Supplementary Materials - Unsupervised Domain-Specific Deblurring via Disentangled Representations

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In this document, we provide additional materials to supplement our main submission. In the first section, we provide further details on how we choose the weight λ_p for the perceptual loss. In the second section, we provide some additional visual results for face and text deblurring experiments. Finally, we show some natural image examples of the proposed method, and some failure cases.

1. Paramter selection for λ_p

As we mentioned in the main submission, the weight for perceptual loss λ_p needs to be tuned so that the deblurred image neither stays too close to the original blurred image, nor contains many artifacts. The quantitative performance and qualitative visualizations are shown in Table 1 and Fig. 1 respectively. If setting the λ_p too high ($\lambda_p = 1$), the deblurred images become very blurred (Fig. 4(b)), and both the quantitative performance and visualization results are poor. In contrast, if λ_p is set too low ($\lambda_p = 0.01$), the deblurred images contain many artifacts (Fig. 1(d)).

2. Additional visual results

As shown in Fig. 2 and Fig. 3, we present some additional deblurred results for real-world blurred face and text images.

Values	PSNR	SSIM	d_{VGG}
$\lambda_p = 1$	18.40	0.59	78.0
$\lambda_p = 0.1$	**20.81**	**0.65**	**57.6**
$\lambda_p = 0.01$	20.21	0.62	58.7

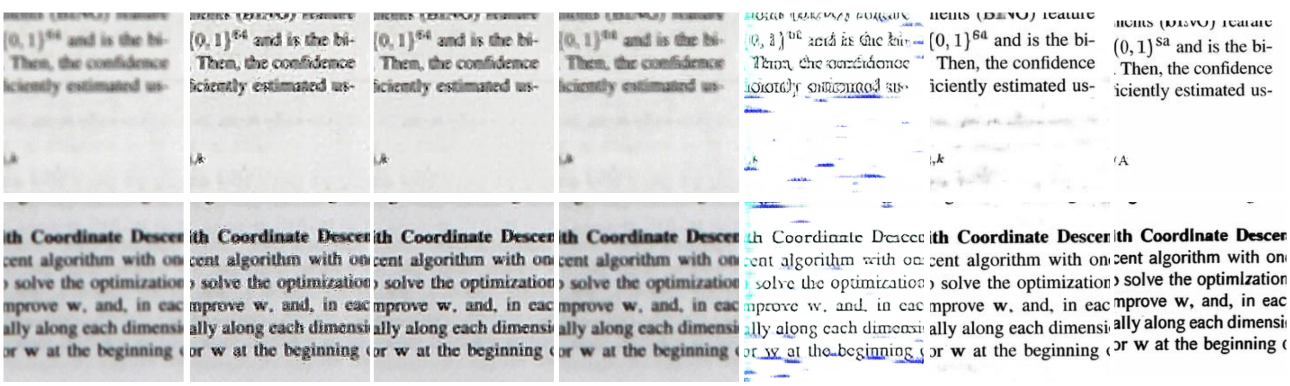
Table 1. Quantitative results for different settings of λ_p.

(a) Blurred (b) $\lambda_p = 1$ (c) $\lambda_p = 0.1$ (d) $\lambda_p = 0.01$ (e) Sharp

Figure 1. Visualizations of sample images with different settings of λ_p. Best viewed by zooming in.

(a) Blurred (b) [7] (c) [8] (d) [9] (e) [6] (f) [10] (g) [2] (h) [3] (i) [5] (j) [11] (k) Ours

Figure 2. Visual comparisons with state-of-the-art methods on real blurred face images. Best viewed by zooming in.



(a) Blurred (b) [7] (c) [8] (d) [5] (e) [11] (f) [1] (g) Ours

Figure 3. Visual comparisons with state-of-the-art methods on real blurred text images. Best viewed by zooming in.

3. Results for COCO dataset

We also tried the proposed method for natural image deblurring. Specifically, we split the COCO dataset [4] into three mutually exclusive sets: sharp set, blurred set and test set. Images in blurred set and test set are blurred in the same way as the CelebA dataset in the main submission, and we use the same framework to train the deblurred model. As shown in Fig. 4, the proposed method can recover the global structures of the latent sharp images. In the given two examples, the red bus and the pizzas become sharper after deblurring. However, if zooming into some local details, we find the results are far from perfect. For example, the characters and headlights on the red bus are not restored that well; the face in the second image contain many artifacts. Meanwhile, the color of the red bus is also distorted.

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(a) Blurred (b) Deblurred (c) Sharp

Figure 4. Visualizations of sample images for COCO dataset. Best view by zooming in.

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