Single Image Deblurring Based on Auxiliary Sobel Loss Function

Jun-Pyo Hong, Sung-Jin Cho, Jeongmin Lee, Seo-Won Ji and Sung-Jea Ko
Department of Electrical Engineering
Korea University
e-mail: *{jphong, sjcho, jmlee, swji}@dali.korea.ac.kr, sjko@korea.ac.kr*

Abstract

This paper presents an effective auxiliary loss function which uses the Sobel operator to improve the performance of image deblurring methods based on deep learning. Conventional deep learning-based image deblurring methods exploit mean square error (MSE) loss function that simply measures the intensity difference in pixel-wise manner. Although recovering the lost high-frequency component is the main purpose of image deblurring, MSE loss function often fails to train the network in recovering the high-frequency components. To alleviate this issue and further improve the performance of conventional methods, we propose an auxiliary Sobel loss function which guides the network to focus on recovering the high-frequency components of resultant images. The experiment results show that the networks trained by the Sobel loss function and the conventional MSE loss function outperform the existing methods in both quantitative and qualitative evaluations.

Keywords: Deblur; Deep learning; Sobel operator

1. Introduction

Motion blur caused by camera shake and/or object motion is one of the most common degradations that occur when taking photos. Therefore, image deblurring is an important and active research area in computer vision. In recent years, based on the great success of the convolutional neural network (CNN), various image deblurring methods using CNN were presented [1-3]. Although loss functions can significantly affect the network's learning [4], it has received a little attention and the most of conventional methods have focused on constructing network architectures. The most of conventional image deblurring methods exploit mean square error (MSE), computing the difference of pixel values between the resultant image and the target image to train the networks. However, networks trained with MSE loss function often produce images with insufficient details, because this loss function cannot guide the network to focus on recovering high-frequency components. Kupyn *et al.* presented DeblurGAN [5] and DeblurGAN-v2 [6] that exploit generative adversarial network (GAN) as an auxiliary loss function to supplement the unsatisfactory details of resultant images. However, due to the characteristic of the GAN that generates plausible but not real texture, these methods recorded significantly low peak-signal-to-noise-ratio (PSNR) compared to the other methods.

To solve the limitations of the conventional loss functions, we propose an auxiliary Sobel loss function which induces networks to generate result images where the high-frequency components are closer to target images. The proposed loss function shows better deblurring performance over the conventional MSE loss function on the same network model.

2. Proposed Method

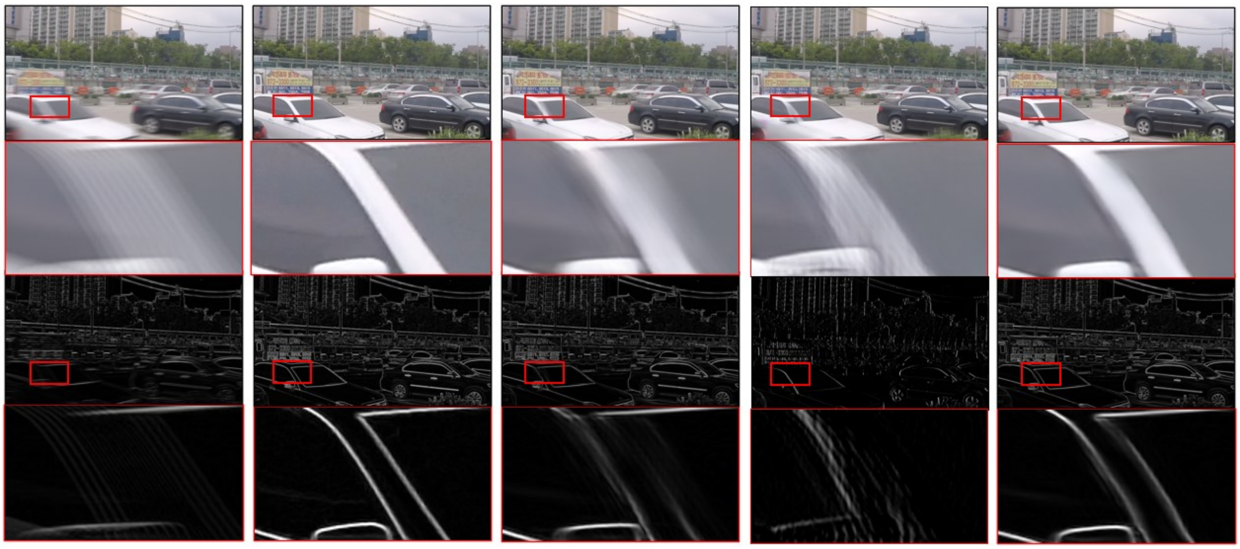
Sobel operator consists of horizontal and vertical Sobel kernels. Each Sobel kernel can be decomposed as the products of an averaging and a differentiation kernel. The horizontal and vertical Sobel kernel G_x, G_y can be written as

$$\begin{aligned} G_x &= [1 \quad 2 \quad 1]^T * [+1 \quad 0 \quad -1], \\ G_y &= [+1 \quad 0 \quad -1]^T * [1 \quad 2 \quad 1]. \end{aligned} \tag{1}$$

Sobel operation detects clear and emphasizing edge maps, since the differential kernel $[+1 \quad 0 \quad -1]$ obtains the gradient magnitude of the image and the averaging kernel $[1 \quad 2 \quad 1]$ reduces unnecessary noise in the image. The high-frequency components of the image I which are acquired by Sobel operation as follows:

$$f_{sobel}(I) = \sqrt{(G_x * I)^2 + (G_y * I)^2}. \tag{2}$$

As shown in Figure 1, Sobel edge map of the sharp image in (b) contains sharp edges, while the blurry image in (a) does not. Since the goal of deblurring is recovering sharp images, we directly minimize the distance between the resultant image and the target image in image in Sobel edge space to ensure that the extra penalty is given in high-frequency areas when training the net-



(a) (b) (c) (d) (e)

Figure 2. Visualization of experimental results and their corresponding Sobel edge maps. (a) Input blurry image, (b) Target sharp image. (c) Zhang *et al.* [2] (without Sobel loss), (d) DeblurGAN-v2 [6], (e) Zhang *et al.* [2] (with Sobel loss).

Table 1. The average PSNR and SSIM on the GoPro dataset.

	Sobel	PSNR (dB)	SSIM
Gao *et al.*	×	30.96	0.942
Gao *et al.*	✓	**31.27**	**0.945**
Zhang *et al.*	×	31.39	0.948
Zhang *et al.*	✓	**31.69**	**0.955**

works. So proposed Sobel loss function can be written as follows:

$$L_{sobel}(R,T) = \frac{1}{N}|f_{sobel}(R) - f_{sobel}(T)| \qquad (3)$$

where R and T denote the output and target image, respectively. The loss value is normalized by the total number of pixel elements N.

While the MSE loss function assures the overall accuracy of the image, Sobel loss function gives the network a high-frequency reconstruction guidance with clear and sharp images. Finally, the proposed loss function is defined as follows:

$$L_{total} = L_{MSE} + \lambda L_{sobel} \qquad (4)$$

where L_{MSE} denotes MSE loss function, and λ is the weight of the auxiliary loss component which was experimentally set to 0.05 in this paper.

3. Experiments

We evaluated our loss function on the state-of-the-art image deblurring networks (Gao *et al.* [1] and Zhang *et al.* [2]) which were trained with MSE loss function. For a fair comparison, we trained networks with the proposed loss function in the same learning schedule and database (GoPro DB [3]) used by the authors.

For quantitative evaluation, we chose PSNR and SSIM, which are widely used to measure image quality. As seen in Table 1, the networks trained with the proposed loss achieved higher PSNR and SSIM compared to MSE loss function in both networks. As shown in Figure 1 (e), incorporating the proposed loss function resulted in restoring the image closer to the target image compared to the result of using only the MSE loss function in (c). Also, the output of the proposed method showed the sharper result in the edge area, such as the automobile's A-filler in the figure. Moreover, while DeblurGAN-v2 network produces unrealistic texture which decrease image quality as seen in Figure 1 (d), ours produces clear edge structure.

4. Conclusion

We have presented the auxiliary Sobel loss function to improve the performance of networks in single image deblurring. In contrast to the previous loss function, our loss function utilizes the high-frequency components of the images so that the network can focus on restoring the high-frequency components. The experiment results show that the networks train with proposed loss function outperform the existing methods in both quantitative and qualitative evaluations.

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