Supplementary: Structure-Aware Motion Deblurring Using Multi-Adversarial Optimized CycleGAN

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***Abstract*—This supplementary document provides more experimental results together with the ground truth images, which could not be fit in the main paper due to the page limit.**

I. Ablation Study

A. Comparison on Multi-Adversarial Architecture

Fig. 1 shows some results of multi-adversarial architecture G_S with three different discriminators. Fig. 1(b) is the result at the final resolution level (256×256) with single discriminator D_{S256}. Fig. 1(c) and Fig. 1(d) are the results at the final resolution level (256×256) with two discriminators D_{S128} and D_{S256} and with three discriminators D_{S64}, D_{S128} and D_{S256}, respectively. It illustrates that deblurring effects can be improved with the increase of adversarial constraint level.

B. Comparison on Different Unsupervised and Supervised CNN-Based Methods

Fig. 2 shows the deblurring results by different methods. Compared with other classical methods, especially the supervised CNN-based method [2] and unsupervised GAN-based method [1], our method has obvious advantages for motion deblurring. It also shows the effectiveness of our multi-adversarial learning architecture.

C. Comparison on Different Components in Our Model

Fig 3 shows the visual effectiveness of different components in our model. Fig 3(a) are the results by the original Cycle-GAN (as baseline). Fig 3(b) are the results by the baseline with multi-adversarial loss. Fig 3(c) are the results by item Fig 3(b) with edge input and edge loss. Fig 3 (d) are the results by item Fig 3(c) with MSSIM and perceptual loss. The experimental results show that the key components we proposed in our deblurring model can effectively improve the overall deblurring effect.

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II. Performance on Benchmark Datasets

A. Performance Comparison on Text Dataset

Fig. 4 presents several examples from the BMVC_TEXT dataset [3] to illustrate the qualitative comparisons of other methods with ours. In Fig. 4, especially in the central character part, our deblurring results can achieve the clearest characters. These examples are sufficient to prove that our method can achieve quite effective results on BMVC_TEXT dataset [3].

B. Performance Comparison on Real Face Dataset

Fig. 5 presents the visual comparisons with other state-of-the-art approaches on real blurred face images. In Fig. 5, especially in the color border area, the deblurring results by our method can reconstruct more structural information. These examples are sufficient to prove that our method can achieve quite effective results on face dataset [8].

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Fig. 1: Deblurred results of multi-adversarial generator. (a) Blurred images. (b) Results with single discriminator D_{S256}. (c) Results with two discriminators D_{S256} and D_{S128}. (d) Results with three discriminators D_{S256}, D_{S128} and D_{S64}.

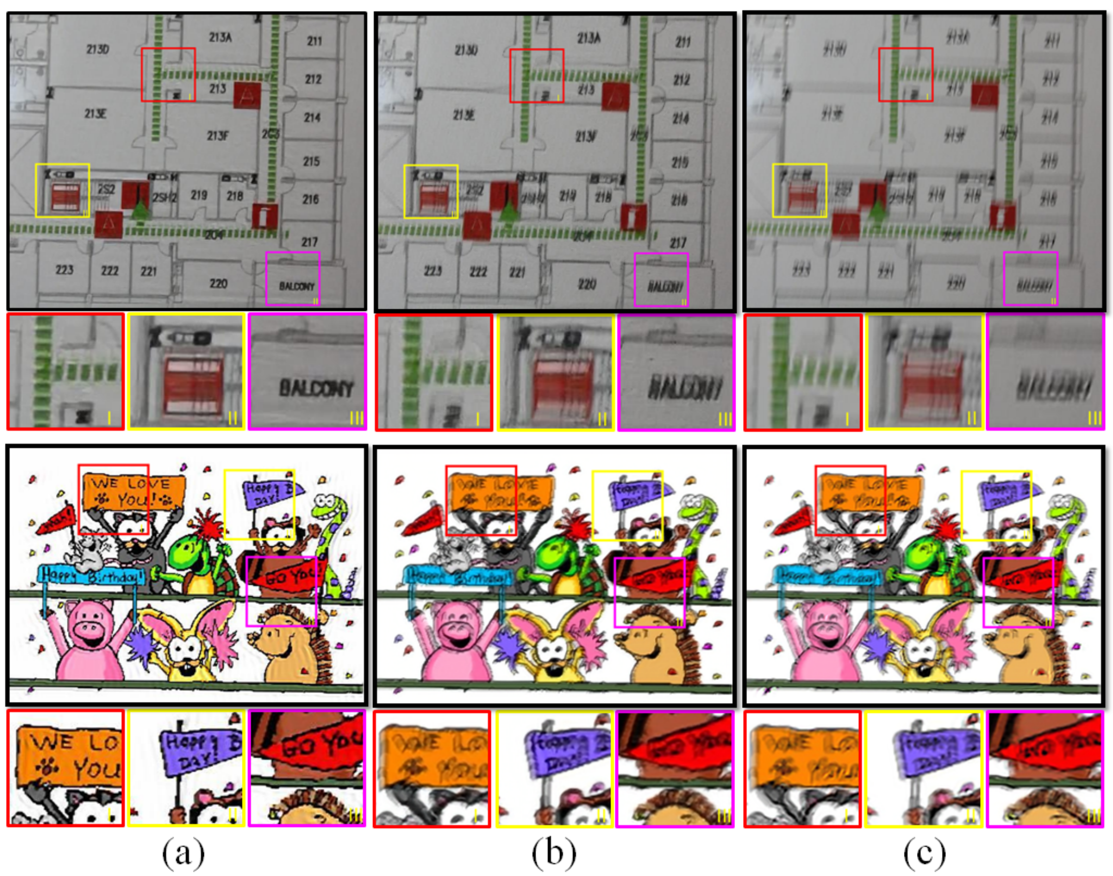
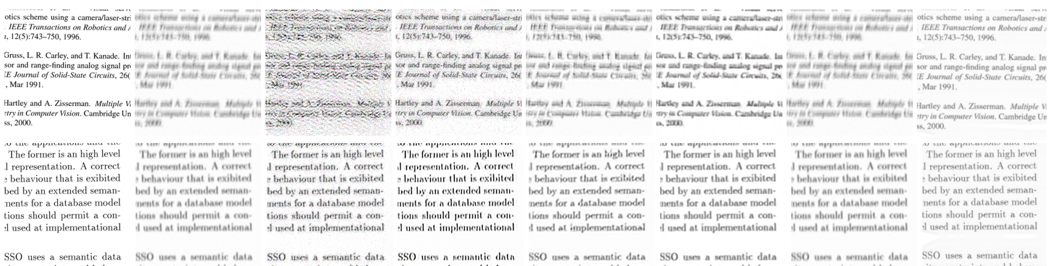


Fig. 2: Comparison of deblurred images by our unsupervised multi-adversarial deblurring method with other classical supervised and unsupervised approaches. (a) Deblurring results by our method. (b) Deblurring results using unsupervised GAN-based method [1]. (c) Deblurring results using supervised CNN-based method Sun *et al.* [2].

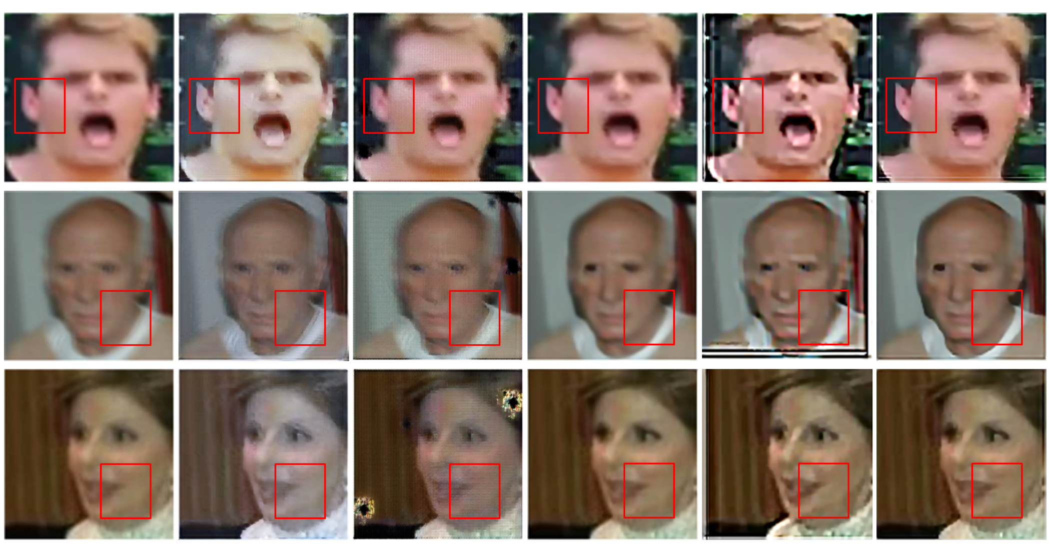
(a) (b) (c) (d)

Fig. 3: The visual effectiveness of different components in our model. (a) original CycleGAN (as baseline); (b) baseline + multi-adversarial loss; (c) item (b)+edge input and edge loss; (d) item (c)+MSSIM+perceptual loss. The experimental results show that the key components we proposed can effectively improve the overall deblurring effect.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4: Comparison of deblurred images by our method and other popular approaches on the images from BMVC_TEXT dataset [3]. (a) Blurred images. (b) Deblurring results using Pan [4]. (c) Deblurring results using Pan [5]. (d) Deblurring results using Xu [6]. (e) Deblurring results using Sun [2]. (f) Deblurring results using MS-CNN [7]. (g) Deblurring results using CycleGAN [1]. (h) Our results. It shows the characters in our results are much clearer.



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

Fig. 5: Comparison of deblurred images by our method and other popular approaches on several images from face dataset [8]. (a) Blurred images. (b) Deblurring results using CycleGAN [1]. (c) Deblurring results using DiscoGAN [9]. (d) Deblurring results using MS-CNN [7]. (e) Deblurring results using Pan [5]. (f) Deblurring results by our method.