Supplementary Material
Meta Transferring for Deblurring

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In this part, we provide additional material to supplement the main submission. First, we show the details of our reblur-deblur meta-transferring algorithm. Next, we analyze the effectiveness of applying meta-learning to the reblulrring model. Lastly, we present more qualitative deblurring results.

1 Reblur-deblur meta-transferring algorithm

Algorithm 1 and Algorithm 2 detail the proposed reblur-deblur meta-training and meta-testing scheme. In the meta-training stage, we regard delurring on each video V_i as a task to obtain task-specific (video-specific) model weights. We update the reblurring and deblurring models by the support set to produce adaptive model weights $\tilde{\theta}_i^{RB}$ and $\tilde{\theta}_i^{DB}$. Next, all the blurred frames in the video with the ground truth are used as the query set to meta-train the reblurring (θ^{RB}) and deblurring (θ^{DB}) models. In the meta-testing stage, we generate the support set as in the meta-training stage for any test video V_i^{test}. After the update, the meta-learned reblurring and deblurring models can adapt the task at inference time to obtain better results.

2 Analysis of reblurring model meta-learning

In table 1, we demonstrate the effectiveness of applying meta-learning to reblurring and deblurring models. We compared the results on the DVD dataset obtained using the deblurring models with 1) no meta-learning (denoted as “Baseline"), 2) the meta-learned deblurring

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Table 1: Comparisons among different meta-transferring schemes. We demonstrate the results obtained using various deblurring models with no meta-learning (Baseline), meta-learned deblurring (D meta), and meta-learned reblurring and deblurring (R+D meta).

Meta scheme	Baseline	D meta	R+D meta
MIMOUNet+	29.43	29.58 (+0.15)	29.70 (+0.27)
MPRNet	29.68	30.03 (+0.35)	30.04 (+0.36)
Restormer	29.67	29.91 (+0.24)	30.01 (+0.34)
CDVD-TSP	30.83	30.94 (+0.11)	30.97 (+0.13)

Algorithm 1: Reblur-deblur meta-training stage

Input : Training videos: $\{V_k\}_{k=1}^{I}$;
Pre-trained models: θ^{RB}, θ^{D}, and θ^{DB};
Learning rates: α and β;

while *not converged* **do**
  Sample a video $V_i = \{B_n, S_n\}_{n=1}^{N}$;
  Sample M pseudo-sharp patches and its neighboring patches $\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}_{m=1}^{M}$ from $\{B_n\}_{n=1}^{N}$ by self-shift;
  Initialization: $\{\tilde{\theta}_i^{RB}, \tilde{\theta}_i^{D}, \tilde{\theta}_i^{DB}\} = \{\theta^{RB}, \theta^{D}, \theta^{DB}\}$;
  foreach $m \in M$ **do**
    Generate pseudo-blurred patches: $\tilde{B}_{\Omega_m} = f^{RB}(\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}; \tilde{\theta}_i^{RB})$;
    Update by adversarial loss: $\tilde{\theta}_i^{D} = \tilde{\theta}_i^{D} - \alpha \nabla_{\tilde{\theta}_i^{D}} (\mathcal{L}_{adv})$;
    Update by reblurring loss: $\tilde{\theta}_i^{RB} = \tilde{\theta}_i^{RB} - \alpha \nabla_{\tilde{\theta}_i^{RB}} (\mathcal{L}_{RB})$;
  end
  foreach $m \in M$ **do**
    Generate pseudo-blurred patches $\tilde{B}_{\Omega_m} = f^{RB}(\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}; \tilde{\theta}_i^{RB})$;
    Update by deblurring loss:
    $\tilde{\theta}_i^{DB} = \tilde{\theta}_i^{DB} - \beta \nabla_{\tilde{\theta}_i^{DB}} (\mathcal{L}(f^{DB}(\tilde{B}_{\Omega_m}; \tilde{\theta}_i^{DB}),\ \tilde{S}_{\Omega_m}))$;
  end
  Validate the adapted models by whole $V_i = \{B_n, S_n\}_{n=1}^{N}$ and update:
  $\theta^{RB} = \theta^{RB} - \alpha \nabla_{\theta^{RB}} \sum_{n=1}^{N} \mathcal{L}_{char}(f^{RB}(S_n; \tilde{\theta}_i^{RB}),\ B_n)$;
  $\theta^{DB} = \theta^{DB} - \beta \nabla_{\theta^{DB}} \sum_{n=1}^{N} \mathcal{L}(f^{DB}(B_n; \tilde{\theta}_i^{DB}),\ S_n)$;
end

model (denoted as “D meta"), and 3) the meta-learned reblurring and deblurring models (denoted as “R+D meta"). As seen, updating both reblurring and deblurring models can produce better results for test-time adaptation.

3 Qualitative results on real-world dataset

In addition to the qualitative results on synthetic datasets in our main submission, Fig.8 shows more results on the RealBlur-J [4] dataset. The visual comparisons, obtained by state-of-the-art methods with or without our reblur-deblur meta-transferring scheme, demonstrate

Algorithm 2: Reblur-deblur meta-testing stage

Input : A test video: $V_i^{test} = \{B_n\}_{n=1}^N$;
Meta-trained model: θ^{RB}, θ^{DB},
Pre-trained discriminator: θ^D;
Learning rates: α and β;

Sample M pseudo-sharp patches and its neighboring patches $\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}_{m=1}^M$ from $\{B_n\}_{n=1}^N$ by self-shift;
Initialization: $\{\tilde{\theta}_{test}^{RB}, \tilde{\theta}_{test}^{D}, \tilde{\theta}_{test}^{DB}\} = \{\theta^{RB}, \theta^{D}, \theta^{DB}\}$;
foreach $m \in M$ **do**
  Generate pseudo-blurred patches $\tilde{B}_{\Omega_m} = f^{RB}(\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}; \tilde{\theta}_{test}^{RB})$;
  Update by adversarial loss: $\tilde{\theta}_{test}^{D} = \tilde{\theta}_{test}^{D} - \alpha \nabla_{\tilde{\theta}_{test}^{D}} (\mathcal{L}^{adv})$;
  Update by reblurring loss: $\tilde{\theta}_{test}^{RB} = \tilde{\theta}_{test}^{RB} - \alpha \nabla_{\tilde{\theta}_{test}^{RB}} (\mathcal{L}^{RB})$;
end
foreach $m \in M$ **do**
  Generate pseudo-blurred patches $B_m^P = f^{RB}(\{\tilde{S}_{\Omega_{m,t-2}}, ..., \tilde{S}_{\Omega_{m,t+2}}\}; \tilde{\theta}_{test}^{RB})$;
  Update by deblurring loss:
  $\tilde{\theta}_{test}^{DB} = \tilde{\theta}_{test}^{DB} - \beta \nabla_{\tilde{\theta}_{test}^{DB}} (\mathcal{L}(f^{DB}(\tilde{B}_{\Omega_m}; \tilde{\theta}_{test}^{DB}),\ \tilde{S}_{\Omega_m}))$;
end
Complete deblurring by the adapted weights: $\{O_n = f^{DB}(B_n; \tilde{\theta}_{test}^{DB})\}_{n=1}^N$

the proposed approach can restore the degraded images better. Our method utilizes rich internal information to boost performance for real blurred images never seen before.

4 Qualitative results on synthetic datasets

In this section, we provide more visual results on synthetic datasets, including DVD [5] and REDS [2]. The visual comparisons, obtained by state-of-the-art methods with or without our reblur-deblur meta-transferring scheme, demonstrate the proposed approach can restore the degraded images better.

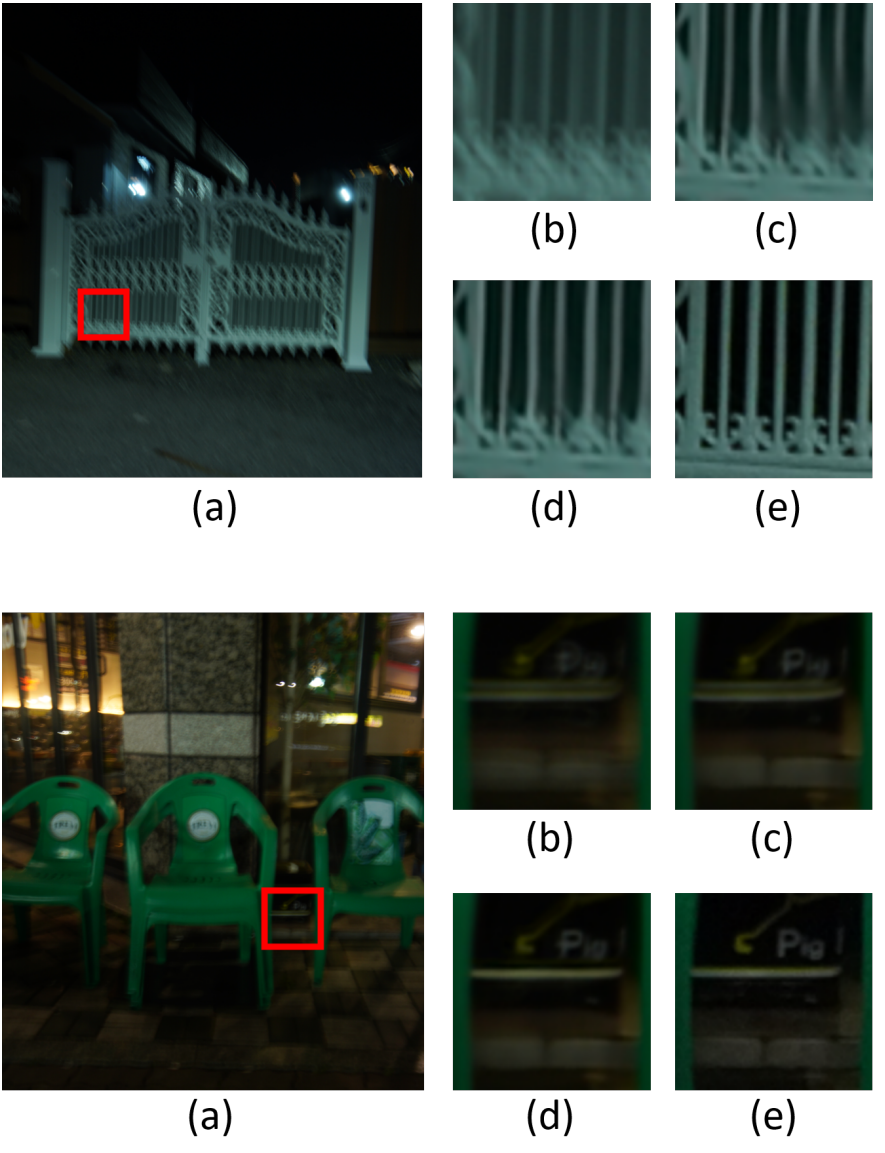

Figure 1: Qualitative comparisons of MPRNet [8] deblurring results on RealBlur-J datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

Figure 2: Qualitative comparisons of MIMOUNet+ [11] deblurring results on RealBlur-J datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

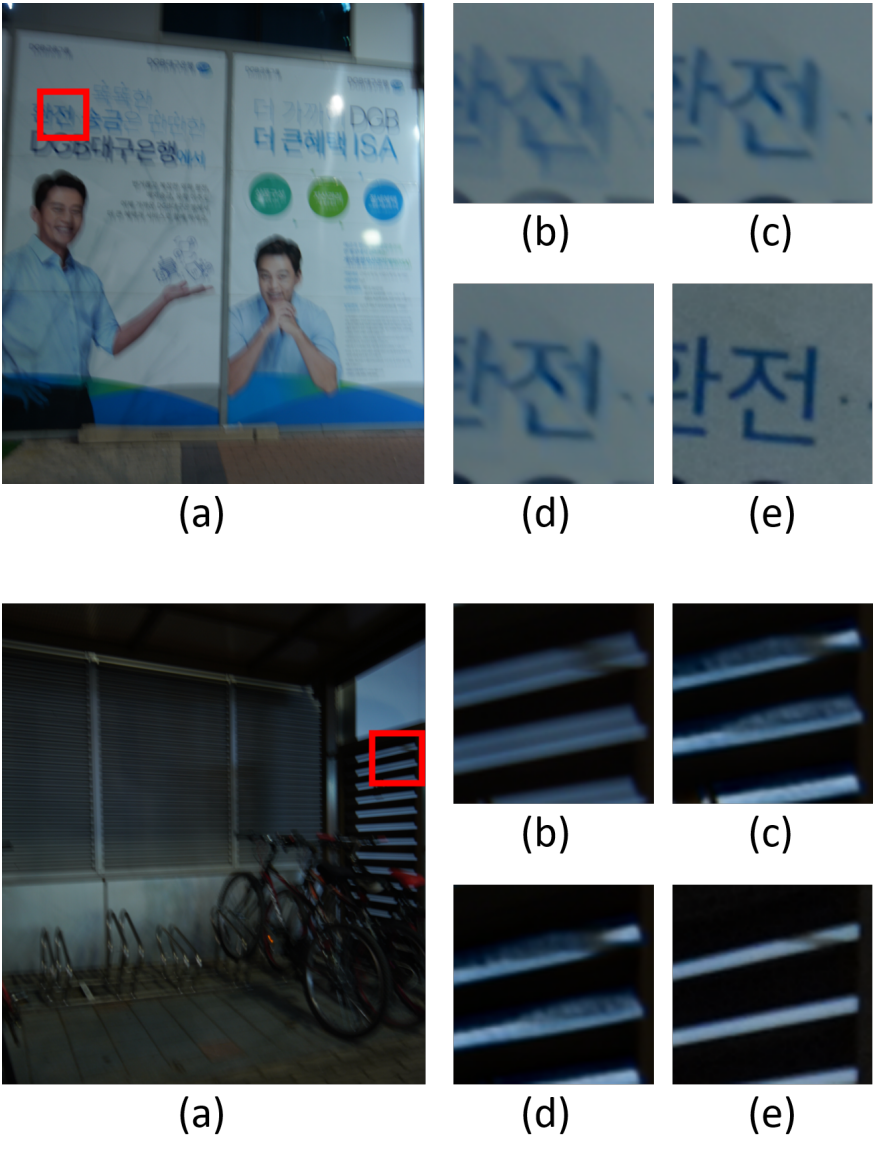

Figure 3: Qualitative comparisons of Restormer [7] deblurring results on RealBlur-J datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

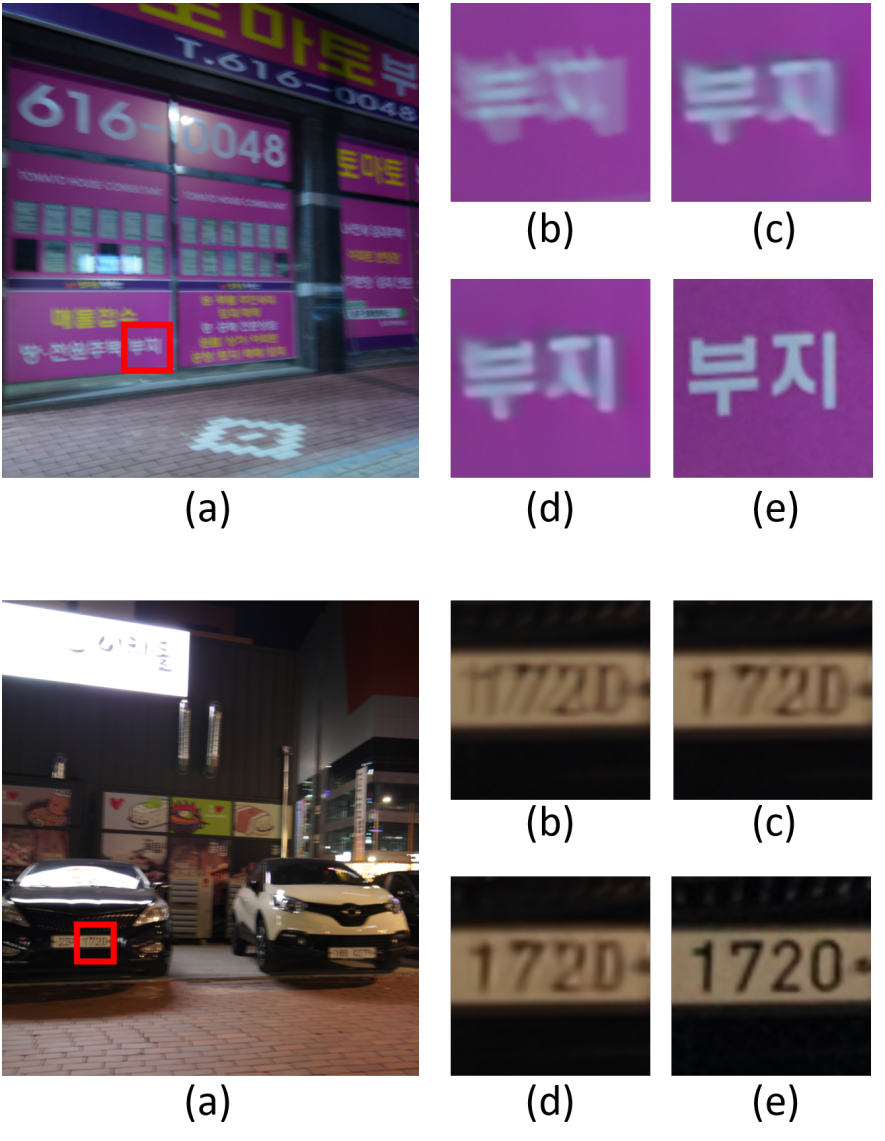

Figure 4: Qualitative comparisons of CDVD-TSP [3] deblurring results on RealBlur-J datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

Figure 5: Qualitative comparisons of MPRNet [6] deblurring results on DVD and REDS datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

Figure 6: Qualitative comparisons of MIMOUNet+ [11] deblurring results on DVD and REDS datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

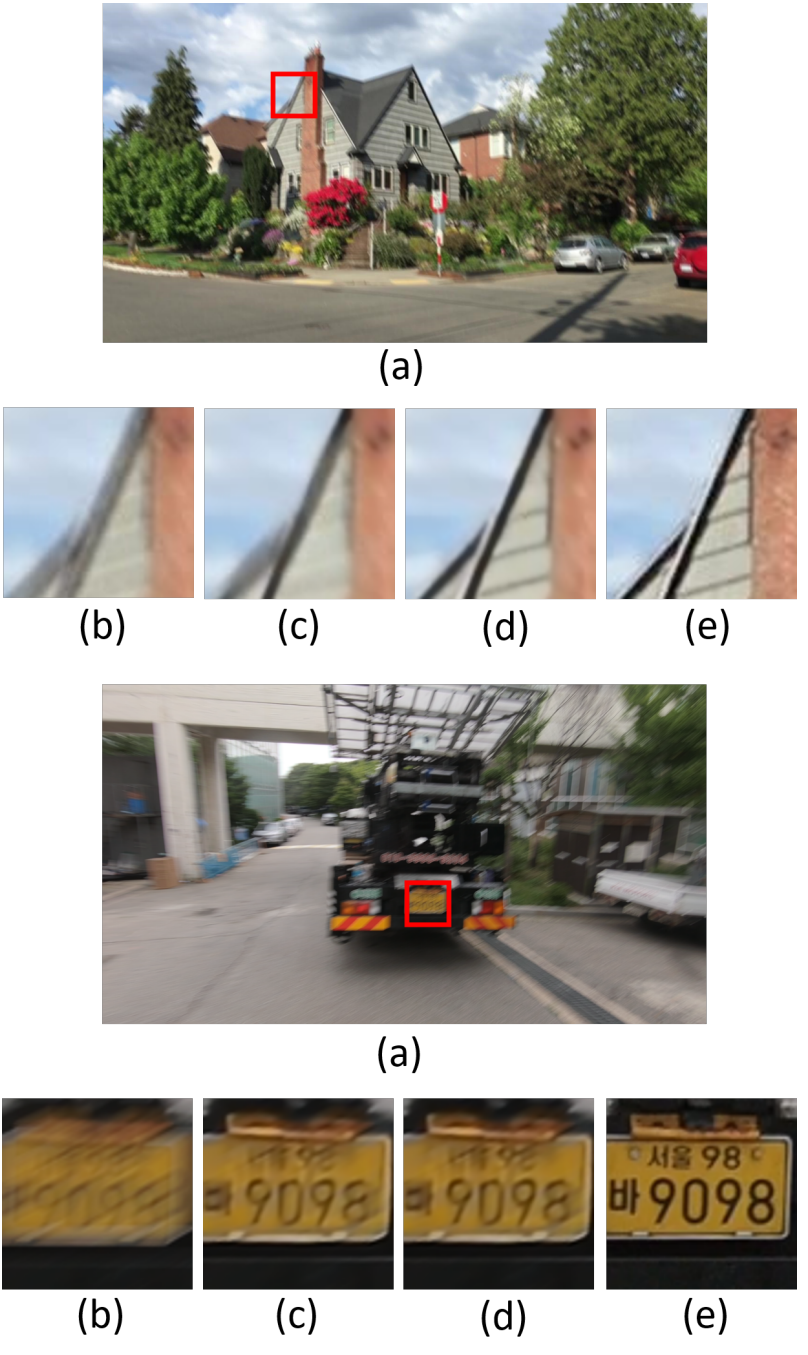

Figure 7: Qualitative comparisons of Restormer [7] deblurring results on DVD and REDS datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

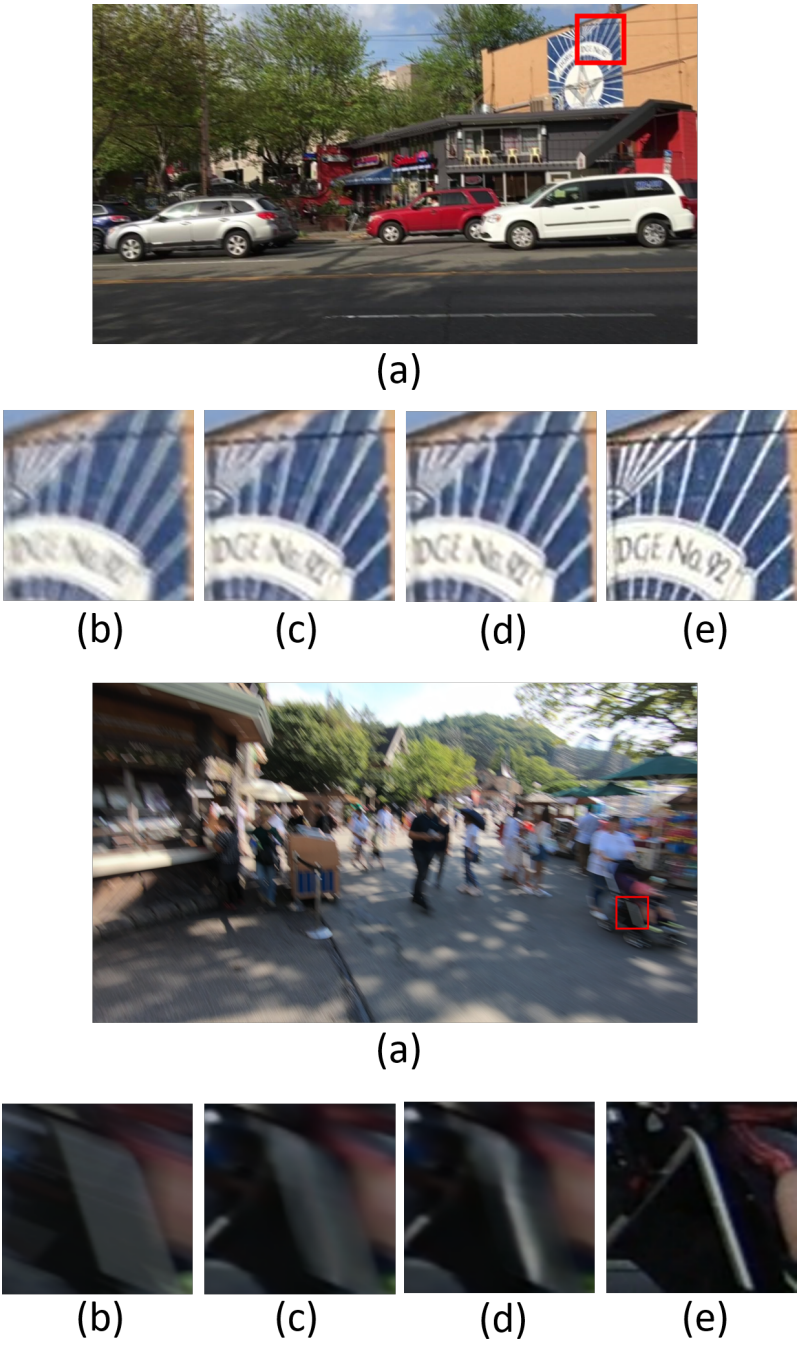

Figure 8: Qualitative comparisons of CDVD-TSP [3] deblurring results on DVD and REDS datasets. (a) Blurred input. (b) A zoom-in blurred patch, and its deblurred results using (c) Baseline and (d) Baseline /w our meta-transferring scheme. (e) Ground truth.

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