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Generative AI with Kernel-adaptive Diffusion for High-resolution Satellite Image Inpainting Across Urban, Forest, and Agricultural Landscapes

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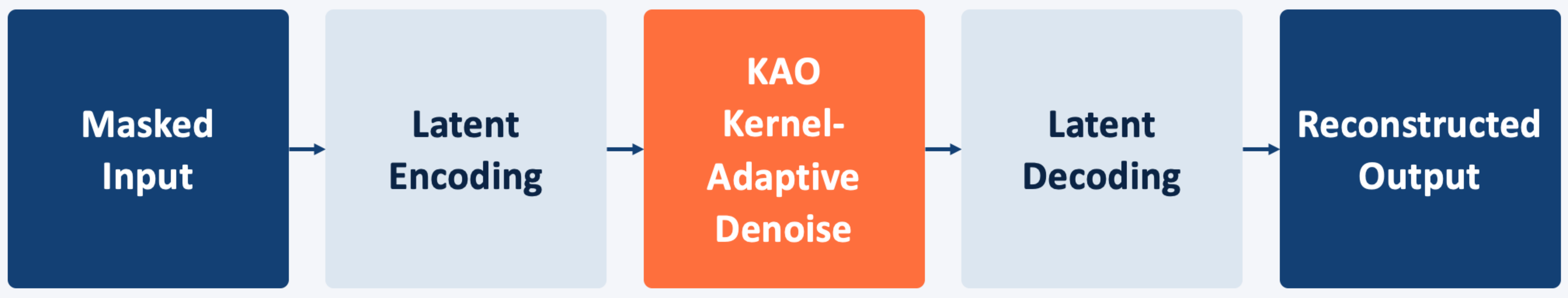
https://kaopanboonyuen.github.io/KAO

Abstract

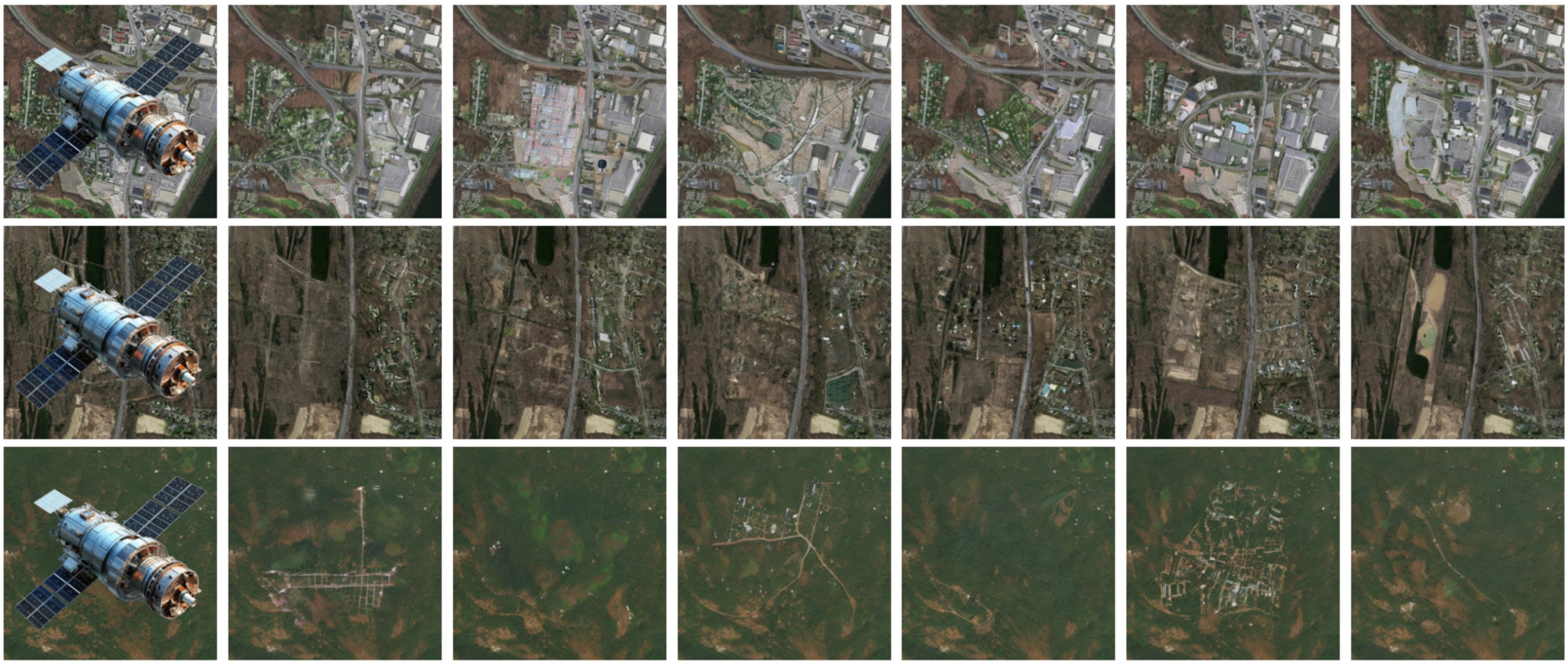
Satellite image inpainting is essential for restoring missing regions in remote sensing images. We propose **KAO**, a diffusion-based framework using **Kernel-Adaptive Optimization** and Latent Space Conditioning to achieve efficient and accurate VHR satellite image restoration. KAO improves inpainting performance through Explicit Propagation and forward-backward fusion on challenging datasets such as DeepGlobe and Massachusetts Roads Dataset.

Diffusion Models for Satellite Image Inpainting



GitHub

Qualitative Comparison Of Satellite Image Inpainting Across Seven Models



Satellite Mask | Stable Diffusion [16] | RePaint [12] | SatDiff [14] | DPS [3] | PSLD [17] | **KAO (Ours)**

KAO: Kernel-Adaptive Optimization for Satellite Image Inpainting

Algorithm 1 KAO: Kernel-Adaptive Optimization for Satellite Image Inpainting with Post-Conditioning via Token Pyramid Transformer (TPT).

Require: Diffusion model $(\mu_\theta(\cdot), \Sigma_\theta(\cdot))$, input satellite image x_0, number of diffusion steps T, mask m, and set of latent tokens $\mathcal{H}$

$x_T \leftarrow$ sample from $\mathcal{N}(0, I)$
for t from T to 1 **do**
  Step 1: Kernel-Adaptive Denoising (p-sample)
  $\mu^*, \Sigma^* \leftarrow \mu_\theta(x_t), \Sigma_\theta(x_t)$
  $x_{t-1}^{infr} \leftarrow$ sample from $\mathcal{N}(\mu^*, \Sigma^*)$
  Step 2: Adaptive Noisy Condition Estimation (q-sample)
  $\mu, \Sigma \leftarrow \mu_q(x_0), \Sigma_q(x_0)$
  $x_{t-1}^{cond} \leftarrow$ sample from $\mathcal{N}(\mu, \Sigma)$
  Step 3: Post-Conditioning via KAO in Latent Space
  for h in $\mathcal{H}$ **do**
    Token-wise Adaptive Conditioning via TPT
    $h^* \leftarrow h^{infr} \odot (1 - D(m)) + h^{cond} \odot D(m)$
    Kernel-Guided Feature Propagation via TPT
    $\hat{h} \leftarrow \mathrm{TPT}_\gamma^{-1}[\phi[\omega; \mathrm{TPT}_\gamma(D(m), h^{cond})]]$
  end for
  Step 4: Kernel-Blended Reconstruction of Satellite Image
  $x_{t-1} \leftarrow x_{t-1}^{infr} \odot (1 - m) + x_{t-1}^{cond} \odot m$
end for
return x_0 ▷ Final KAO-based satellite image reconstruction

Results

Massachusetts Roads Dataset

Method	FID↓	Prec.↑	Rec.↑
Stable Diffusion	6.98	0.59	0.69
RePaint	6.12	0.65	0.71
LatentPaint	4.44	0.71	0.81
SatDiff	3.99	0.88	0.86
DPS	3.67	0.89	0.87
PSLD	3.42	0.91	0.89
KAO (Ours)	**3.11**	**0.93**	**0.91**

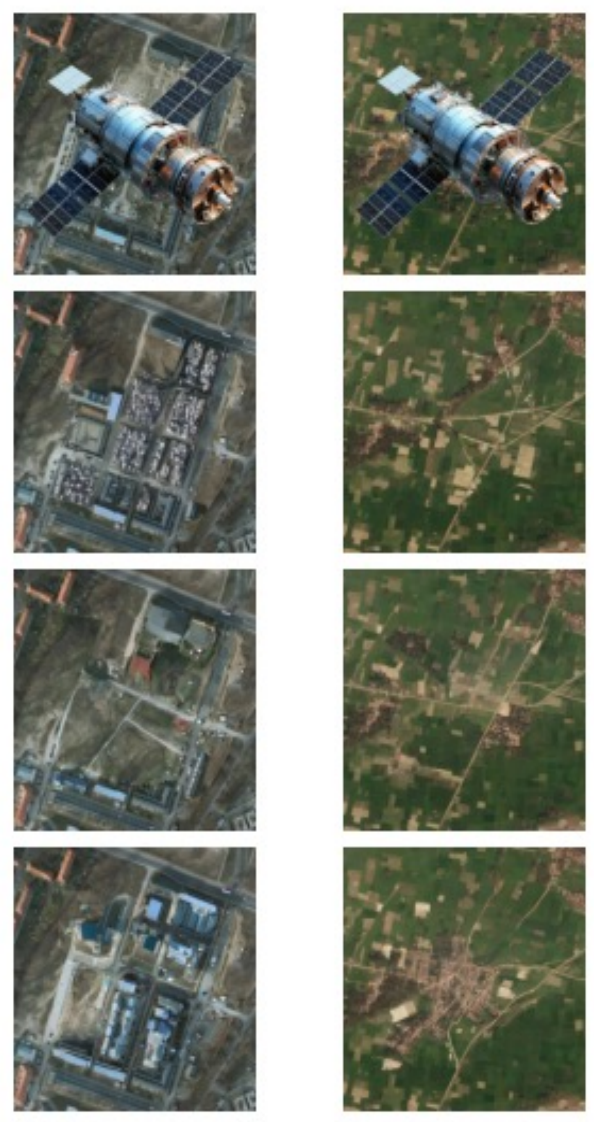
DeepGlobe 2018 Dataset

Method	FID↓	Prec.↑	Rec.↑
Stable Diffusion	5.62	0.51	0.44
RePaint	5.19	0.59	0.47
LatentPaint	2.55	0.61	0.51
SatDiff	1.98	0.80	0.55
DPS	1.76	0.82	0.56
PSLD	1.65	0.84	0.58
KAO (Ours)	**1.42**	**0.88**	**0.63**

↓9% FID VS. PSLD (MASS.)

↓14% FID VS. PSLD (DEEPGLOBE)

6/6 METRICS WON ON BOTH SETS



Reference

Panboonyuen, Teerapong. "KAO: Kernel-Adaptive Optimization in Diffusion for Satellite Image." **IEEE Transactions on Geoscience and Remote Sensing** (IEEE TGRS 2025).

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