Paper #8620

Unsupervised Remote Sensing Haze Removal Based on Saliecy-Guided Transmission Refinement

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17 April, 2024

1 Introduction

Introduction

Remote Sensing Haze Removal

In the realm of remote sensing, the quality of images captured can often be compromised by atmospheric conditions such as haze.

This not only affects the visual appeal but also hinders the extraction of valuable information from these images.

Introduction

Current Dehazing Methods

- Prior-based methods

Extract haze features manually and conclude the priors to dehaze.

- Learning-based methods

The supervised learning-based methods have great performances but rely on haze-free references in training.

To avoid this defect, several unsupervised methods are proposed.

Introduction

Current Dehazing Methods

- Prior-based methods

Prior-based methods use models to describe the cause of haze. The commonly used model is the atmospheric scattering model.

To estimate the parameters in atmospheric scattering model, several methods based on prior theories such as dark channel priorare proposed. These methods extract haze features manually and conclude the priors to dehaze.

Introduction

Current Dehazing Methods

- Learning-based methods

With the development of deep neural networks, learning-based methods have appeared in recent years. The supervised learning-based methods have great performances but rely on haze-free references in training.

To avoid this defect, several unsupervised methods are proposed.

Introduction

Unsupervised Learning-based methods

Current unsupervised methods are designed for natural scene dehazing but are not applied to remote sensing images because of the differences in imaging mechanisms.

- Complex mapping relationships

- Abundant texture and spectrum information

Introduction

Major Innovations

a) We propose an unsupervised framework for remote sensing image dehazing. Our approach effectively preserves the rich texture and spectrum information through transmission refinement.

b) A saliency-guided transmission refinement method enhances the accuracy of transmission estimation. It decomposes transmission maps under different conditions and recombines them using saliency guidance.

c) We propose a loss function that consists of energy loss and texture loss. The energy loss component provides an energy reference, and the texture loss improves the preservation of texture details.

2 Methodology

Methodology

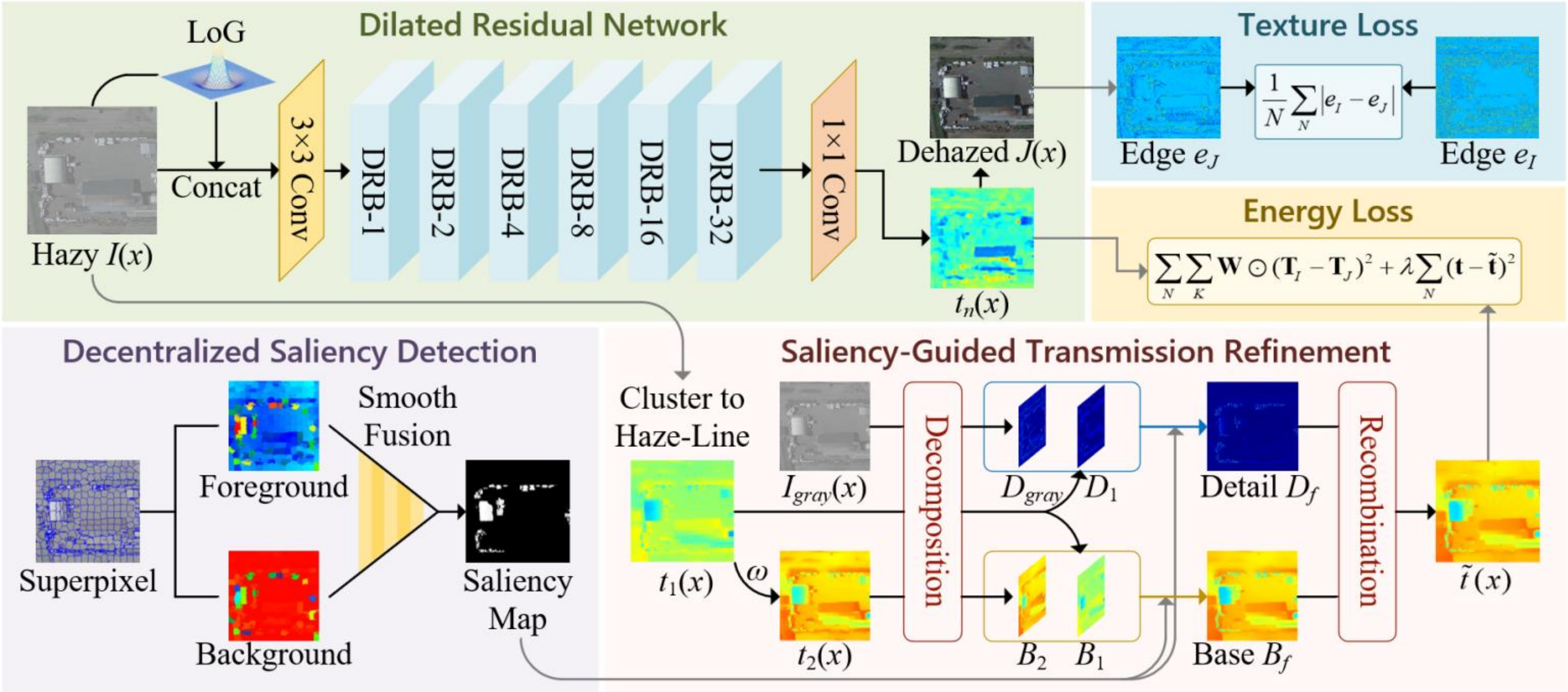


Fig. 1. The framework of the proposed method.

Methodology

2.1 Haze Model of Remote Sensing Images

The universal atmospheric scattering model:

$$\mathbf{I}(x) = t(x) \cdot \mathbf{J}(x) + [1 - t(x)] \cdot \mathbf{A} \tag{1}$$

According to the non-local prior:

$$r_{\max} = \max_{x \in H}[r(x)] = \left\| \mathbf{J}(x) - \mathbf{A} \right\| \tag{2}$$

Introduce a suppression parameter ω to suppress energy over-reduction for remote sensing images:

$$t_2(x) = \omega t_1(x) = \frac{\omega r(x)}{r_{\max}} \tag{3}$$

2.2 Decentralized Saliency Detection

Background:

$$\overline{s}(p) = 1 - \exp\left[-\frac{\sum_{i=1}^{N} d^2(p, p_i)}{2\sigma_b^2} \right] \quad (4)$$

Foreground:

$$s(p) = \sum_{i=1}^{N} d_c(p, p_i) \exp\left[-\frac{d_s^2(p, p_i)}{2\sigma_s^2} \right] \quad (5)$$

Smooth weight:

$$w(p,q) = \exp\left[-\frac{d_c^2(p,q)}{2\sigma_c^2} \right] + \lambda \quad (6)$$

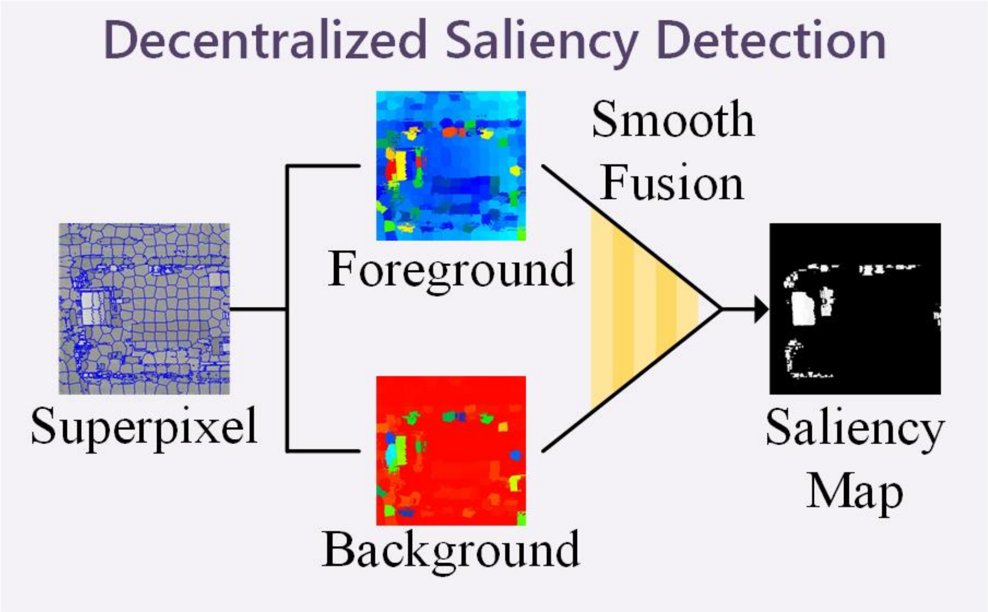


Fig. 2. Decentralized saliency detection.

2.3. Saliency-Guided Transmission Refinement

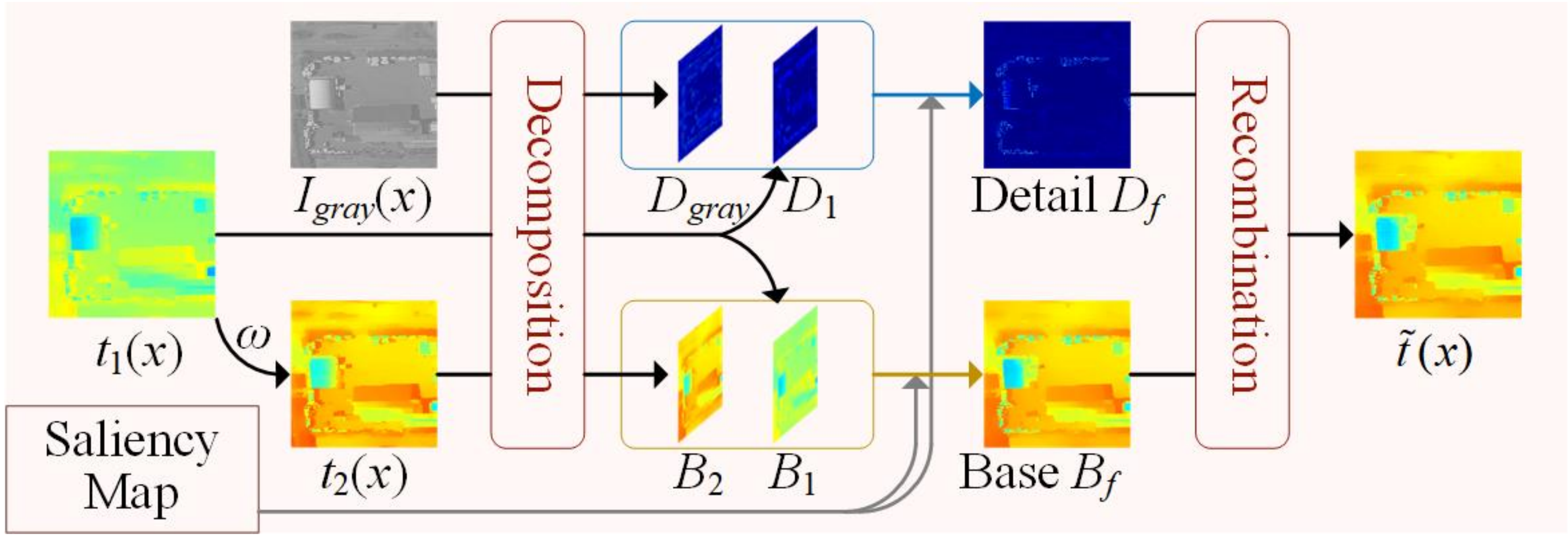


Fig. 3. Saliency-Guided Transmission Refinement.

Decomposition:

$$B = \frac{1}{2}[F^{BF}_{\sigma_s,\sigma_r}(I) + F^{WLSF}_{\lambda}(I)] \quad (7)$$

$$D = I - B \quad (8)$$

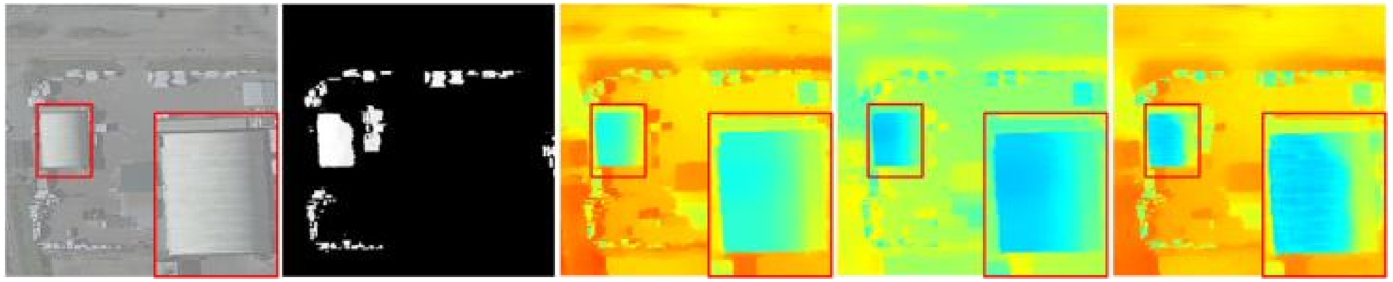
Recombination:

$$B_f = \alpha B_1 + (1-\alpha)B_2 \quad (9)$$

$$D_f = \frac{1}{4}(1-\alpha)(D_1 + D_{gray}) + \alpha D_{gray} \quad (10)$$

Methodology

2.3. Saliency-Guided Transmission Refinement



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

Fig. 4. Results of saliency-guided transmission refinement. (a) Hazy image. (b) Saliency Map. (c) $t_1(x)$. (d) $t_2(x)$. (e) $\tilde{t}(x)$.

After transmission refinement, color distortions in the base layer are effectively suppressed, and the texture in the detail layer is better preserved.

Methodology

2.4. Network and Loss Function

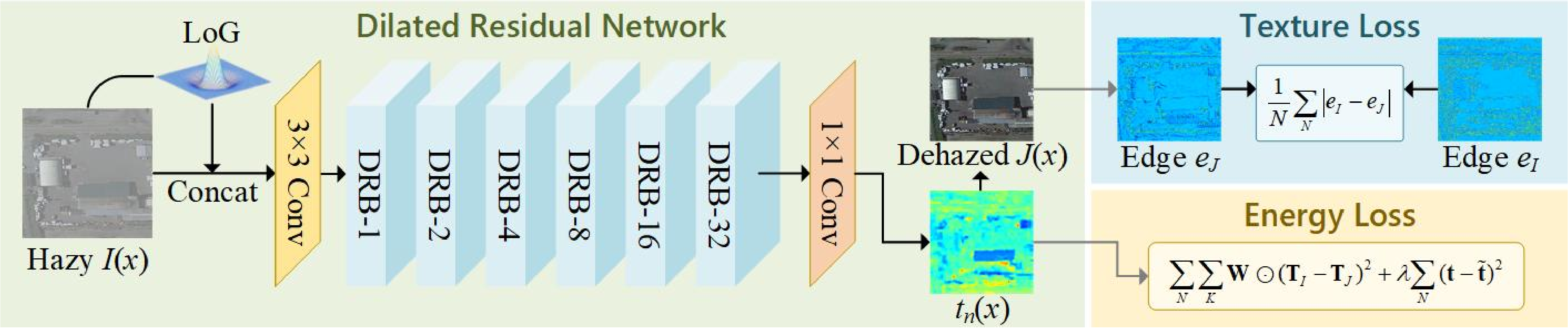


Fig. 5. Network and loss funtion.

2.4. Network and Loss Function

We input an extra texture channel extracted by the Laplacian of Gaussian (LoG) filter from the hazy image to enhance the learning of texture.

Then there are 6 dilated residual blocks (DRBs), each containing 2 convolution layers and a dilated convolution layer. The kernel size of the layers above is 3×3.

The batch normalization (BN) and ReLU are set after convolution, while only BN is set after dilated convolution. At last, a 1×1 convolutional layer obtains the transmission map $t_n(x)$.

Finally, we get the airlight A by the method in DCP and calculate haze-free image $J(x)$ by (1).

2.4. Network and Loss Function

The loss function of the network combines the energy loss with the texture loss.

The energy loss is transformed from the energy function of image matting:

$$L_e = \sum_N \sum_K \mathbf{W} \odot (\mathbf{T}_I - \mathbf{T}_J)^2 + \lambda \sum_N (\mathbf{t} - \tilde{\mathbf{t}})^2 \tag{11}$$

The texture loss is calculated from the edge maps obtained by the Laplacian of Gaussian filter:

$$L_t = \frac{1}{N} \sum_N \left| e_I - e_J \right| \tag{12}$$

3 Experiments

Experiments

Table 1. Average evaluation statistics on test dataset.

Type	Prior-based	Supervised		Unsupervised			
Method	SLP	FFA	MCFN	DCPL	RDN	USID	Ours
PSNR	14.85	**27.43**	23.63	20.42	21.73	19.89	<u>23.63</u>
SSIM	0.6343	**0.8721**	0.8421	0.8089	0.8291	0.6928	<u>0.8473</u>
FSIM	0.8407	<u>0.9830</u>	0.9665	0.9389	0.9699	0.8666	**0.9887**
DAQ	0.8095	0.8848	0.7961	0.8142	**0.9274**	0.8549	<u>0.8962</u>

Experiments

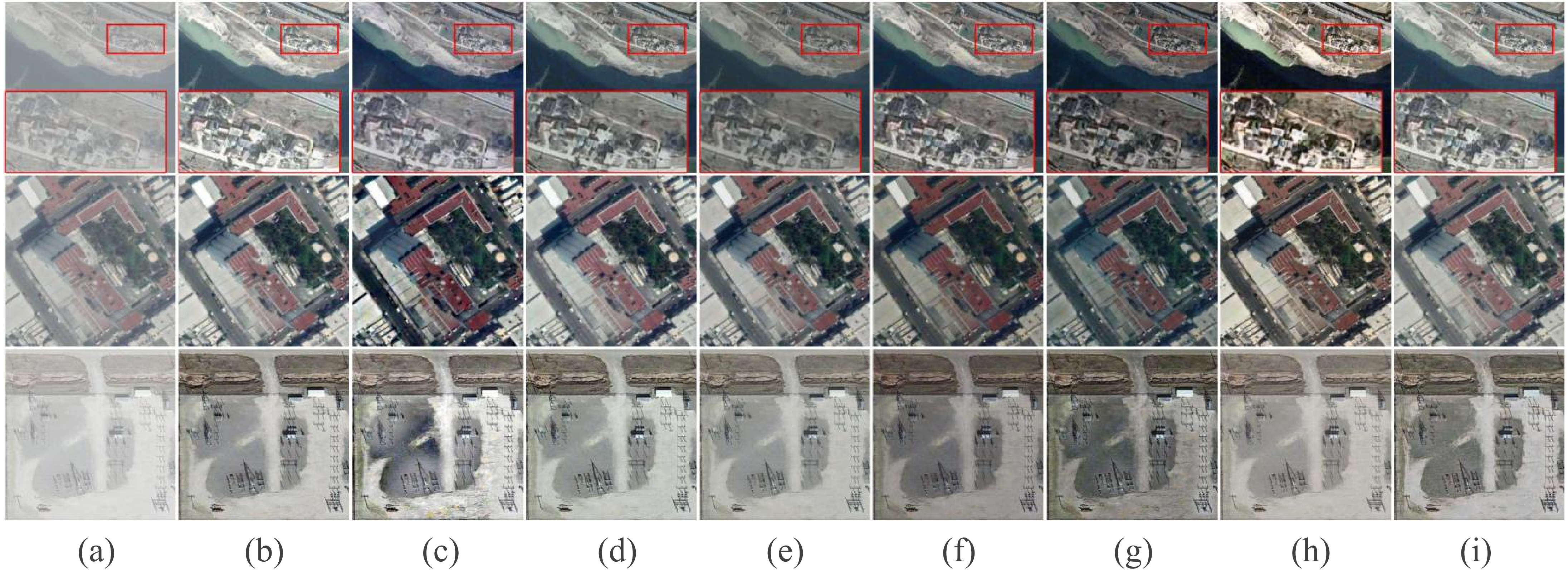


Fig. 6. Results of different dehazing methods on remote sensing images. (a) Hazy images. (b) Clear images. (c) SLP. (d) FFA-Net. (e) MCFN. (f) DCPL. (g) RDN. (h) USID-Net. (i) Our method.

Experiments

Table 2. Ablation study about various configurations.

DRB	STR	Texture Loss	PSNR	SSIM
			20.68	0.8144
√			21.52	0.8325
√	√		23.41	0.8456
√		√	23.46	0.8460
√	√	√	**23.63**	**0.8473**

4 Conclusion

Conclusion

In this paper, an unsupervised remote sensing image dehazing method based on saliency-guided transmission refinement is proposed.

Transmission refinement detects the regions rich in texture information and improves the fineness of transmission. Then we design a loss function containing energy loss and texture loss, which provides energy reference from the coarse transmission as well as improves learning ability to texture.

Experiments verify that the proposed method has outstanding visual performance, and can restore the color information as well as preserve the texture details.

Thank you for listening!