Meta Transferring for Deblurring

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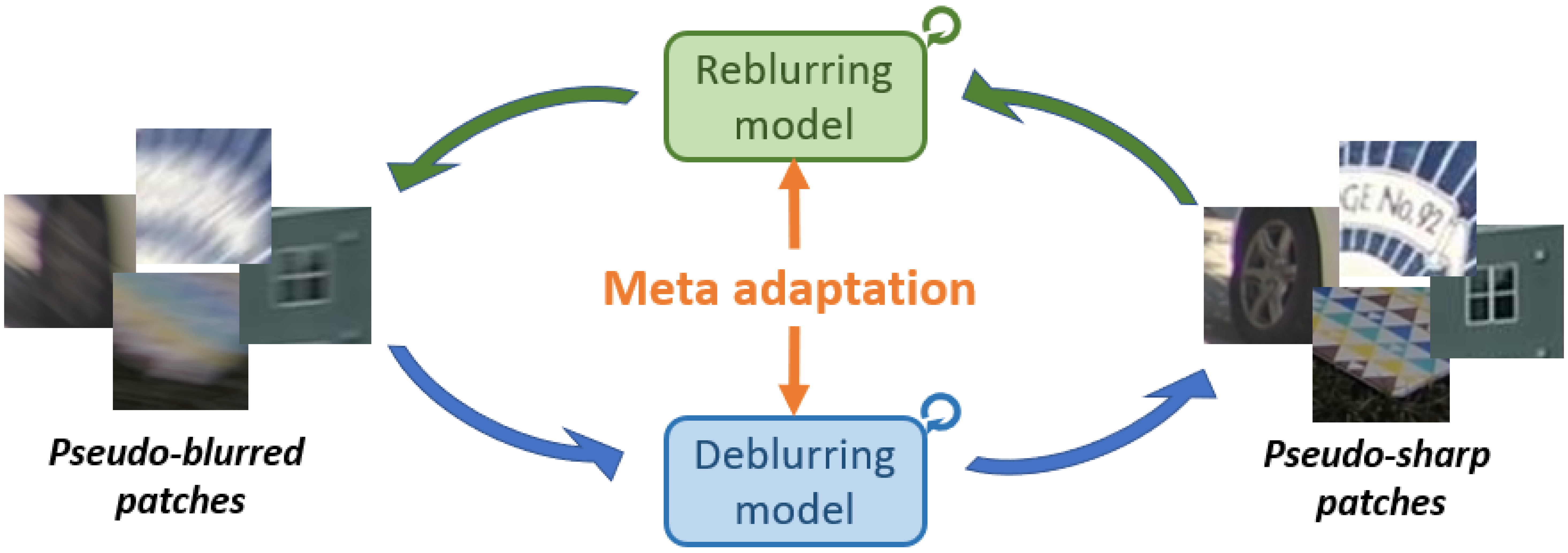
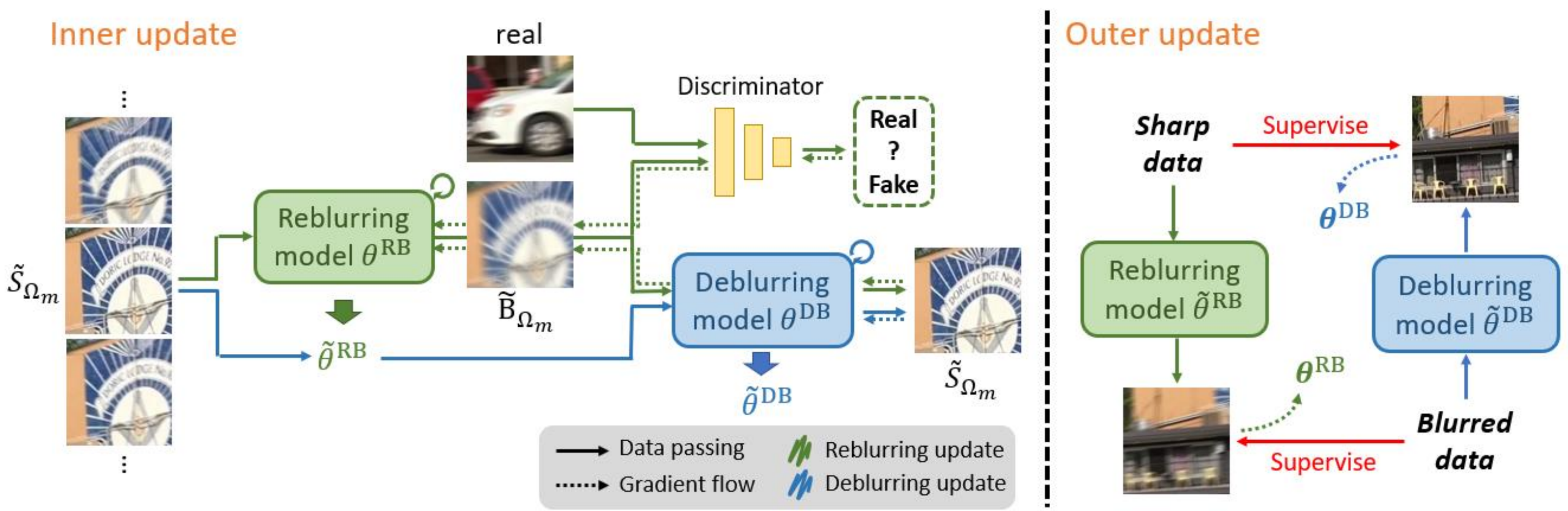


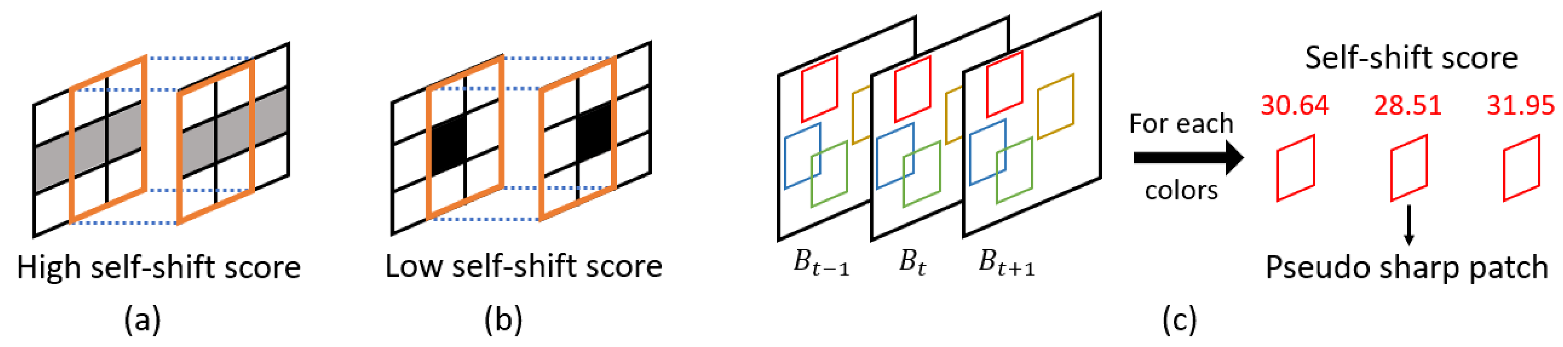
Introduction

This work proposes a reblur-deblur meta-transferring scheme to generate pseudo-blurred and pseudo-sharp pairs to achieve test-time adaptation in meta-learning. Our reblurring model can transfer blurred patterns homogeneous to the task to pseudo-sharp patches selected to synthesize pseudo-blurred patches, which can serve as pseudo-sharp-and-blurred pairs as the support set in meta-learning. Our contributions are three-fold. First, we propose a novel reblur-deblur meta-transferring scheme that can generate pseudo-blurred and pseudo-sharp pairs for meta-learning. Second, the proposed scheme facilitates meta-learning for dynamic scene deblurring without extra training data needed. Third, extensive experimental results show that our method improves the performance of existing deblurring models on various datasets, including DVD, REDS and RealBlur-J.

Proposed Method



The paper proposes a reblur-deblur meta-transferring scheme for test-time adaptation, composed of meta-training and meta-testing phases. In a meta-training scenario, we consider deblurring each video in the training set as a task. Figure above depicts the proposed reblur-deblur meta-transferring training scheme, where the inner update trains a deblurring model on the support set generated by the reblurring model, and the outer update trains the deblurring and reblurring models adapted to the query set. Because of no ground truth at inference, we instead use the proposed reblurring model to generate pseudo-blurred patches from pseudo-sharp patches selected from blurred video frames.



Based on our observation that a scene often has various blurring degrees in multiple frames in a blurred video, we can pick relatively sharp patches in blurred frames to be pseudo-sharp patches. To choose sharp patches, we propose to measure the blurring degree by a self-shift method, as shown in above figure, and those with the least blur are selected. The method simulates the idea of image gradient. The sharp images usually have a smaller PSNR score with the shifted images. The relatively sharp and blur patches are used to update reblurring model by adversarial loss and cycle loss to create pseudo-blurred patches. These pseudo-blurred and pseudo-sharp are then used as the support set to update deblurring model. For the query set, we use the whole video frames to evaluate the effectiveness of adaptive reblurring and deblurring models. In meta-testing, given any testing video, we update reblurring model and deblurring model as in the meta-training phase to adapt to testing video, without using the ground truth. Lastly, we inference the testing blurred images of current video on the adaptive models.

Experimental Results

Evaluation results on three datasets and four SOTA deblurring models. "Baseline" means the deblurring results obtained using the original models pre-trained on GoPro. "Meta" means the results using "Baseline" with our reblur-deblur meta-transferring scheme.

		DVD		REDS		RealBlur-J	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
MIMOUNet+	Baseline	29.43	0.914	26.43	0.859	27.63	0.837
	Meta	**29.70**	**0.917**	**26.73**	0.859	**28.11**	**0.851**
MPRNet	Baseline	29.68	0.918	26.85	0.864	28.70	0.873
	Meta	**30.04**	**0.921**	**27.05**	0.864	**28.75**	**0.876**
Restormer	Baseline	29.67	0.916	26.93	0.867	28.96	0.879
	Meta	**30.01**	**0.921**	**27.21**	0.867	**29.07**	**0.885**
CDVD-TSP	Baseline	30.86	0.938	27.17	0.891	28.69	0.873
	Meta	**30.97**	**0.939**	**27.52**	**0.892**	**29.15**	**0.887**