Poisson mixing [27]. For example, Bhat et al. displayed a summed up streamlining system for investigating inclination area arrangements in different image and video handling undertakings [16]. Xu et al. planned a structure-surface deterioration problem with a relative aggregate variety measure and understood a progression of direct condition frameworks [17].

These improvement based strategies as a rule get the outcomes utilizing scanty grid solvers which have been significantly best in class utilizing multi-level and multigrid preconditioning [18], [19]. In spite of ongoing huge advance, if there should arise an occurrence of image smoothing, all the current solvers are as yet a request of size slower than the best in class neighborhood channels [8], [9]. If you don't mind allude to [19] for nitty gritty investigation of the runtime productivity and precision of these solvers.

3. METHOD

In this segment, we first present a proficient option of looking for the arrangement of a target work characterized on weighted L2 standard (1) by breaking down it into each spatial measurement and tackling the network with a succession of 1D quick solvers. At that point, this approach is stretched out into more broad cases, by fathoming target capacities characterized on weighted Lγ standard (0 < γ < 2) or utilizing an accumulated information term, which can't be achievable in the current EP channels. The adaptability and proficiency of our approach empower a huge quickening of a scope of uses, which regularly require comprehending a vast straight framework.

A. 1D Fast Global Smoother

In the first place, we consider the WLS vitality work characterized with a 1D flat information flag f h and a 1D direct flag g h along the x measurement (x = 0, • , W − 1). The WLS vitality work for the 1D flag moves toward becoming:

$$\sum_x \left((u_x^h - f_x^h)^2 + \lambda_t \sum_{i \in \mathcal{N}_h(x)} w_{x,i}(g^h)(u_x^h - u_i^h)^2 \right)$$

where Nh(x) is an arrangement of two neighbors for x (i.e., x−1 and x+ 1). The 1D smoothing parameter λt is characterized to recognize it with that of unique WLS definition (3), and will be itemized in Section IV-B. The 1D yield arrangement u h that limits the above condition is composed as a direct framework:

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$$(\mathbf{I}_h + \lambda_t \mathbf{A}_h)\mathbf{u}_h = \mathbf{f}_h.$$

Ih is a character lattice with a size of W × W. uh and fh speak to the vector documentations of u h and f h, separately. Ok is a three-point Laplacian lattice with a size of W × W. The straight framework in (7) can be composed as takes after:

$$\begin{bmatrix} b_0 & c_0 & 0 & \cdots & 0 \\ \ddots & \ddots & \ddots & 0 & 0 \\ 0 & a_x & b_x & c_x & 0 \\ 0 & 0 & \ddots & \ddots & \ddots \\ 0 & \cdots & 0 & a_{W-1} & b_{W-1} \end{bmatrix} \begin{bmatrix} u_0^h \\ \vdots \\ u_x^h \\ \vdots \\ u_{W-1}^h \end{bmatrix} = \begin{bmatrix} f_0^h \\ \vdots \\ f_x^h \\ \vdots \\ f_{W-1}^h \end{bmatrix}$$

with limit conditions a0 = 0 and cW−1 = 0. Here, u h x and f h x are the x th components of uh and fh. hatchet, bx, and cx speak to three nonzero components in the x th line of (Ih + λtAh), which can be composed as

$$\begin{aligned} a_x &= \lambda_t \mathbf{A}_h(x, x-1) = -\lambda_t w_{x,x-1}, \\ b_x &= 1 + \lambda_t \mathbf{A}_h(x, x) = 1 + \lambda_t(w_{x,x-1} + w_{x,x+1}), \\ c_x &= \lambda_t \mathbf{A}_h(x, x+1) = -\lambda_t w_{x,x+1}. \end{aligned}$$

Indeed, unraveling (7) turns out to be considerably less demanding than explaining (3), as the three-point Laplacian grid Ah turns into a tridiagonal lattice, whose nonzero components exist just in the corner to corner, the left and right diagonals. Such a framework has a correct (nonapproximate) arrangement acquired utilizing the Gaussian end calculation with an O(N) intricacy (here N = W) [20]. Our answer for (7) is a correct least of the given vitality work (6) characterized on the 1D measurement, and all the more essentially the 1D solver is quick.

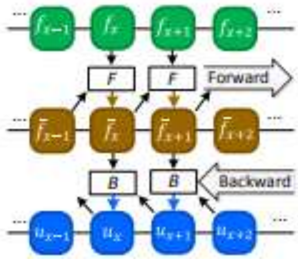
The arrangement uh for the 1D motion in (7) is gotten in a recursive way. Middle of the road yields c˜x and ˜f h x are recursively registered along a forward bearing as takes after:

$$\begin{aligned} \tilde{c}_x &= c_x/(b_x - \tilde{c}_{x-1}a_x) \\ \tilde{f}_x^h &= (f_x^h - \tilde{f}_{x-1}^h a_x)/(b_x - \tilde{c}_{x-1}a_x) \end{aligned}, \quad (x = 1, \cdots, W-1)$$

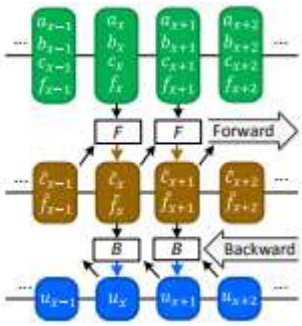
with c˜0 = c0/b0 and ˜f h 0 = f h 0 /b0. Then, an output u h x is recursively obtained along a backward direction as

$$u_x^h = \tilde{f}_x^h - \tilde{c}_x u_{x+1}^h, \quad (x = W-2, \cdots, 0)$$

with $u_{W-1}^h = \tilde{f}_{W-1}^h$.



(a) Local EP recursive filters



(b) Global smoother

Fig. 2. Recursive data propagation on a 1D signal f of (a) local EP recursive filters [9], [10], [23] and (b) our 1D global smoother. 'F' and 'B' denote simple arithmetic operations. Although the arithmetic operations used in both methods are different, they share a similar data propagation scheme; the output u is recursively computed along forward and backward directions. Specifically, intermediate results (a) f¯x and (b) c˜x and f˜x are recursively computed using (28) and (8), respectively, in the forward operation ('F'). Then, the output ux is obtained using (29) for

(a) and (9) for (b) in the backward operation ('B'). Our global smoother, however, achieves a much better smoothing quality than the local EP filters, also with a comparable runtime.

Such a calculation technique is thoughtfully like that of some O(N) distinct image sifting calculations, for example, the recursive channel (RF) of the DT [9] and the recursive reciprocal channel [10], [23] (see Appendix A for more points of interest). Figure 2 outlines the information spread plans of these neighborhood EP recursive channels and our worldwide smoother for 1D signals. Our worldwide plan accomplishes a greatly improved smoothing quality than those productive EP channels (e.g. no radiances), as appeared in Figure 1, yet with a similar runtime, since our answer yields a correct least for the 1D vitality work (6).

Figure 3 analyzes the smoothing quality on 1D flag. The creator gave MATLAB codes of existing EP channels were somewhat changed, with the goal that they chip away at 1D flag. The best outcomes were acquired by tuning the parameters of the GF and DT techniques. Every one of these techniques experience the ill effects of less straightening and additionally corona antiquities, yet our strategy produces incredible outcomes with sharp edges protected. We additionally research the execution of these EP channels in Figure 3(e)-(g), when connected with various emphasess. Here, the weight bits are recomputed with middle of the road comes about each cycle, and the range portion parameters were set moderately littler to stay away from over-smoothing amid emphasess, = 0.1 2 and σr = 0.2. Indeed, even after various cycles, the GF and the RF of the DT still have a trouble in straightening the flag or potentially creates corona antiques. Interestingly, the standardized convolution (NC) channel of Figure 3 (f) smoothes comparable areas while saving pertinent edges extremely well, which is reliable with what was accounted for in [9]. Such outcomes, in any case, are achievable just by repeating the NC channel notwithstanding for 1D flag, and evaluating the aggregate number of cycles turns out to be much all the more difficult with regards to a multi-dimensional flag (e.g. 2D image). In fact, the GFlike sifting appeared in Figure 3 (e) might be alluring in a few applications where an area protecting smoothing is required, e.g. tangling.

B. Separable Approximate Algorithm

Presently, we consider a strategy for productively smoothing a 2D flag utilizing our 1D solver. When all is said in done, explaining a direct framework characterized with more neighbors in a 2D image is generally computationally requesting, even with ongoing meager grid solvers [19]. In this manner, concentrating on some low-level vision errands where a four-neighbor N4 (or an eight-neighbor N8) smoothness requirement is regularly used to characterize an earlier term, we decay a 2D spatial area along each spatial measurement, with the goal that our 1D solver is straightforwardly pertinent to the disintegrated 1D signals. The most widely recognized approach of smoothing a multidimensional flag in a detachable way is to consecutively apply the 1D solver along each measurement of the flag [30], [31]. For a given 2D image, the 1D solver is iteratively connected along the lines and the segments of the image. In the 2D smoothing setting, a solitary emphasis comprising of flat and vertical 1D solvers isn't sufficient to spread data crosswise over edges, prompting the 'streaking ancient rarity' which is basic in distinct calculations [9], [10].

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In this manner, we perform 2D smoothing by applying consecutive 1D worldwide smoothing activities for a different number of cycles. In this plan, the measure of spatial smoothing is logically lessened by altering λt in (7), considering that middle outcomes are coarsened amid emphasess. This methodology decreases streaking curios which might be caused by the distinguishable smoothing calculation.

Algorithm 1 : Separable global smoother for 2D image smoothing

Target Operation: $\mathbf{u} = (\mathbf{I} + \lambda\mathbf{A})^{-1}\mathbf{f}$
Input: 2D image $f(x, y)$; $\mathbf{f}$ ($S \times 1$ vector)
Input: 2D guide image $g(x, y)$; $\mathbf{g}$ ($S \times 1$ vector)
($g = f$ for image filtering, $g \neq f$ for joint filtering)
Output: 2D image $u(x, y)$; $\mathbf{u}$ ($S \times 1$ vector)
Parameters and Notations
T: iteration num., S=HW: image size
λ: smoothing parameter
$\mathbf{A}_h$ (or $\mathbf{A}_v$): $W \times W$ (or $H \times H$) three-point Laplacian matrix
f^h, g^h, u^h: 1D hor. signal of f, g, u; $\mathbf{f}_h$, $\mathbf{g}_h$, $\mathbf{u}_h$ ($W \times 1$ vector)
f^v, g^v, u^v: 1D ver. signal of f, g, u; $\mathbf{f}_v$, $\mathbf{g}_v$, $\mathbf{u}_v$ ($H \times 1$ vector)

Algorithm
Initialize $\mathbf{u} \leftarrow \mathbf{f}$
for $t = 1 : T$ **do**
  compute λ_t using (12)
  for $y = 0 : H - 1$ **do**
    $f^h(x) \leftarrow u(x, y)$ for all $x = 0, \cdots, W - 1$
    if (image filtering), **then** $g^h(x) \leftarrow f^h(x)$ for all x
    compute $w_{x,i}$ using g^h for $i \in \mathcal{N}_h(x)$
    build a tridiagonal matrix $\mathbf{A}_h$
    solve $(\mathbf{I}_h + \lambda_t \mathbf{A}_h)\mathbf{u}_h = \mathbf{f}_h$ using (8) and (9)
    $u(x, y) \leftarrow u^h(x)$ for all $x = 0, \cdots, W - 1$
  end
  for $x = 0 : W - 1$ **do**
    $f^v(y) \leftarrow u(x, y)$ for all $y = 0, \cdots, H - 1$
    if (image filtering), **then** $g^v(y) \leftarrow f^v(y)$ for all y
    compute $w_{y,j}$ using g^v for $j \in \mathcal{N}_v(y)$
    build a tridiagonal matrix $\mathbf{A}_v$
    solve $(\mathbf{I}_v + \lambda_t \mathbf{A}_v)\mathbf{u}_v = \mathbf{f}_v$ using (8) and (9)
    $u(x, y) \leftarrow u^v(y)$ for all $y = 0, \cdots, H - 1$
  end
end

4. CONCLUSIONS

This paper has exhibited a proficient edge-saving smoothing strategy in view of the WLS plan, called quick worldwide smoother. The direct framework with an inhomogeneous Laplacian lattice characterized on e.g. a N4 (or N8) framework of a 2D image is disintegrated as a succession of 1D straight sub systems, empowering us to explain them productively utilizing a direct time tridiagonal lattice calculation. We appeared through different examinations that our worldwide smoother beats the cutting edge nearby sifting strategies as far as smoothing quality, yet with an extremely tantamount runtime. Besides, our proficient and adaptable computational instrument was appeared to be specifically pertinent to a few propelled image altering errands, which normally utilize a N4 (or N8) neighbor-based earlier term. We exhibited that in such applications, our solver is a proficient contrasting option to existing tedious extensive direct framework solvers. At last, our adaptable detailing in characterizing information imperatives has prompted more vigorous image altering devices against loose data sources, while keeping up its runtime proficiency.

(a) Color image (b) Input depth (c) Upsampled depth

Fig. 3. Results of depth upsampling for "Teddy" and "Cone" images: (b) Input low-resolution depth maps downsampled with a factor of 8, (c) Upsampled results using our global smoother with σc = 0.024 and λ = 30.0 2 . The upsampling ratio is 8 in each dimension. Please note that for better visualization of (b), the input depth maps are upsampled by a simple nearest neighbor (NN) method.

TABLE III OBJECTIVE EVALUATION FOR DEPTH UPSAMPLING. WE MEASURED THE PERCENTAGE (%) OF BAD MATCHING PIXELS ON 'ALL' (ALL PIXELS IN THE IMAGE) AND 'DISC' (THE VISIBLE PIXELS NEAR THE OCCLUDED REGIONS) REGIONS. WE COMPARE OUR METHOD WITH 2-D JOINT

BILATERAL UPSAMPLING (2-D JBU), 3-D JBU, AND WEIGHTED MODE FILTERING (WMF).

Algo.	Tsukuba		Venus		Teddy		Cone	
	all	disc	all	disc	all	disc	all	disc
Input	10.4	46.2	3.26	36.6	11.9	35.5	14.7	36.4
2-D JBU	9.04	40.4	2.04	22.1	14.0	37.6	14.7	34.8
3-D JBU	7.89	35.0	1.67	17.8	10.7	30.6	12.1	30.0
WMF	4.35	20.2	0.61	5.73	9.51	23.7	9.43	19.2
Ours	4.66	18.4	0.33	3.70	6.70	16.9	4.54	10.3

The proposed worldwide smoother is attainable to numerous other PC vision and PC illustrations applications also. For example, it was noted in [16] that in the slope space smoothing systems, 95% of the aggregate runtime is spent to enhance a slightest square capacity characterized with N4 neighbors, demonstrating that numerous inclination area handling assignments can be fundamentally quickened utilizing our strategy. We likewise trust that our proficient, high caliber, and adaptable computational instrument may drive some (new) applications, where the overwhelming computational cost is a fundamental bottleneck and additionally the ability of heartily taking care of uncertain contributions to an effective way is required.

REFERENCES

[1] P. Perona and J. Malik, “Scale-space and edge detection using anisotropic diffusion,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 12, no. 7, pp. 629–639, 1990.

[2] C. Tomasi and R. Manduchi, “Bilateral filtering for gray and color images,” in IEEE Int. Conf. on Computer Vision, 1998, pp. 839–846.

[3] F. Durand and J. Dorsey, “Fast bilateral filtering for the display of highdynamic-range images,” ACM Trans. Graph., vol. 21, no. 3, pp. 257–266, 2002.

[4] F. Porikli, “Constant time O(1) bilateral filtering,” in IEEE Conf. on Computer Vision and Pattern Recognition, 2008.

[5] Q. Yang, K.-H. Tan, and N. Ahuja, “Real-time O(1) bilateral filtering,” in IEEE Conf. on Computer Vision and Pattern Recognition, 2009, pp. 557–564.

[6] S. Paris and F. Durand, “A fast approximation of the bilateral filter using a signal processing approach,” International Journal of Computer Vision, vol. 81, no. 1, pp. 24–52, 2009.

[7] A. Adams, J. Baek, and M. A. Davis, “Fast high-dimensional filtering using the permutohedral lattice,” Comput. Graph. Forum, vol. 29, no. 2, pp. 753–762, 2010.

[8] K. He, J. Sun, and X. Tang, “Guided image filtering,” in European Conf. on Computer Vision, 2010, pp. 1–14.

[9] E. S. L. Gastal and M. M. Oliveira, “Domain transform for edge-aware image and video processing,” ACM Trans. Graph., vol. 30, no. 4, p. 69, 2011.

[10] Q. Yang, “Recursive bilateral filtering,” in European Conf. on Computer Vision, 2012, pp. 399–413.

[11] J. Lu, K. Shi, D. Min, L. Lin, and M. N. Do, “Cross-based local multipoint filtering,” in IEEE Conf. on Computer Vision and Pattern Recognition, 2012, pp. 430–437.

[12] R. Fattal, “Edge-avoiding wavelets and their applications,” ACM Trans. Graph., vol. 28, no. 3, pp. 1–10, 2009.

[13] A. Levin, D. Lischinski, and Y. Weiss, “Colorization using optimization,” ACM Trans. Graph., vol. 23, no. 3, pp. 689–694, 2004.

[14] D. Lischinski, Z. Farbman, M. Uyttendaele, and R. Szeliski, “Interactive local adjustment of tonal values,” ACM Trans. Graph., vol. 25, no. 3, pp. 646–653, 2006.

[15] 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, 2008.

[16] P. Bhat, C. L. Zitnick, M. F. Cohen, and B. Curless, “Gradientshop: A gradient-domain optimization framework for image and video filtering,” ACM Trans. Graph., vol. 29, no. 2, 2010.

[17] L. Xu, Q. Yan, Y. Xia, and J. Jia, “Structure extraction from texture via relative total variation,” ACM Trans. Graph., vol. 31, no. 6, 2012.

[18] I. Koutis, G. L. Miller, and D. Tolliver, “Combinatorial preconditioners and multilevel solvers for problems in computer vision and image processing,” Computer Vision and Image Understanding, vol. 115, no. 12, pp. 1638–1646, 2011.

[19] D. Krishnan, R. Fattal, and R. Szeliski, “Efficient preconditioning of laplacian matrices for computer graphics,” ACM Trans. Graph., 2013.

[20] G. H. Golub and C. F. Van Loan, Matrix computations (3rd ed.). Baltimore, MD, USA: Johns Hopkins University Press, 1996.

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