Adaptive Actor-Critic Bilateral Filter

Authors: Bo-Hao Chen, Hsiang-Yin Cheng, and Jia-Li Yin
Yuan Ze University, Taoyuan, Taiwan & Fuzhou University, Fuzhou, China

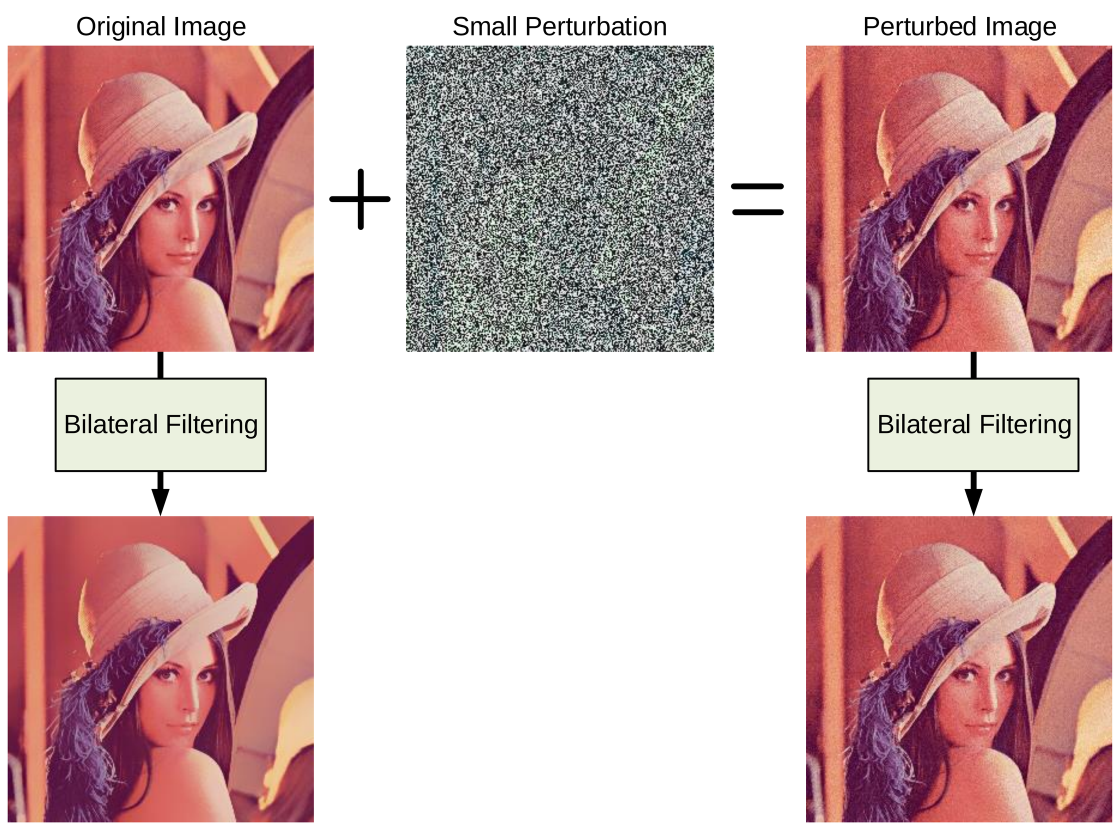
Paper #1162

Abstract

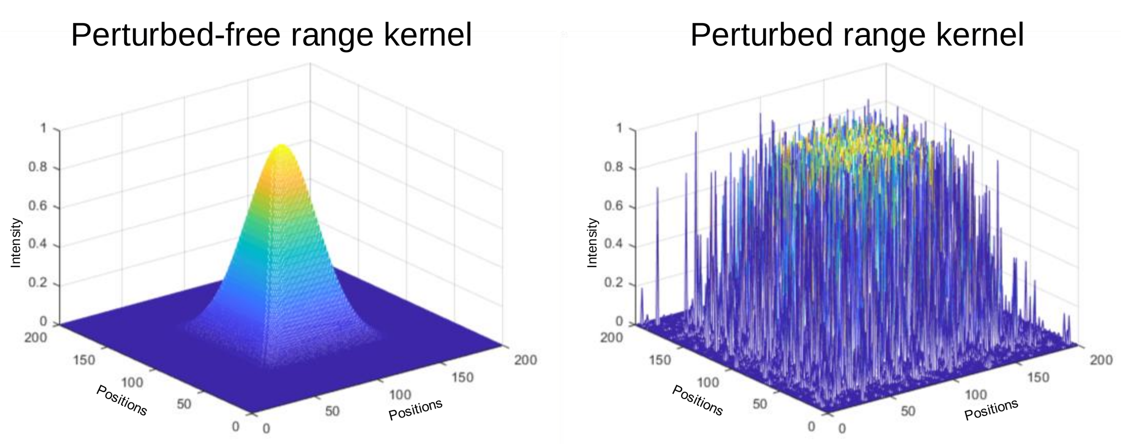
Recent research on edge-preserving image smoothing has suggested that bilateral filtering is vulnerable to maliciously perturbed filtering input. However, while most prior works analyze the adaptation of the range kernel in one-step manner, in this paper we take a more constructive view towards multi-step framework with the goal of unveiling the vulnerability of bilateral filtering. To this end, we adaptively model the width setting of range kernel as a multi-agent reinforcement learning problem and learn an adaptive actor-critic bilateral filter from local image context during successive bilateral filtering operations. By evaluating on eight benchmark datasets, we show that the performance of our filter outperforms that of state-of-the-art bilateral-filtering methods in terms of both salient structures preservation and insignificant textures and perturbation elimination.

Motivation

Researchers have found that small perturbations of the input can emerge in the output of a well-trained convolutional neural network (CNN) for high-level tasks, such as image classification. Though recent works pay attention to these high-level tasks, such perturbations in the low-level tasks, e.g., edge-preserving image smoothing, and their affect to bilateral filtering are usually missing. It turns out that the bilateral filter is also vulnerable to these small perturbations in edge-preserving image smoothing task. See an example below, bilateral filter can produce incorrect smoothing result when filtering input is corrupted with small perturbations that is generally not perceptible by human observers.



Accordingly, attackers can thus craft perturbed inputs that cause BF-based image filters to misbehave for applications that use edge-preserving image smoothing as a preprocessing step. As shown in the example below, this is due to the range kernel qualifies quantities related to pixel values, which would have drastic changes due to small variations of the input.



So, our goal is to propose a variational bilateral filter that is associated with strong perturbation-robustness.

Acknowledgement

This work was supported in part by the Ministry of Science and Technology, Taiwan, under Grant MOST 108-2221-E-155-034-MY3; in part by the Fujian Provincial Youth Education and Scientific Research Project under Grant JAT200055; in part by the Fujian Natural Science Project under Grant No. 2021J05129.

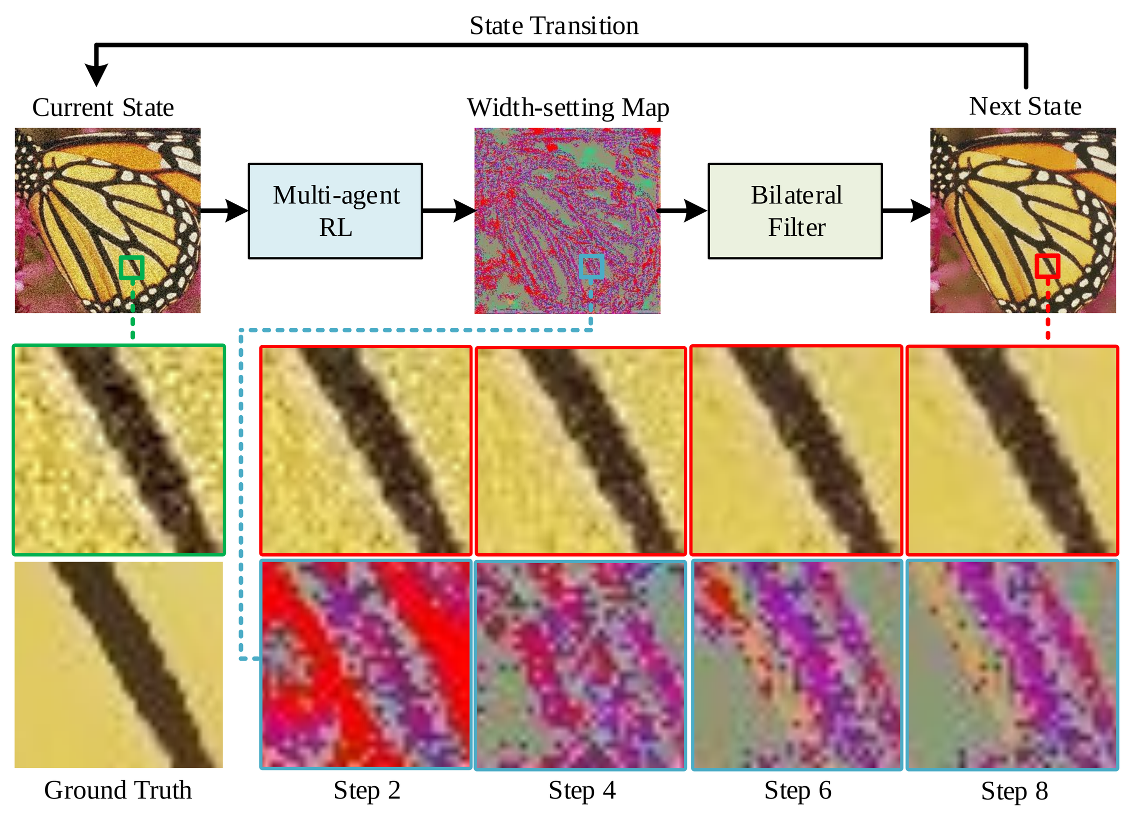
System overview

Given a i-th pixel of input with small perturbation at t-th time step, denoted as a state s_i^t, our target is to develop the optimal width-setting policies $\{\pi_1, ..., \pi_i, ..., \pi_n\} \in \boldsymbol{\pi}$ for the range kernel that can maximize the expected reward r_i^t at the i-th pixel by

$$\pi_i^* = \arg\max_{\pi_i} \mathbb{E}_{\pi_i}\left(\sum_{t=0}^{m} \gamma^t r_i^t\right), \tag{1}$$

where n and m are total numbers of pixels and steps, respectively; and γ^t is the t-th power of discount factor. We measure reward r_i^t on i-th pixel between two consecutive states with ground-truth smoothed pixel $\hat{s}_i$ by

$$r_i^t = \left(\hat{s}_i - s_i^t\right)^2 - \left(\hat{s}_i - s_i^{t+1}\right)^2. \tag{2}$$



Adaptive width-setting scheme

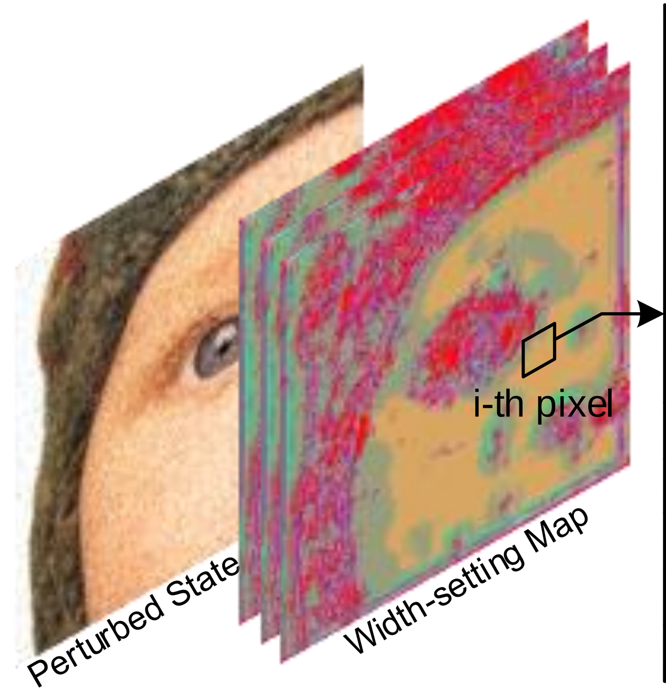
For one episode, each step from state $s^{(0)}$ and explores towards s^m by

$$s_i^{t+1} = f\left(s_i^t; \sigma_i^t\right), \tag{3}$$

where m is total number of steps, $f(\cdot)$ denotes the ordinary BF operation, and σ^t denotes the t-th adaptive width-setting scheme for the range kernel. At each time step t, the i-th agent will choose either increment or decrement by some constants as an action to adjust width setting of range kernel as follows:

$$\sigma_i^{t+1} = \sigma_i^t + a_i^t, \tag{4}$$

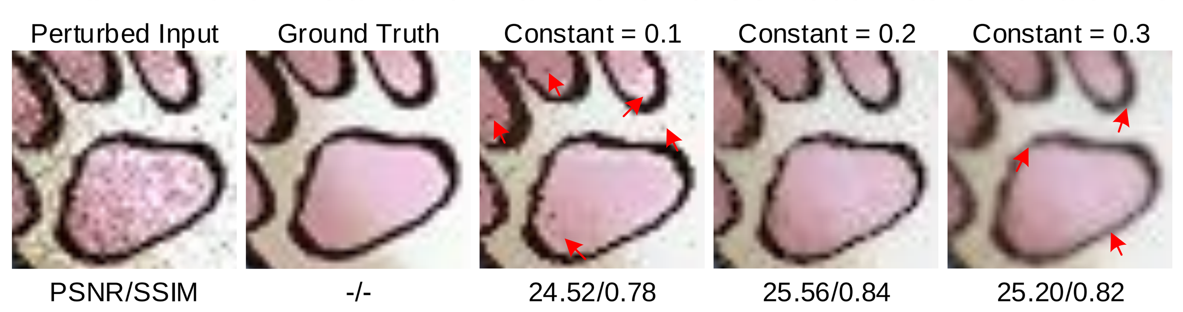
where a_i^t denotes an action for each pixel in predefined action set $\mathcal{A}$.



#	Color	Action
1		$\sigma_i + = -1$
2		$\sigma_i + = -0.8$
3		$\sigma_i + = -0.6$
4		$\sigma_i + = -0.4$
5		$\sigma_i + = -0.2$
6		$\sigma_i + = 0$
7		$\sigma_i + = 0.2$
8		$\sigma_i + = 0.4$
9		$\sigma_i + = 0.6$
10		$\sigma_i + = 0.8$
11		$\sigma_i + = 1$

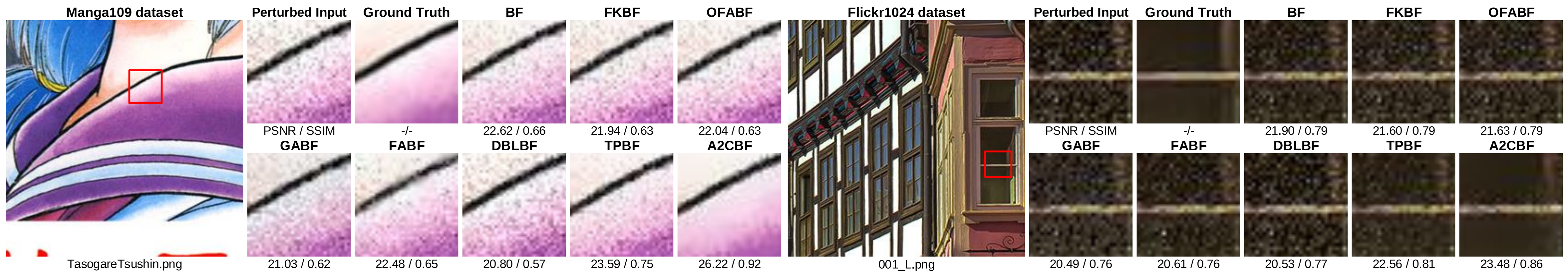
Experimental Results

To verify the effectiveness of different constants for width increase or decrease in our action set, we design three variants of our constant setting ranging from 0.1 to 0.3 for comparison. Results of our A2CBF trained with different constants are demonstrated in the following figure and table.



Dataset	Setting = 0.1	Setting = 0.2	Setting = 0.3
Set5	27.86/0.77	**29.81/0.86**	29.26/0.84
Set14	25.73/0.71	**27.43/0.79**	27.03/0.77
BSDS100	25.75/0.71	**27.32/0.78**	26.99/0.76
Urban100	23.86/0.74	**24.99/0.79**	24.68/0.78
Manga109	24.42/0.78	**25.55/0.84**	25.20/0.82

We compare our A2CBF with eight representative BF-based image filters in the literature: BF [1], FKBF [2], GPABF [3], OFABF [4], GABF [20], FABF [5], DBLBF [7], and TPBF [15]. The results are shown in the following figures. As you can see, our result from Manga109 dataset got not only the best visual quality and also the best PSNR and SSIM values.



Quantitative comparisons are shown in the following table, where bold numbers denote the highest scores. Our A2CBF improves 4.04dB and 0.46 compared with the TPBF, which is the second best on PSNR and SSIM values in Adobe FiveK dataset.

Filter	Set5	Set14	BSDS100	Urban100	Manga109	Adobe FiveK	DTD	Flickr1024
BF	20.99/0.27	20.91/0.39	20.94/0.40	20.89/0.55	21.20/0.52	21.13/0.31	20.98/0.43	21.10/0.47
FKBF	20.76/0.26	20.71/0.38	20.79/0.40	20.76/0.55	21.03/0.52	20.96/0.30	20.89/0.43	20.96/0.47
GPABF	20.66/0.26	20.61/0.38	20.65/0.39	20.65/0.54	20.96/0.52	20.75/0.30	20.78/0.42	20.81/0.46
OFABF	20.80/0.26	20.75/0.38	20.82/0.40	20.79/0.55	21.07/0.52	20.99/0.30	20.90/0.43	20.99/0.47
GABF	21.63/0.31	20.91/0.39	21.49/0.43	20.78/0.55	20.92/0.59	22.08/0.40	21.33/0.45	21.45/0.50
FABF	23.78/0.38	22.01/0.57	23.09/0.48	23.20/0.47	21.98/0.54	23.63/0.28	22.91/0.50	22.40/0.52
DBLBF	20.24/0.24	20.23/0.37	20.22/0.38	20.35/0.53	20.56/0.50	19.91/0.51	19.79/0.40	20.41/0.45
TPBF	25.03/0.47	24.22/0.54	24.50/0.57	23.39/0.66	23.65/0.66	25.36/0.36	24.57/0.58	24.09/0.61
A2CBF	**29.81/0.86**	**27.43/0.79**	**27.32/0.78**	**24.99/0.79**	**25.55/0.84**	**29.40/0.82**	**27.68/0.78**	**26.13/0.78**