ICASSP2018

DEPTH SUPER-RESOLUTION USING JOINT ADAPTIVE WEIGHTED LEAST SQUARES AND PATCHING GRADIENT

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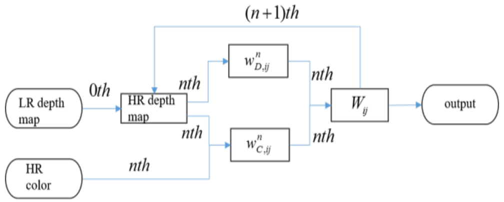
Motivation

Some state-of-the-art approaches apply an aligned RGB image for depth recovery. Unfortunately, these kinds of methods may result in texture copying artifacts and edge blurring artifacts. To address these difficulties, we propose an adaptive weighted least squares framework of choosing different guidance weight for variant conditions flexibly.

Contribution

First of all, in the framework, we propose a joint adaptive color weighting scheme in which the depth maps and color images jointly choose a proper weight term for diverse cases. Then, a patch-based smoothness measuring approach called patching-gradient method (PGM) is proposed to distinguish the discontinuities and smooth areas. Our PGM is robust to dense noise and preserve weak edges effectively. Our framework are effectiveness on suppressing both texture copying artifacts and edge blurring artifacts.

Flowchart



The Proposed Method

Our framework is based on a weighted least squares method. It involves two parts: The data term and the smooth term.

$$D^{n+1} = \arg\min_{D}\{\sum_{i=\Omega_0}(D_i^{n+1}-D_i^0)^2 + \beta\sum_{i=\Omega}\sum_{j=\omega_k(i)} W_{ij}(D_i^{n+1}-D_j^n)^2\}$$

Main contribution 1

$$W_{ij} = w_{C,ij}^{\,n} w_{D,ij}^{\,n}$$

$$w_{C,ij} = \begin{cases} 1 & (\varepsilon_{C,j} \le T_{C1}) \cap (\varepsilon_{D,j} \ge T_{D1}) \\ w_C 1 & (\varepsilon_{C,j} > T_{C2}) \cap (\varepsilon_{D,j} < T_{D2}) \\ w_C 2 & otherwise \end{cases}$$

$$w_C = \exp\left(-\frac{|i-j|^2}{2\sigma_S}\right)\exp\left(-\frac{\sum_{k\in\{R,G,B\}}|I_i^k - I_j^k|^2}{3\times 2\sigma_C^2}\right)$$

$$w_{D,ij} = \exp\left(-\frac{|D_i^n - D_j^n|^2}{2\sigma_D^2}\right)$$

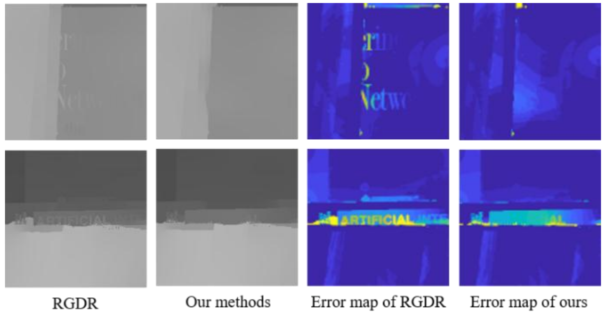
Main contribution 2

$$\varepsilon_j^n = \sqrt{\left(\sum_{p\in\omega_k(j)}\partial_x S_p\right)^2 + \left(\sum_{p\in\omega_k(j)}\partial_y S_p\right)^2} \qquad j\in\omega_k(i)$$

The Solution

$$D^{n+1} = \frac{D_i^0 + 2\beta\sum_{j=\omega_k(i)} W_{ij} D_j^n}{1+2\beta\sum_{j=\omega_k(i)} W_{ij}}, \qquad i\in\Omega$$

The comparison (error map) between RGDR and our method on upsampling of noisy Book dataset.



Results of Patching-gradient method

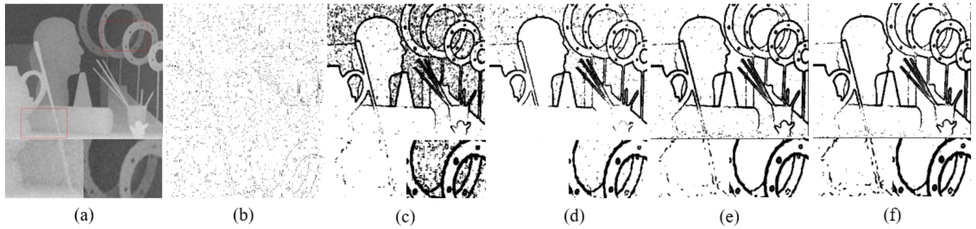


Fig. 2. Examples of edge-detection maps on 8 interpolation of noisy LR depth map. (a) the interpolation of ToF-like degra-dation. (b) Sobel method. (c) Liu et al. (d) Liu et al. (e) Our PGM. (f) Our PGM. Two regions are highlighted by rectangles and enlarged in the second row.

Qualitative Experimental Results

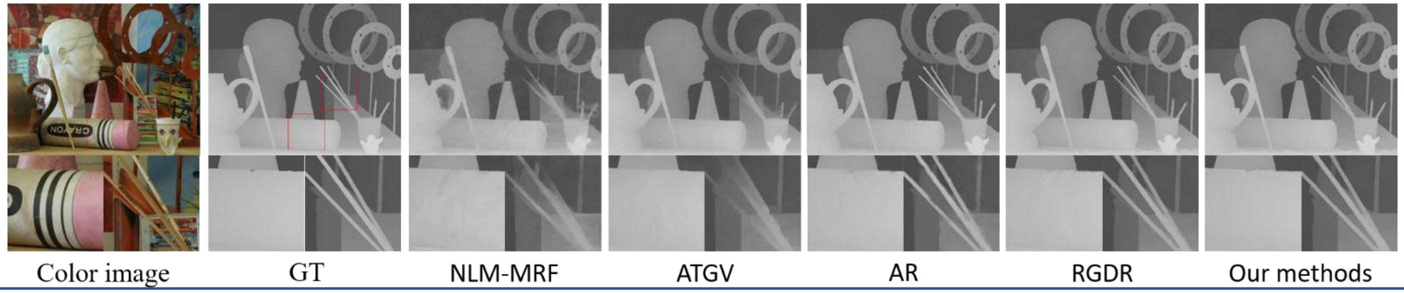


Table 1. Quantitative comparison on noisy ToF-like datasets in terms of MAE. The best evaluation results are in bold.

MAE	Art			Book			Dolls			Laundry			Moebius			Reindeer			Average
	2x	4x	8x	2x	4x	8x	2x	4x	8x	2x	4x	8x	2x	4x	8x	2x	4x	8x	
JBF[9]	1.59	2.06	3.11	0.82	1.24	2.04	0.81	1.20	1.98	0.94	1.38	2.25	0.89	1.28	2.05	0.95	1.36	2.24	1.57
JGF[12]	1.33	1.81	2.90	0.79	1.24	2.05	0.80	1.23	2.01	0.88	1.36	2.23	0.82	1.25	2.03	0.91	1.37	2.26	1.52
NLMMRF[6]	1.66	2.47	3.44	1.19	1.47	2.06	1.19	1.56	2.15	1.34	1.73	2.41	1.20	1.50	2.13	1.26	1.65	2.46	1.83
Guided[20]	1.91	2.23	3.08	0.84	1.12	1.73	0.84	1.11	1.69	1.01	1.31	2.00	0.92	1.19	1.78	1.06	1.32	1.98	1.51
JIDCA[23]	1.69	2.98	3.68	1.53	2.71	3.04	1.54	2.71	2.94	1.45	2.72	3.16	1.55	2.72	2.94	1.65	2.80	3.13	2.50
AR[16]	1.17	1.70	2.93	0.98	1.22	1.74	0.97	1.21	1.71	1.00	1.31	1.97	0.95	1.20	1.79	1.07	1.30	2.03	1.46
WLS[24]	1.25	1.73	2.59	0.74	1.10	1.45	0.85	1.21	1.68	0.83	1.17	1.65	0.80	1.18	1.67	0.84	1.15	1.58	1.30
ATGV[14]	0.80	1.21	2.01	0.61	0.88	1.21	0.66	0.96	1.38	0.61	0.87	1.36	0.57	0.77	1.23	0.61	0.85	1.30	0.99
RGDR[17]	0.71	1.06	1.72	0.57	0.78	1.13	0.64	0.87	1.21	0.54	0.77	**1.12**	0.55	0.76	1.15	0.57	0.80	1.14	0.89
Ours	**0.57**	**0.92**	**1.55**	**0.47**	**0.69**	**1.05**	**0.56**	**0.81**	**1.17**	**0.46**	**0.74**	1.19	**0.45**	**0.69**	**1.12**	**0.48**	**0.74**	**1.10**	**0.82**