Gaussian Splatting for Satellite Images

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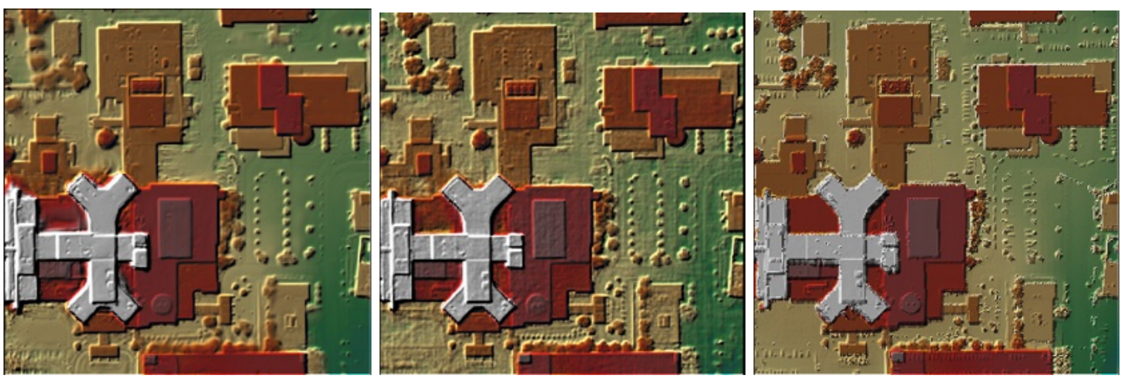
Introduction

We aim to explore whether meaningful 3D structure can be reconstructed from sparse satellite imagery, where each scene includes only 10 to 20 top-down views with varying lighting and quality. Key questions include whether 3D Gaussian Splatting can produce accurate and coherent geometry from this limited input and how well it handles the challenges introduced by RPC camera models and atmospheric inconsistencies. We will use the DFC2019 Track 3 dataset, which provides multi-view satellite images with RPC metadata, and focus solely on implementing 3DGS due to its significantly faster training and rendering times compared to NeRF-based approaches. Our goal is to evaluate the feasibility, performance, and limitations of 3DGS in this underexplored setting, which has seen limited investigation in prior work. Additionally, if time permits, we aim to create engaging interactive visualizations from the splat outputs.



3DGS, NERF, and Ground Truth from *EOGS: Gaussian Splatting for Earth Observation* [6]

Objectives

In our first stage of data processing, we aim to extract and estimate extrinsics and intrinsics (such as rotation, translation, and camera focal length) based on the metadata provided within the image dataset's metadata to set up our multi-view stereo system. Based on existing literature on 3DGS for satellite image reconstruction, we hope to achieve performance metrics similar to or better than current 3DGS implementations for satellite image photogrammetry (approximately 3-6 minutes of computation time and mean elevation error of ~1.0 to 1.50). Using an open-source 3DGS visualizer will also be useful in testing and verifying the accuracy of the outputs.

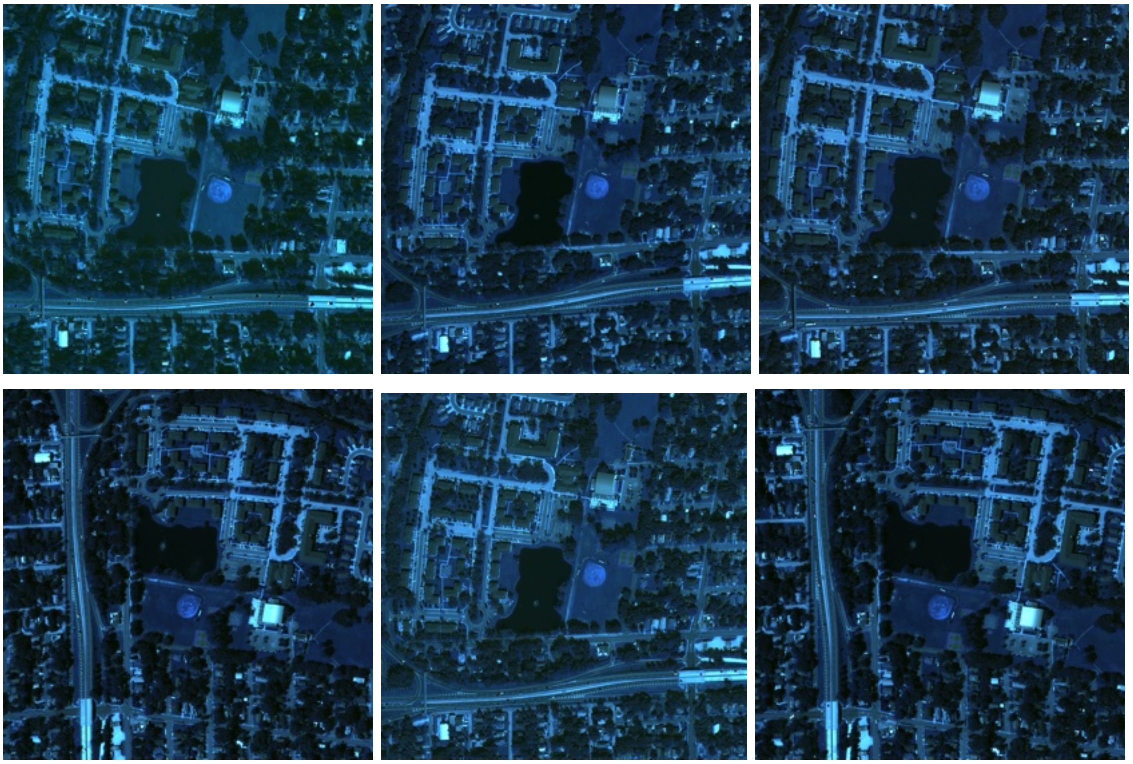
Related Works

Typical research around satellite image processing has focused on problems such as segmentation and classification, while 3D reconstruction is a more recent area of interest within the field. Earlier investigations utilized NeRF's for satellite image reconstructions as "digital surface models". Marí et al.

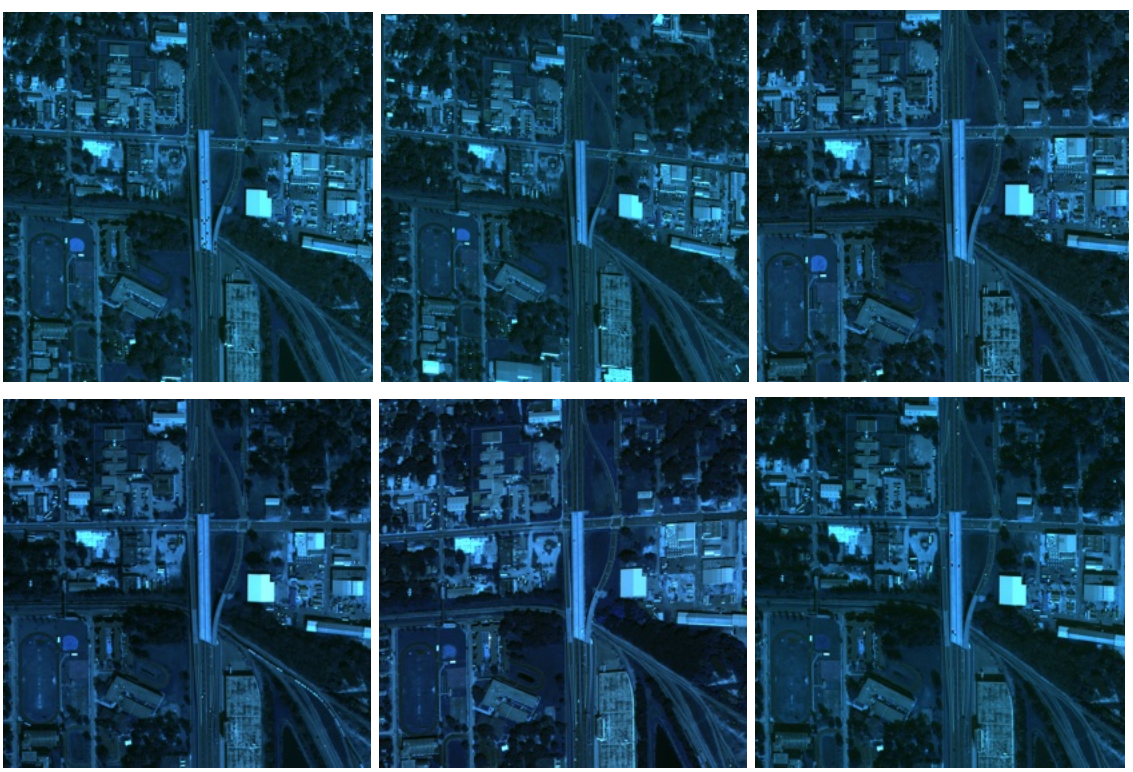
introduced methods of "Sat-NeRFs" [1] and "Earth Observation NeRFs" (EO-NeRFs) [2] which utilize shadow modeling to extract color and height data. However, expensive runtime can be critical drawbacks for these solutions' applicability of these NeRF solutions. Studies such as Billouard et al.'s paper on "SAT-NGP" aim to develop faster methods via graphics primitives to reduce 20 hours of computation time to ~13-14 minutes, although there is some loss in quality in the outputs [3]. As a faster alternative to NeRF's, 3D Gaussian splatting is a real-time radiance field renderer introduced by Kerbl et al. [4], which brought up the question: could we perform real time 3D reconstructions with only satellite images and 3DGS? Recent studies investigated 3DGS as an efficient alternative while applying similar methodologies such as shadow mapping from NeRF methods. Wu et al.'s paper on "Aerial Gaussian Splatting" applies scene partitions and ray-gaussian intersections for surface reconstructions, performing at smaller RMSE and better similarity scores than existing NeRF methods [5]. Aira et al. introduced "Earth Observation Gaussian Splatting" (EOGS) which adapts the shadow model to consider "geometrically consistent shadows" and a "sun camera" to estimate elevations, resulting in runtimes at ~3 minutes (~8 times faster than SAT-NGP and ~300 times faster than EO-NeRF) [6].

Dataset

For our project we will use study utilizes Track 3 of the 2019 IEEE GRSS Data Fusion Contest (DFC2019), which comprises 110 scenes with approximately 20 multi-angle satellite images per scene (about 2,200 images total) [7]. Each scene includes multiple perspective views captured from slightly different angles, providing the multi-view geometry necessary for 3D reconstruction. The dataset also includes rasterized Digital Surface Models (DSMs) that serve as ground truth heightmaps, enabling quantitative evaluation of our reconstruction results. For our proof-of-concept approach, we selected a small subset of representative scenes to demonstrate the feasibility of 3D Gaussian Splatting reconstruction.



6 different satellite views of Scene 020 from Track 3 of the 2019 IEEE GRSS dataset



6 different satellite views of Scene 079 from Track 3 of the 2019 IEEE GRSS dataset

Preliminary Work

Our preliminary work focused on exploring and understanding the dataset characteristics. The data differs significantly from standard RGB image scenes typically used in 3D reconstruction tasks. Instead, these are 8-band VNIR multispectral images. Our exploration showed that this spectral data will likely need preprocessing to convert it into a format suitable for Gaussian Splatting.

During our dataset analysis, we observed that the number of views per scene varies across the dataset, ranging from 15 to 20 images per scene. This variability is not particularly problematic since Gaussian Splatting does not require strictly consistent numbers of training views. We also noted some disturbances in certain views, likely due to lens distortion that might be recoverable with the metadata. A challenging aspect of this dataset is the limited variation in viewing angles between images of the same scene. Most images are captured from nearly top-down perspectives with only slight variations, which could be potentially difficult for the 3DGS model to accurately reconstruct 3D geometry. We also identified several open-source implementations of 3D Gaussian Splatting, to determine the most suitable approach.

References

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