Adaptive Network Combination for Single-Image Reflection Removal: A Domain Generalization Perspective

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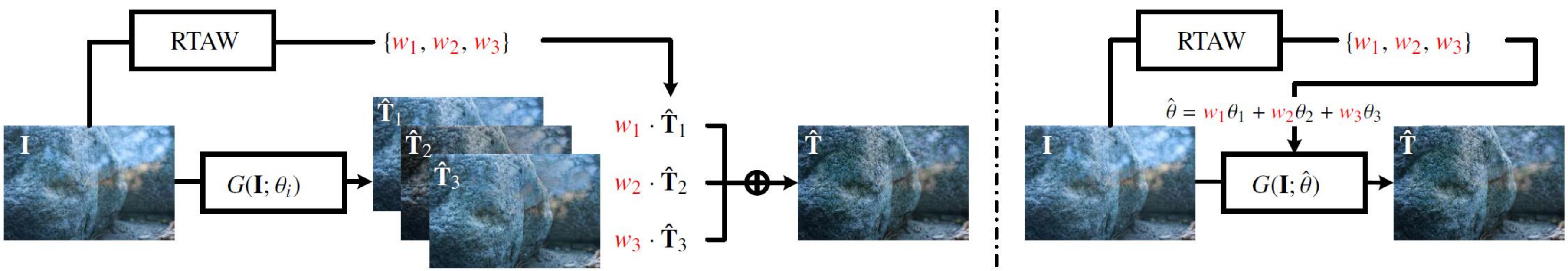
Problems & Ideas

- Problems of conventional reflection removal approaches:
  - Domain gaps of reflection types in various training sets are neglected.
  - The pre-trained models are fixed during inference, which cannot adapt to the test image flexibly.
- Ideas: Train a domain expert for each domain and process the test image by adaptively combining the domain experts. The leave-one-domain-out method and an in-domain expert loss are deployed for training.



Two network combination methods are presented. Left: the output fusion scheme mixes the output of each domain expert, where the weights are predicted by a reflection type-aware weighting module. Right: the network interpolation scheme first obtains a particular model by interpolating the parameters, and then the input image is processed by the model within a single forward pass.

Main Contributions

- Contributions:
  - By analyzing the diversity of existing SIRR datasets, we propose to learn single-image reflection removal (SIRR) models from a domain generalization perspective, and provide adaptive network combination (AdaNEC) methods for combining multiple domain experts during inference;
  - A reflection type-aware weighting (RTAW) module is presented to predict expert-wise weights for AdaNEC. An in-domain expert (IDE) loss is further introduced for training RTAW, which is also applicable to domain generalization in high-level vision tasks;

Method	*Real20* (20)		*Wild* (55)		*Postcard* (199)		*Solid* (200)		*Nature20* (20)		Average (474/494)	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
ERRNet [5]	22.07	0.781	25.13	0.889	22.76	0.864	24.62	0.898	20.86	0.757	23.79	0.877
$\text{ERRNet}_{\text{OF}}$ w/o $\bar{w}_i$	22.70	**0.791**	24.60	0.865	**23.15**	0.871	24.91	0.895	20.46	0.756	24.04	0.877
$\text{ERRNet}_{\text{OF}}$	**22.80**	0.790	**25.26**	**0.890**	23.08	**0.874**	**25.26**	**0.904**	**20.99**	**0.768**	**24.24**	**0.885**
$\text{ERRNet}_{\text{NI}}$ w/o $\bar{w}_i$	22.37	0.787	24.63	0.865	23.14	0.874	24.75	0.894	20.53	0.757	23.96	0.878
$\text{ERRNet}_{\text{NI}}$	**22.81**	**0.791**	**25.69**	**0.895**	**23.56**	**0.884**	**25.13**	**0.902**	**21.20**	**0.771**	**24.44**	**0.889**

The proposed method can boost the performance of existing methods by a large margin, where the training data and testing protocol are identical to the backbone method. Besides, by solving the problem from a domain generalization perspective, our method performs well on unseen data (e.g., Nature20). Please refer to the paper for more results.