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S2A: Wasserstein GAN with Spatio-Spectral Laplacian Attention for Multi-Spectral Band Synthesis

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Content

Introduction

What is attention learning?

Attention learning is a human vision inspired algorithm that learns to automatically attend to relevant attributes of an object.

- Attention learning has not received much attention, despite its remarkable progress.
- Explore attention learning in multi-spectral super-resolution.
- Direct super-resolution is intractable.
- Reformulate as conditional multi-spectral band synthesis.

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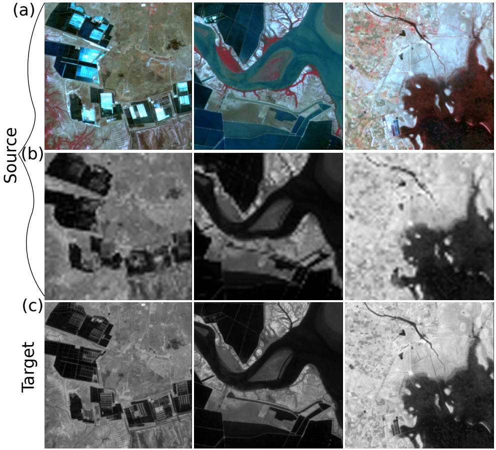

Figure: Paired training data.

Proposed Methodology

Overall Pipeline

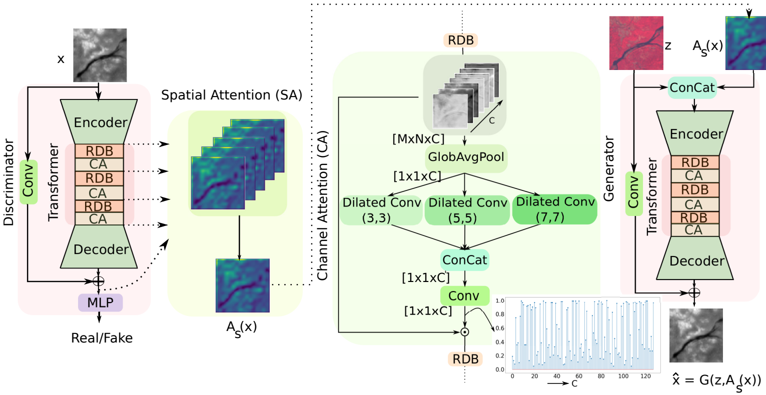

Figure: Spatio-Spectral Laplacian Attention.

Proposed Methodology

- **Adversarial Loss**

$$\min_{G} \max_{D} \mathbb{E}_{x\sim\mathbb{P}_x}\left[D\left(x\right)\right] - \mathbb{E}_{\hat{x}\sim\mathbb{P}_{\hat{x}}}\left[D\left(\hat{x}\right)\right] - \lambda\, \mathbb{E}_{\tilde{x}\sim\mathbb{P}_{\tilde{x}}}\left[\left(\|\nabla_{\tilde{x}} D\left(\tilde{x}\right)\|_2 - 1\right)^2\right], \tag{1}$$

  where $\mathbb{P}_{\tilde{x}}$ denotes the distribution of samples along the line of samples from $\mathbb{P}_x$ and $\mathbb{P}_{\hat{x}}$.

- **Spatial Attention from Discriminator**

$$\begin{aligned} A_s(x) &= \mathcal{N}\left(D_s(x)\right), \\ D_s(x) &= \sum_{i=1}^{K} \mathcal{N}\left(\sum_{j=1}^{C} |A_{ij}(x)|\right), \end{aligned} \tag{2}$$

where $\mathcal{N}(.)$ normalizes inputs to [0,1] range.

- **Spatial Attention Loss**

$$\mathscr{L}_{sa} = \mathbb{E}_{\hat{x}\sim\mathbb{P}_{\hat{x}}, y\sim\mathbb{P}_y}\left[\|A_s(\hat{x}) - A_s(y)\|_2^2\right]. \tag{3}$$

- **Domain Adaptation Loss**

$$\mathscr{L}_{da} = \mathbb{E}_{\tilde{y}\sim\mathbb{P}_{\tilde{y}}, y\sim\mathbb{P}_y}\left[\|A_s(\tilde{y}) - A_s(y)\|_2^2\right], \tag{4}$$

where $\mathbb{P}_{\tilde{y}}$ denotes the distribution of upsampled coarse resolution band.

- **Pixel Loss**

$$\mathscr{L}_{p} = \mathbb{E}_{z\sim\mathbb{P}_s, \tilde{y}\sim\mathbb{P}_{\tilde{y}}, y\sim\mathbb{P}_y}\left[\|G(z, A_s(\tilde{y})) - y\|_2^2\right]. \tag{5}$$

- **Discriminator Objective**

$$\min_{D} \mathbb{E}_{\hat{x}\sim\mathbb{P}_{\hat{x}}}\left[D\left(\hat{x}\right)\right] - \mathbb{E}_{x\sim\mathbb{P}_{x}}\left[D\left(x\right)\right] \\ + \lambda_{gp}\mathbb{E}_{\tilde{x}\sim\mathbb{P}_{\tilde{x}}}\left[\left(\left\|\nabla_{\tilde{x}} D\left(\tilde{x}\right)\right\|_{2} - 1\right)^{2}\right] \\ + \lambda_{sa}\mathscr{L}_{sa} + \lambda_{da}\mathscr{L}_{da}, \tag{6}$$

where λ_{gp}, λ_{sa}, and λ_{da} represent the weights assigned to gradient penalty, spatial attention, and domain adaptation loss, respectively.

- **Generator Objective**

$$\min_{G} - \mathbb{E}_{z\sim\mathbb{P}_{s},\tilde{y}\sim\mathbb{P}_{\tilde{y}}}\left[D\left(G\left(z, A_{s}(\tilde{y})\right)\right)\right] \\ + \lambda_{p}\mathbb{E}_{z\sim\mathbb{P}_{s},\tilde{y}\sim\mathbb{P}_{\tilde{y}},y\sim\mathbb{P}_{y}}\left[\left\|G\left(z, A_{s}(\tilde{y})\right) - y\right\|_{2}^{2}\right], \tag{7}$$

where λ_{p} represents the weight assigned to pixel loss.

Experiments
Ablation Study

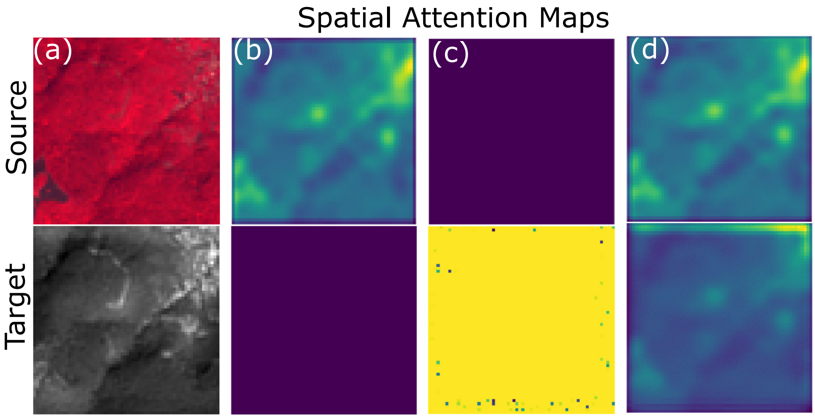

Figure: Spatial attention maps from various discriminators. Encoder and final attention maps are shown in upper and lower row, respectively.

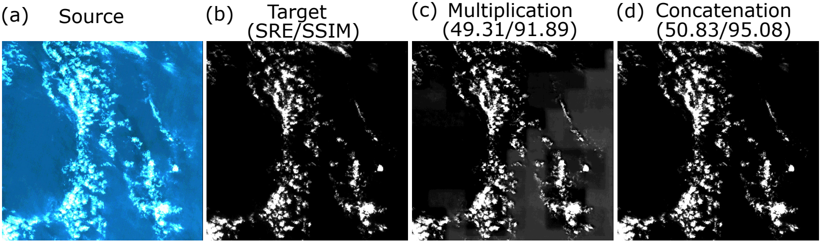

Figure: Comparison between element-wise multiplication and concatenation of spatial attention map (contrast stretched).

Experiments
Qualitative Analysis

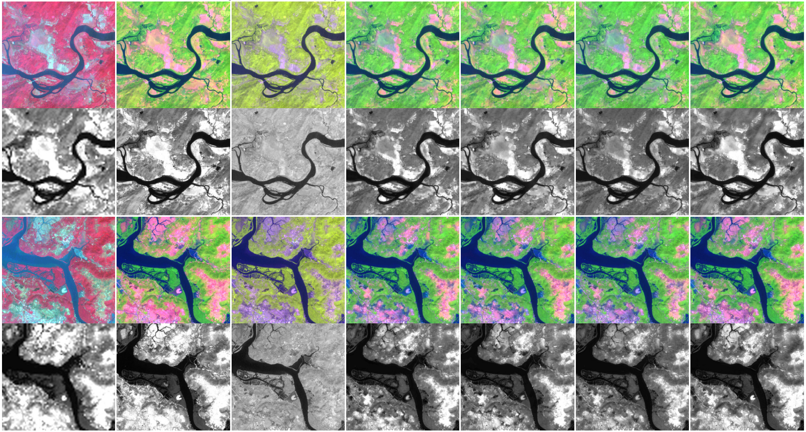

Figure: Analysis of multi-temporal LISS-3 SWIR band.

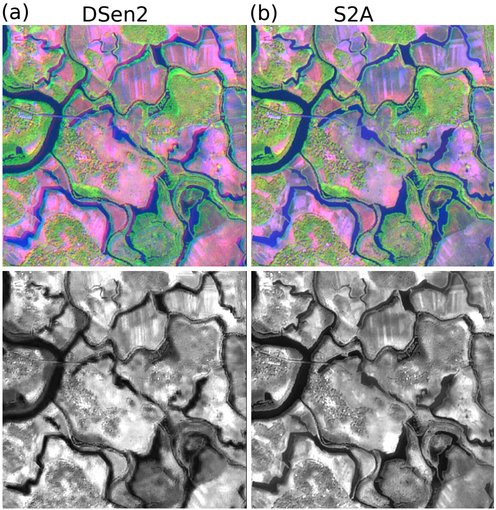

Figure: Analysis of multi-resolution (4x) LISS-4 SWIR band synthesis.

Method	RMSE	SSIM(%)	SRE(dB)	PSNR(dB)	SAM(deg)
AeroGAN [31]	21.62	86.03	44.62	36.50	12.15
DSen2 [21]	14.14	93.85	50.04	41.94	7.88
DeepSWIR [33]	13.75	94.02	50.35	42.27	7.66
ALERT [32]	12.97	94.54	50.81	42.80	7.48
S2A (ours)	11.74	95.08	50.83	42.76	6.87

Table: Quantitative analysis on LISS-3. First, second and third methods are highlighted as red, green and blue, respectively.

Experiments
Analysis of Multi-Sensor Data

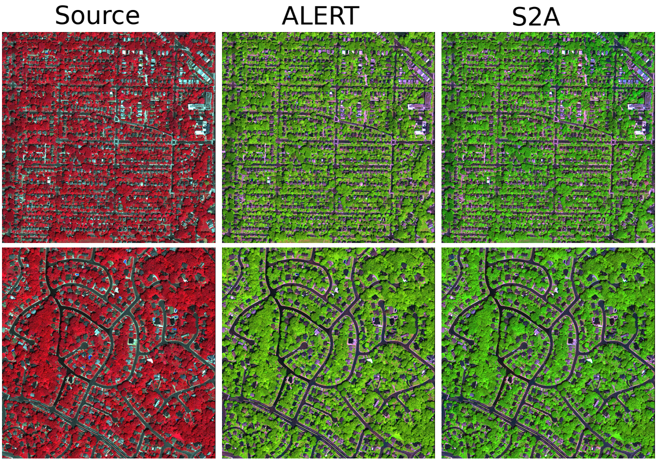

Figure: Analysis of multi-sensor (12x) WV-2 SWIR synthesis (Target domain: synthesized SWIR (R), NIR (G) and R (B)).

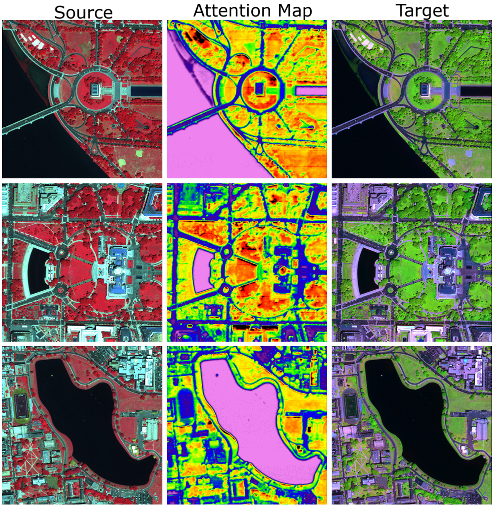

Figure: Spatial attention maps in multi-sensor band synthesis.

Applications of Synthesized Band
Wetland Delineation

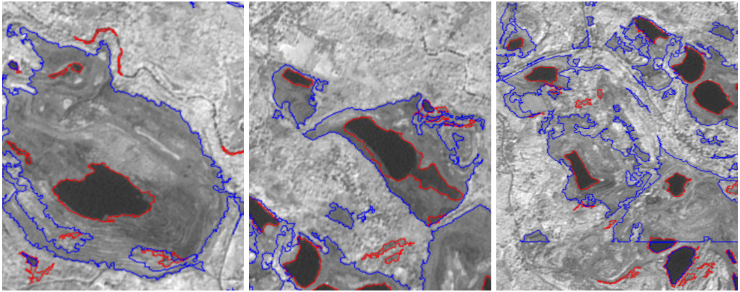

Figure: Wetland boundary detection using synthesized high resolution SWIR (Red) and existing high resolution NIR (Blue).

Applications of Synthesized Band

Modified Normalized Difference Water Index (MNDWI)

Method	AeroGAN [31]	DSen2 [21]	DeepSWIR [33]	ALERT [32]	S2A (ours)
IoU	97.181	98.891	98.853	99.066	99.117

Table: Quantitative comparison of MNDWI. S2A performs favorably against state-of-the-art methods.

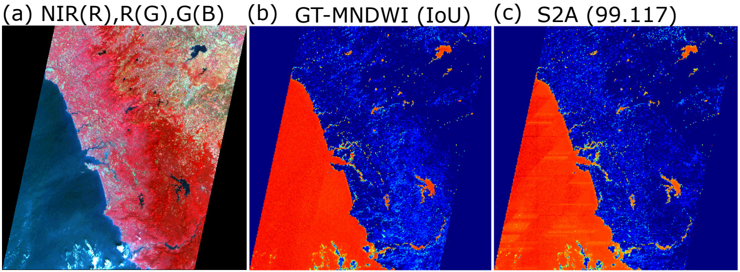

Figure: Qualitative comparison of MNDWI with ground truth.

Applications of Synthesized Band
Value Added Product

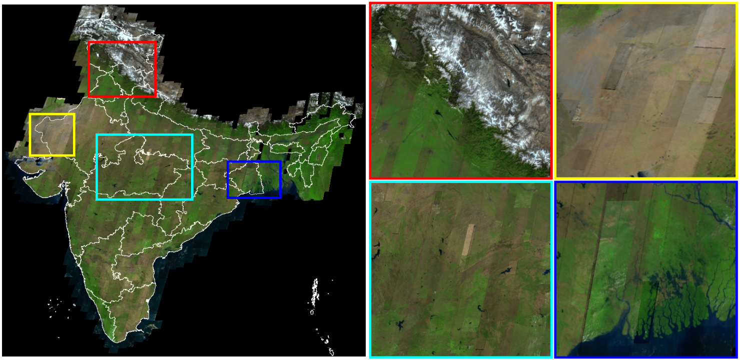

Figure: Large area mosaic of synthesized SWIR (R), NIR (G), and R (B) without relative radiometric normalization. Highlighted portions include hilly, desert, main land, and coastal region over Indian land terrains (stretched for visualization).

Concluding Remarks

- Formulated the ill-posed super-resolution problem as conditional band synthesis.
- Developed a WGAN+GP based adversarial framework encapsulating spatial and Laplacian spectral channel attention.
- Introduced two new cost functions: spatial attention loss and domain adaptation loss to improve scientific fidelity.

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- Critically analyzed the qualitative and quantitative results.
- Experimented on three different satellite imagery: LISS-3, LISS-4 and WorldView-2.
- Discussed several applications: wetland delineation, water masking and additional value product generation.

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- Regulate the process of band synthesis through spatio-spectral Laplacian attention.
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