Aerial Image Dehazing with Attentive Deformable Transformers

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Supplementary Material

Overview

The supplementary material contains:

- Conceptual Differences between Proposed Method and Existing Methods
- Loss Functions
- More Discussion about Ablation Study
- More Qualitative Results

1 Conceptual Differences between Proposed Method and Existing Methods

The conceptual differences between the networks of the existing methods and the proposed method are provided in Table S 1. The proposed method incorporates all the essential blocks required for effective aerial image dehazing.

2 Loss Functions

We train the proposed network using L_1 loss ($\mathbb{L}_1$), edge loss ($\mathbb{L}_{Edge}$) and perceptual loss ($\mathbb{L}_p$). The detailed equations of these loss functions are:

2.1 L_1 Loss

$\mathbb{L}_1$ loss aims at reduction of the per pixel difference between the output image (I_O) and ground truth (I_{GT}), which can be formulated as:

$$\mathbb{L}_1 = \|I_O - I_{GT}\|_1 \tag{1}$$

2.2 Edge Loss

Edge loss ($\mathbb{L}_{Edge}$) aims at improving the edge details by calculating the discrepancies between edges of the output image and ground truth image. It can be represented as:

$$\mathbb{L}_{Edge} = \|\psi(I_O) - \psi(I_{GT})\|_1 \tag{2}$$

where, $\psi(\cdot)$ is Sobel operator.

2.3 Perceptual Loss

The perceptual loss ($\mathbb{L}_P$) aims at improving the perceptual quality of the output by calculating the differences between output and ground truth at various feature levels. The pretrained layers of VGG-16 [1] model are used as feature space for the loss calculation. The perceptual loss can be represented mathematically as:

$$\mathbb{L}_P = \left\|\Phi_{i\in(3,8,15)}(I_O) - \Phi_{i\in(3,8,15)}(I_{GT})\right\|_1 \tag{3}$$

where, $\Phi_i(\cdot)$ is i^{th} layer of VGG-16 model.

3 More Discussion about Ablation Study

The description regarding which blocks and loss functions are used in each network setting in ablation study is provided in Table S 2.

Method	**Publication**	**Local Dependency**	**Global Dependency**	**Geometric Adaptability**	**Edge Boosting Skip Connections**
SPA-GAN [7]	-	✓	×	×	×
Huang *et al.* [9]	WACV-20	✓	×	×	×
SkyGAN [10]	WACV-21	✓	×	×	×
UFormer [8]	CVPR-22	✓	✓	×	×
Proposed Method	-	✓	✓	✓	✓

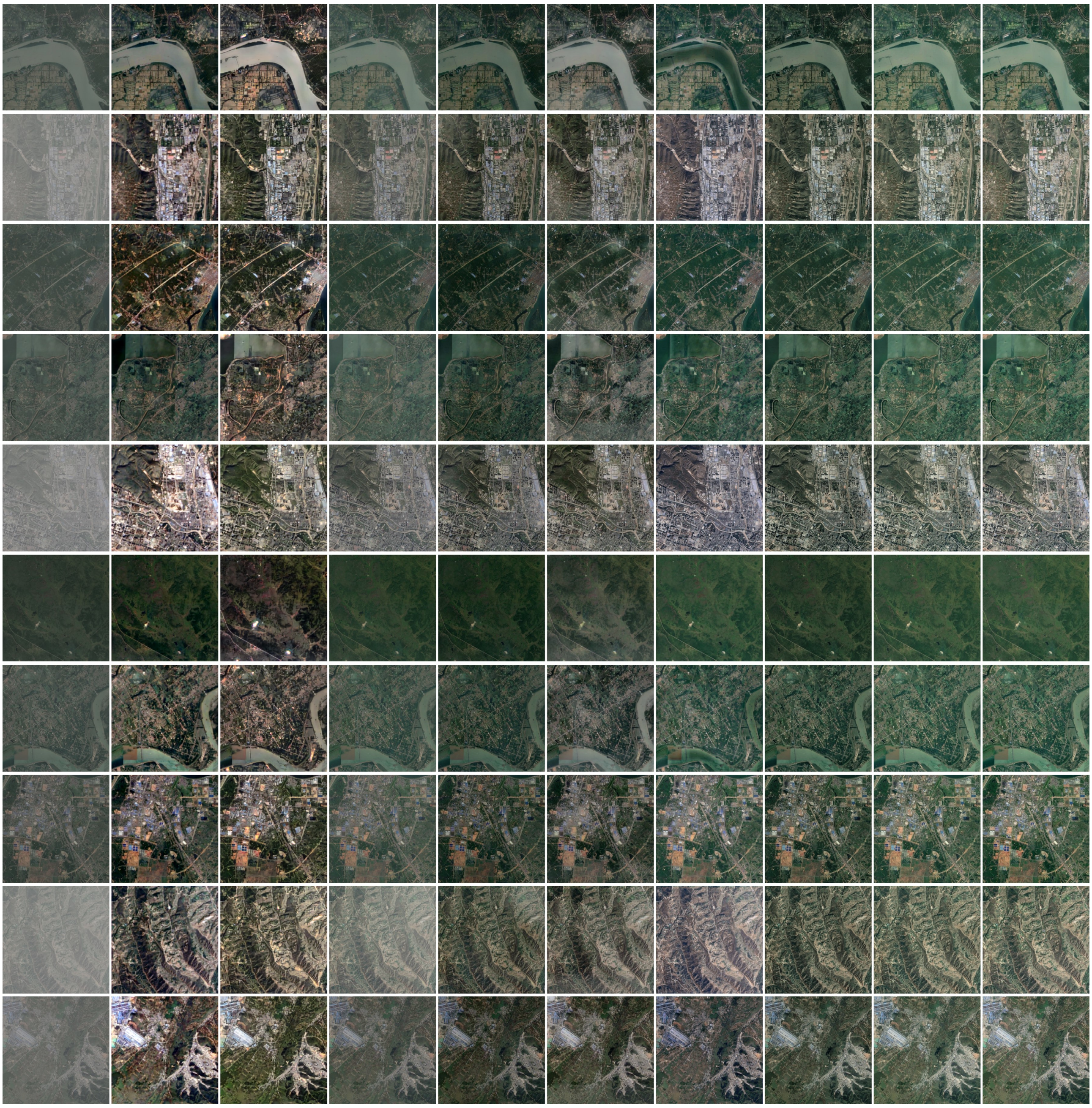
Table S 1: Conceptual comparison of the proposed method with existing state-of-the-art methods.

Setting	**Attention Type**	**Offset Extraction Type**	**Skip Connection Type**	**Loss Functions**
Network 1	Vanilla Attention [11]	Spatially Attentive	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 2	DW-MSA [8]	Spatially Attentive	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 3	Deformable MSA	Deformable [12]	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 4	Deformable MSA	Modulated Deformable [13]	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 5	Deformable MSA	Spatially Attentive	No Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 6	Deformable MSA	Spatially Attentive	Regular Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$
Network 7	Deformable MSA	Spatially Attentive	Edge Boosting Skip Connection	$\mathbb{L}_1$
Network 8	Deformable MSA	Spatially Attentive	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge}$
Proposed	Deformable MSA	Spatially Attentive	Edge Boosting Skip Connection	$\mathbb{L}_1 + \mathbb{L}_{Edge} + \mathbb{L}_P$

Table S 2: Details regarding modules and losses used in each network setting *(DW-MSA: DepthWise convolution based Multi-head Self Attention)*.

4 More Qualitative Results

We provide more qualitative results on RICE dataset for aerial haze removal in Figure S 1. We compare the qualitative results with state-of-the-art methods GCANet [2], USID [3], MSBDN [4], TSDNet [5], RDNet [6], SPA-GAN [7] and UFormer [8]. As seen from the results, the proposed method is able to maintain more spatial content and color balance.



Input GCANet [2] USID [3] MSBDN [4] TSDNet [5] RDNet [6] SPA-GAN [7] UFormer [8] Ours Ground Truth

Figure S 1: Qualitative results comparison of the proposed method with existing state-of-the-art methods on RICE dataset for aerial haze removal.

References

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