







Motivations

- Aerial images provide high-resolution, detailed views but are costly and effort-intensive to capture, often relying on UAVs or drones
- In contrast, ground images are abundant, costavailable through effective, and autonomous crowdsourcing platforms
- Ground-to-aerial (G2A) image synthesis offers a promising, cost-effective solution by generating aerial images from corresponding ground views



"The image shows an urban street intersection with several buildings on each side. The buildings are mostly commercial and residential with a few trees and cars along the street. There is a German car repair shop on the right side of the intersection. The street is paved and has a bike lane. There are a few people walking on the street."

One sample from our VIGORv2 dataset. Top left is the aerial image, top middle is the street-view image, top right is the layout map, and bottom is the text description

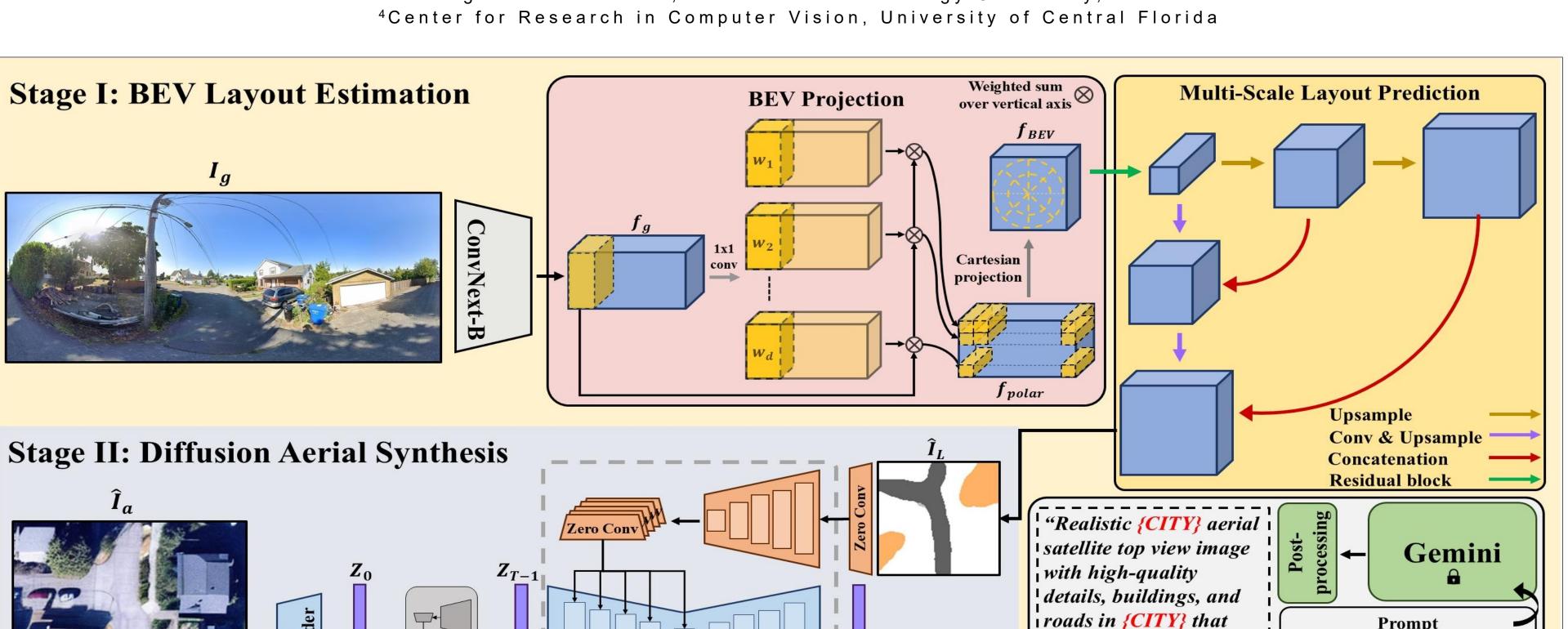
VIGORv2

- Expanded Modality: VIGORv2 extends the original VIGOR dataset by adding 105,214 center-aligned aerial-ground image pairs, BEV layout maps, and text descriptions of ground images
- Geographical Splits: Introduce geographically non-overlapping training and testing splits to prevent data leakage

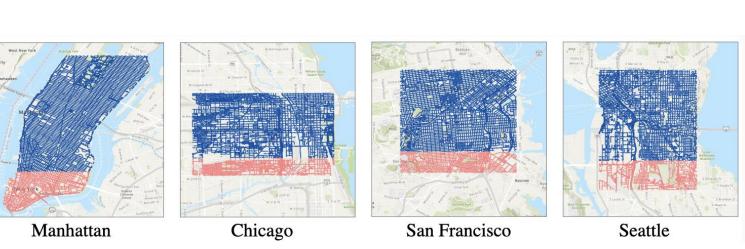
Cross-View Meets Diffusion: Aerial Image Synthesis with Geometry and Text Guidance

Ahmad Arrabi^{1,*}, Xiaohan Zhang^{1*}, Waqas Sultani³, Chen Chen⁴, Safwan Wshah^{1,2†}

¹Department of Computer Science, University of Vermont, Burlington, USA ²Vermont Complex Systems Center, University of Vermont, Burlington, USA ³Intelligent Machine Lab, Information Technology University, Pakistan



ControlNet

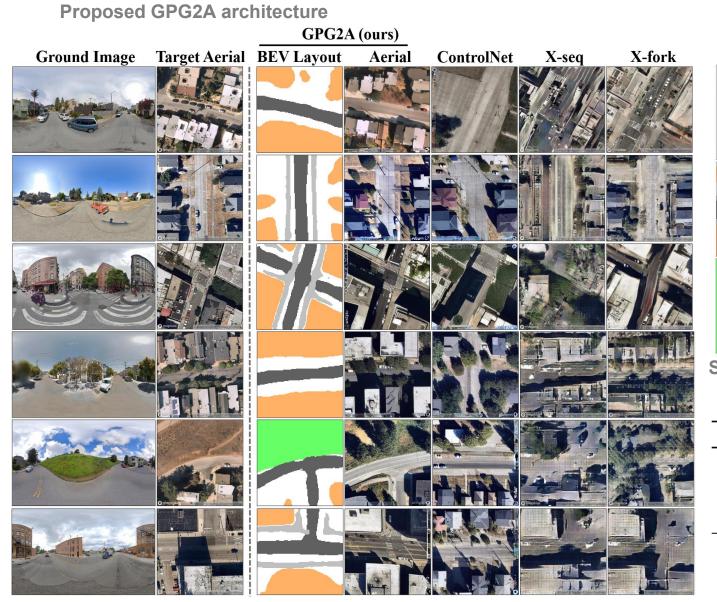


 $\times (N-1)$

Geographically split of the training (blue) and testing (red) data of VIGORv2 $Sim_s = \frac{1}{N} \sum_{i=1}^{N} \frac{2 - 2 \times (f^a \cdot \hat{f}^a)}{4},$ $FID_{SAFA} = ||\mu^a - \hat{\mu}^a|| + Tr(\Sigma^a + \hat{\Sigma}^a - 2(\Sigma^a \hat{\Sigma}^a)^{\frac{1}{2}})$

Method	Same-area			Cross-area			
1.23310	$ Sim_s\downarrow$	$Sim_c \downarrow$	FID _{SAFA}	$\downarrow Sim_s \downarrow$	$Sim_c \downarrow$	$\overline{\mathrm{FID}_{\mathrm{SAFA}}}\downarrow$	
X-seq	0.392	0.438	0.411	0.392	0.454	0.570	
X-fork	0.341	0.423	0.151	0.372	0.445	0.357	
ControlNet [†]	0.435	0.415	0.154	0.446	0.405	0.386	
ControlNet [‡]	0.369	0.412	0.110	0.409	0.420	0.220	
GPG2A (ours)	0.295	0.402	0.079	0.333	0.392	0.197	

Benchmarking with vanilla ControlNet, X-fork, and X-seq.



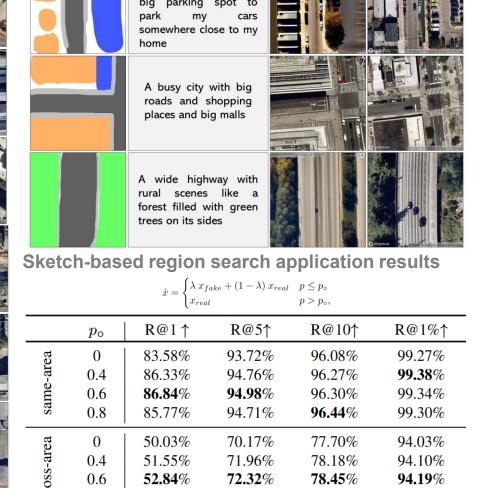
probably has the

characteristics:

{KEY WORDS}"

I following objects and

This is a qualitative comparison of same-area (top 3 rows) and cross-area (bottom 3 rows) images



0.8 50.11%

• focus on giving a general

Dynamic Text Prompt

70.98% Data augmentation on SAFA by using our **GPG2A** synthesized images



Model Overview

Why Two stages?

- The problem is simplified! reducing the domain gap between aerial and ground views
- The BEV layout map explicitly preserves geometry correspondence between the views
- Leverage strong pre-trained diffusion foundation models (stage II).

Why add text?

To further improve the synthesis quality and fuse surrounding information not fully represented in the BEV layout map.

FOV	BEV Ac	curacy	Synthesis Quality			
	Avg F1	mIoU	$\overline{Sim_s\downarrow}$	$Sim_c \downarrow$	$FID_{SAFA}\downarrow$	
90° 180° 270° 360°	0.259 0.411 0.458 0.565	0.149 0.258 0.297 0.394	0.413 0.385 0.369 0.295	0.414 0.406 0.404 0.402	0.290 0.181 0.143 0.079	

Ablation study on input ground image with variant field-of-view (FOV).

Applications

- 1. Sketch-based Region Search
- Sketch: Draw what you have in mind
- **Describe:** Add text about the area
- Discover: GPG2A synthesizes an image, and we find the closest match from a database
- 2. Data Augmentation for Cross-view Geolocalization: Leveraging the synthesized aerial images from GPG2A to augment cross-view geolocalization training