



Overview

Automatic, simple 3D mesh models from satellite images

- Build on existing commercial point cloud generation software (Raytheon Intersect Dimension)
- Segment scene into buildings, bridges, and terrain
- Model buildings/bridges with geometric primitives
 - Regularized planar roof sections
 - Cylindrical and spherical roofs
- Texture map using multiple satellite images
- Deploy on AWS with web-based application for easy use
- Release open source software





DSM – from point cloud



DTM – Fit from DSM



nDSM = DSM - DTM

Key References

Preprocessing

- Render a Digital Surface Model (DSM)
- Pansharpen and orthorectify images to DSM
- Normalized Difference Vegetation Index (NDVI) from ortho images to help remove trees
- Estimate Digital Terrain Model (DTM) with cloth simulation filter (Zhang et al. [2])
- Normalized DSM (nDSM) to factor out terrain





[1] Purri et al. Material segmentation of multi-view satellite imagery. CoRR/Arxiv, 2019. [2] Zhang et al. An easy-to-use airborne lidar data filtering method based on cloth simulation. Remote Sensing, 8(6):501, 2016. [3] Xu et al. A hierarchical roof topology structure for robust building roof reconstruction from point clouds. Remote Sensing, 9(4):354, 2017 [4] Qi et al. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. NIPS 2017.

Urban Semantic 3D Reconstruction from Multiview Sat

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See companion paper on materials [1]

Semantics & Shape Fitting

- Semantic segmentation from MSI, nDSM, & NDVI inputs
- > Two-class (building / background) first, use OSM roads to separate building / bridge
- \succ Simple thresholding (NDVI > 0.1 and nDSM > 2m) + morphology as a baseline
- Compared three deep networks (GoogLeNet [7], DenseUNet [5]+[6], PSPNet [8])
- Use segmentation to filter building/bridge points from point cloud
- Classify points as flat, sloped, cylindrical, or spherical with PointNet++ [4]
- Fit roof segments per shape category
- Hierarchical roof topology tree [4] applied to planar segments



Threshold Segmentation



Augment limited curved training samples by "bending" planar samples

[5] Ronneberger et al. U-Net: Convolutional Networks for Biomedical Image Segmentation. MICCAI 2015. [6] Huang et al. *Densely Connected Convolutional Networks*. CVPR 2017. [7] Szegedy et al. Going Deeper with Convolutions. CVPR 2015. [8] Zhao et al. *Pyramid Scene Parsing Network*. CVPR 2017.



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GoogLeNet	0.84	0.89	0.75	0.79	0.80	0.66						
DenseUNet	0.87	0.85	0.75	0.63	0.86	0.57	Downtown Omaha – 1.36 km ²					
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Geolocation Error (m)				1.58		2.24	San Diego, CA					
Z-RMSF (m)				1.29		0.60						
H-RMSE (1.80		2.06								
Run Time		4.80		2.28								

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Software

- Web Application
- > 3D model and map-based visualization
- Data and job management
- Deployed on Amazon Web Services

Raytheon point cloud estimation code is not open source but binaries are available to the US Government with Government Purpose Rights.

https://github.com/Kitware/Danesfield-App





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Primordial Genetics – 0.35 km² San Diego, CA

Software named Danesfield in honor of the WWII center for 3D aerial photographic intelligence

> Algorithms in Python with some C++

Environment configured with Conda or Docker

Open source: Apache License Ver 2.0 //

Acknowledgements





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Danesfield Web Application