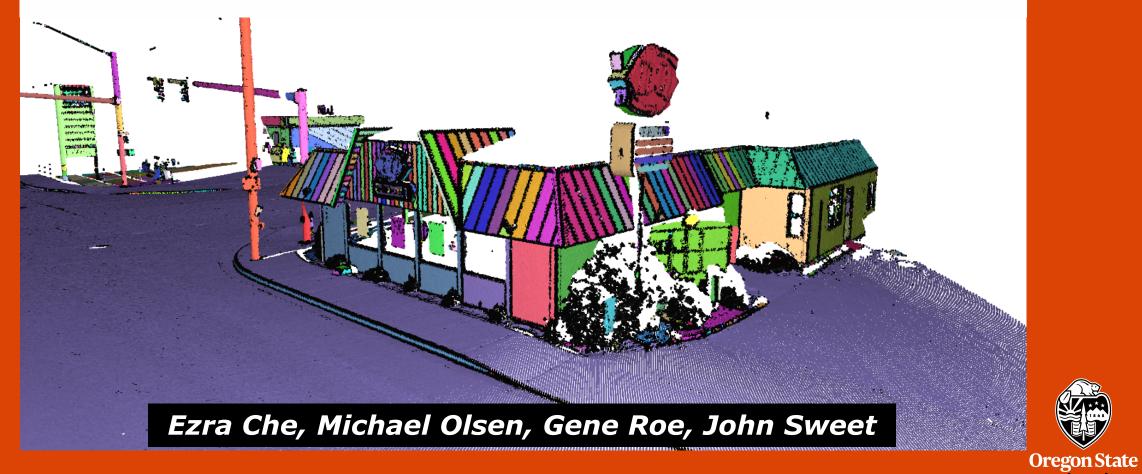
Efficient Point Cloud Segmentation of Transportation Assets





COLLEGE OF ENGINEERING

School of Civil and Construction Engineering

EZdataMD, LLC

University

Preview of Key Takeaways



- Mo-norvana mobile lidar processing framework
 - Automatic (saving time & cost of manual processing)
 - Efficient (faster than other methods by orders of magnitude)
 - Managing Data via Trajectory (supports Per-point QA/QC)
 - Point Cloud Segmentation and Feature Extraction





Importance of Asset Management

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Illinois County Pay \$3M to Settle Case Over Missing Stop Sign in Fatal Crash

October 17, 2018



Stolen Stop Sign Causes Serious Crash in Benton City

Updated on: 4/15/2019



Missing stop sign blamed for Hyrum crash; victim requires plastic surgery

Rested 2.40.24.014.10(2017) (Updated 2.11) PM (1) 10, 2017 Br Cert Woldow) &

Missing stop sign causes crash that seriously injures woman

Jury must decide if missing stop sign or dangerous driving caused fatal crash near Langham

The Crown says Robert Major's dangerous driving caused a fatal crash on Highway 16. The defence blames the crash on a missing stop sign.

MCADAM, SASKATOON STARPHOENIX Updated: January 25, 2019



Missing stop sign blamed for serious crash

enjamin Griffiths, James Feltor © Posted Sep 24,2018 | 🗨 0



\$45 Million Lawsuit Stems from Missing Stop Sign Accident in Queens

On behalf of Law Offices of Nussin S. Fogel | Mar 6, 2018 | Diving Accidents

Missing stop sign blamed for crash that hurt three people

Danielle Furfaro and Reuven Fenton

January 11, 2018 | 10:59pm | Updated

Man claims missing intersection stop sign caused crash

kuthor: Arrianee LeBeau Published: 6:46 PM EDT March 15, 2013 Jpdated: 6:58 PM EDT March 15, 2017

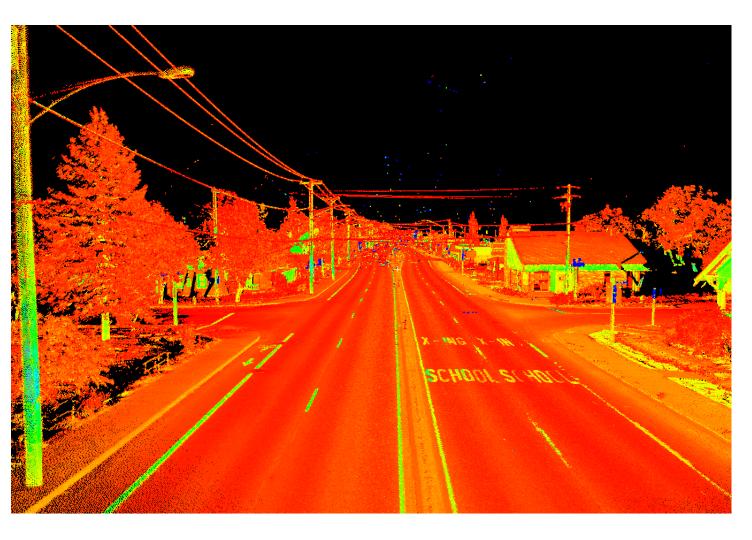


Mobile Lidar Technology Benefits

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- Geo-referenced
- Safety
- Accuracy
- Efficiency
- Rich Information
- More Applications



Challenges with Data Processing





- Large Data Volumes
- Loss of Detailed Information

https://www.directionsmag.com/pressrelease/5771

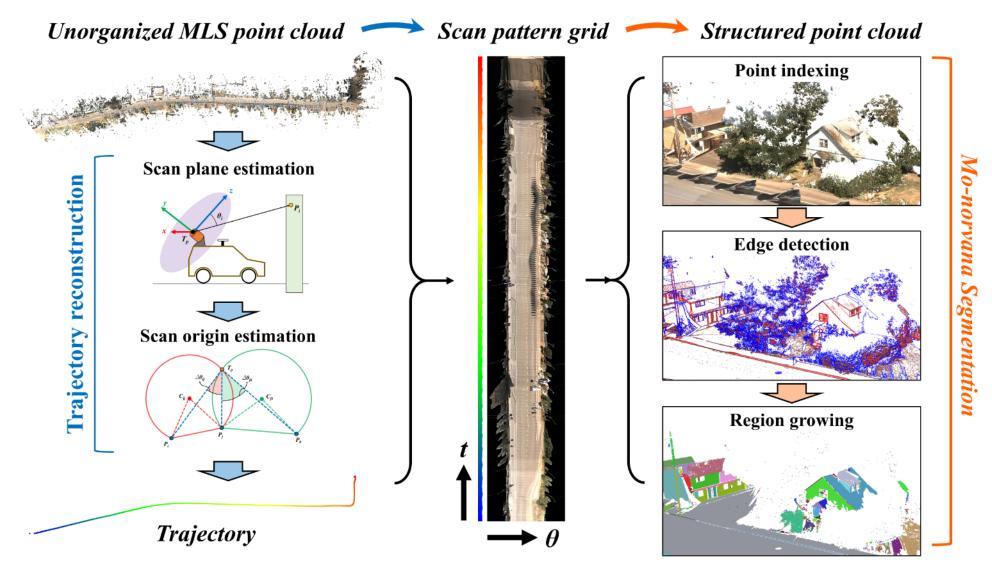
- Time & Labor Intensive
- Limited Applications

Example of data cleaning

https://www.youtube.com/watch?v=VmaspCVXWN8&t=1s

Mo-Norvana Technology

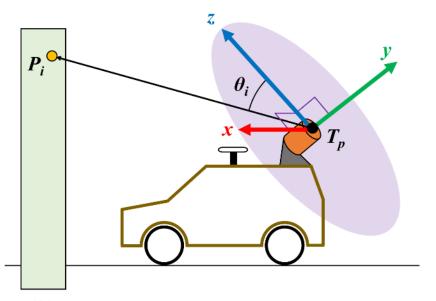




(Che & Olsen, 2019) 6

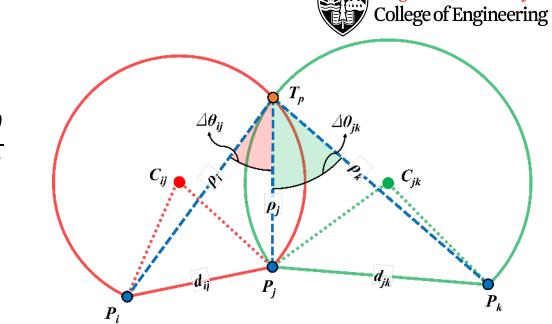
Oregon State University

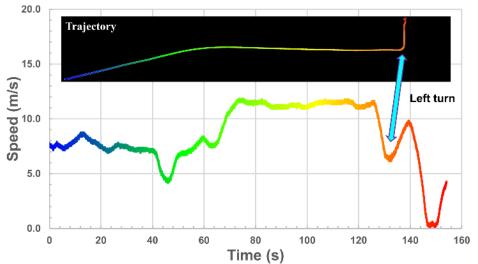
Trajectory reconstruction



$$\omega = \frac{2\pi}{f} = \frac{d\theta}{dt}$$

 $\Delta \theta = \omega \times \Delta t$





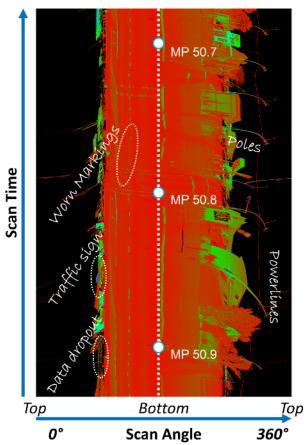
	Vert. error (m)	Horz. Error (m)	3-D error (m)	
Max.	0.086	0.142	0.200	
Min.	-0.140	0.000	0.000	
Median	0.000	0.002	0.002	
Avg.	0.000	0.004	0.004	
RMSE	0.004	0.008	0.009	

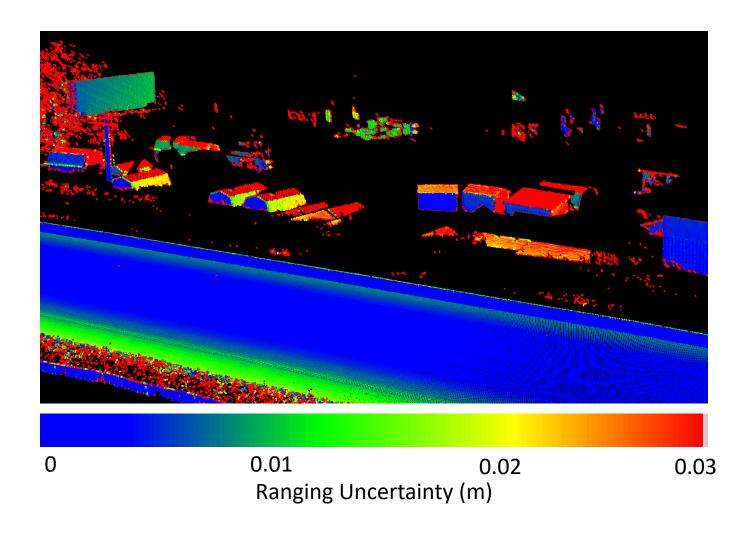
(Che & Olsen, 2019) 7

How Trajectory Can Be Used

- Data management
- Per-point QA/QC
- Visualization & Annotation





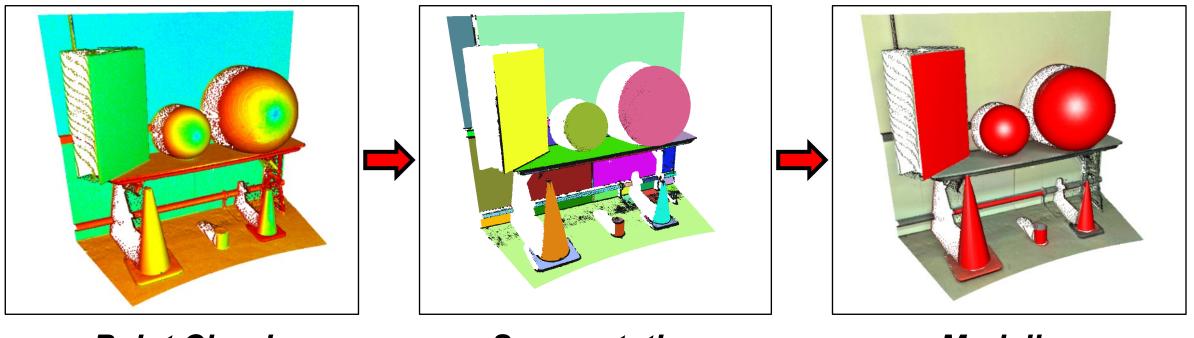




Point Cloud Segmentation



- Groups points with similar attributes
- Supports feature extraction, classification, modeling, analysis...



Point Cloud

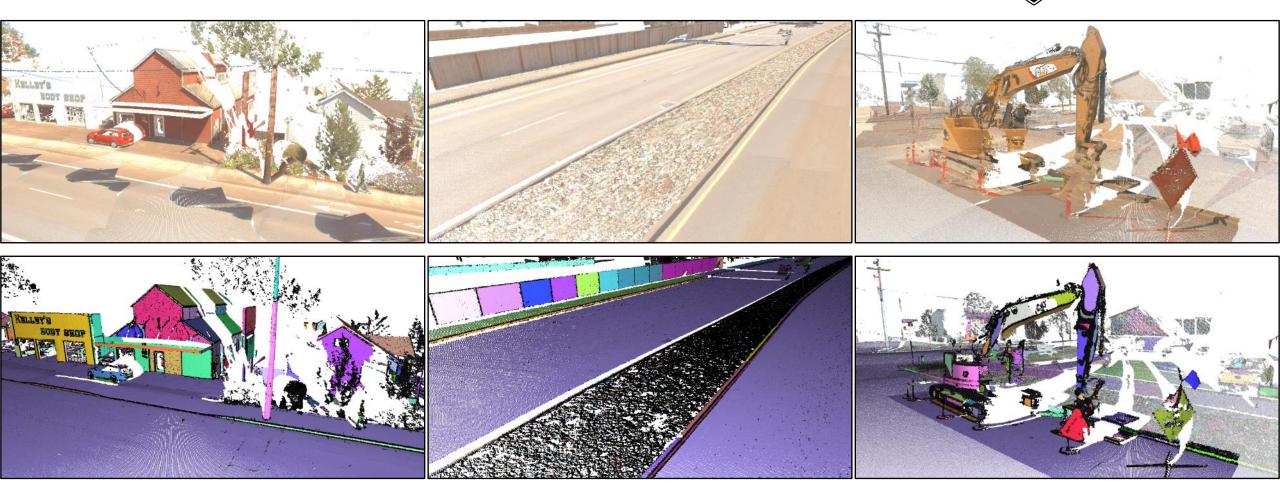
Segmentation



Mo-Norvana Segmentation Oregon State University College of Engineering Current point 🔵 Neighbor point (a) MLS point cloud Skipped point Non-neighbor point — Shared edge Points with the same 0 Driving direction (c) Segmentation (b) Edge Detection 43 Power line Handrails Vegetation (**Che** & Olsen, 2019)¹⁰

Segmentation Results



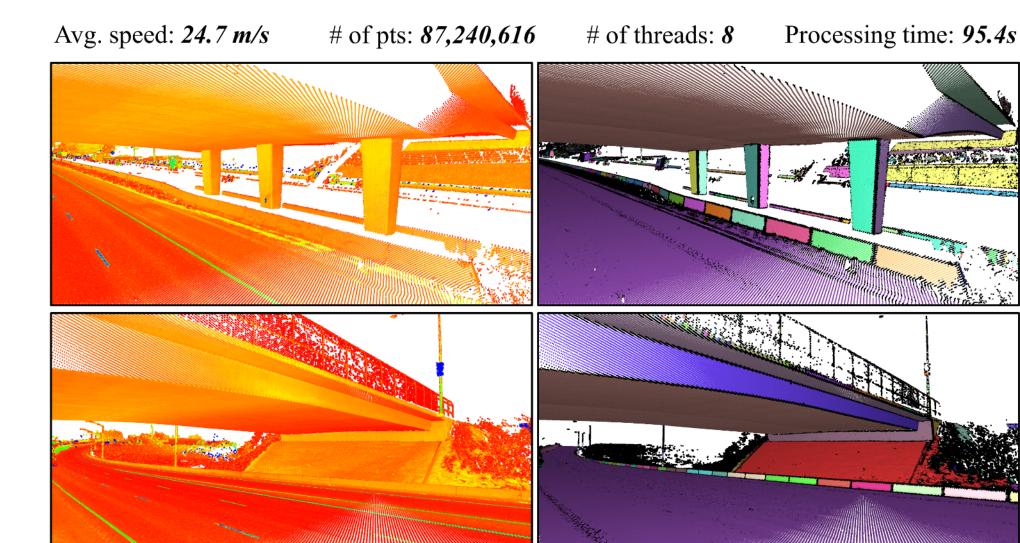


(Che & Olsen, 2019)¹¹

(Che & Olsen, 2018) ¹²

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Freeway Data

1 thread

2 threads

4 threads 8 threads

300

250

Computational Performance

					go	
	CPU	# of points	time	pts/sec.		
Mo-norvana	Intel Core E5620 @ 2.40 GHz (4 cores, 8 threads)	263M	276s	0.953M	008 (Se	
Vo et al., 2015	Intel Core i7-3770 @ 3.40 GHz	6M	38s	0.158M	ation 400	
Xu et al., 2017	Intel Core i7-4790 @ 3.60 GHz	13M	14400s	0.001M	put	
Yang et al., 2013	Intel Core i3-540 @ 3.07 GHz	105M	3241s	0.032M	O D D D D D D D D D D D D D D D D D D D	

1200

0

50



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200

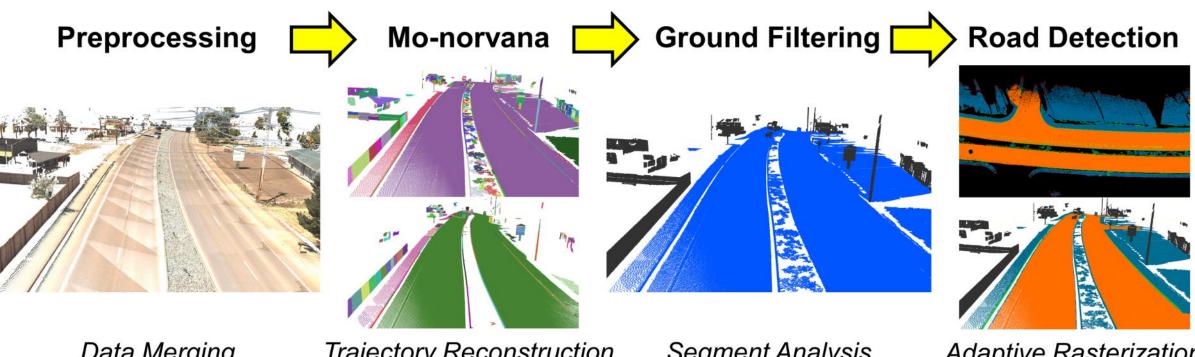
100

150

of points (million points)

VROOM Road Detection



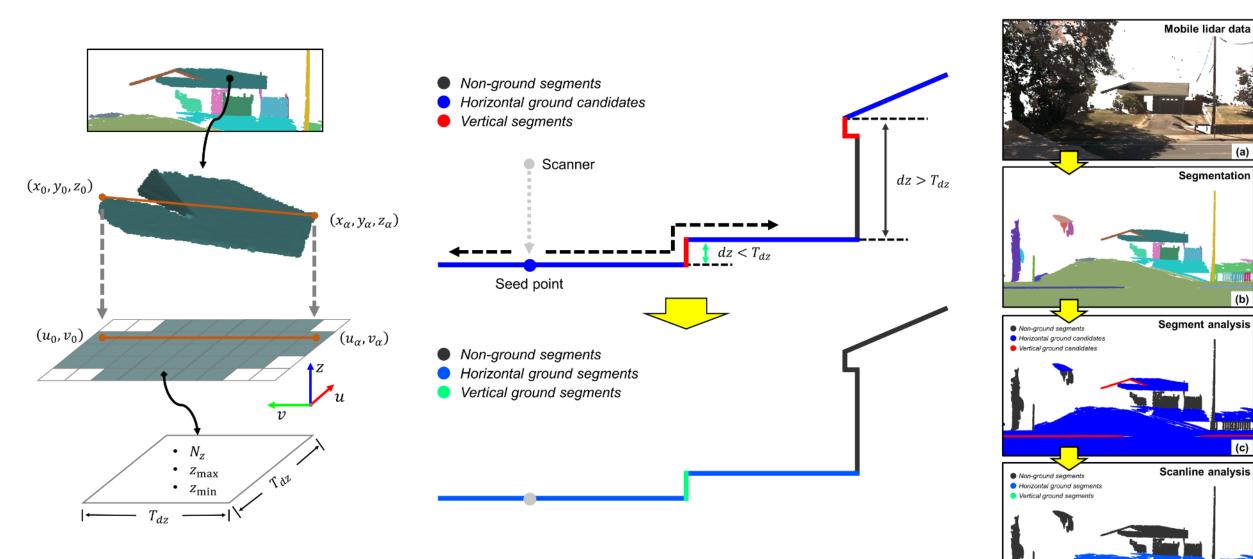


Data Merging Data Splitting Trajectory Reconstruction Segmentation Segment Analysis Scanline Analysis

Adaptive Rasterization Vehicle Access Analysis

Ground filtering

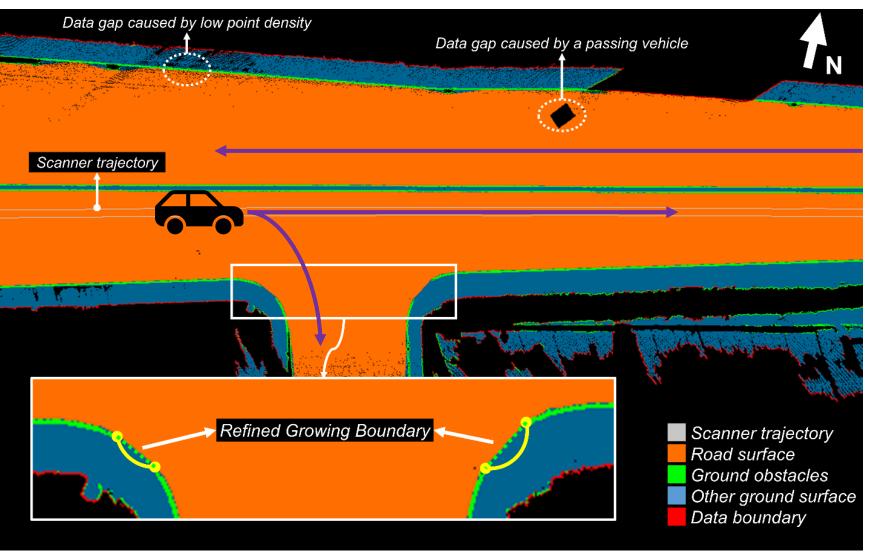




(Che et al., under review)

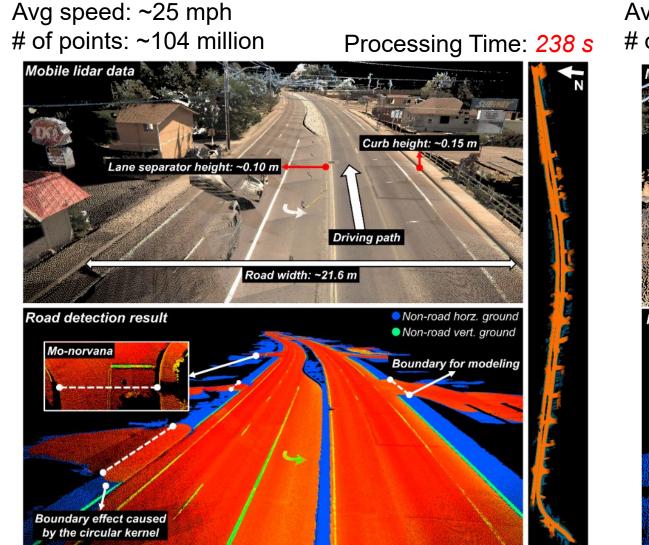
Road Detection





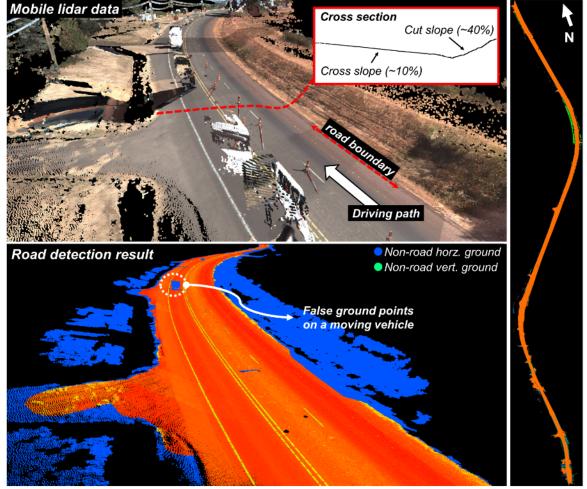
Road Detection Results



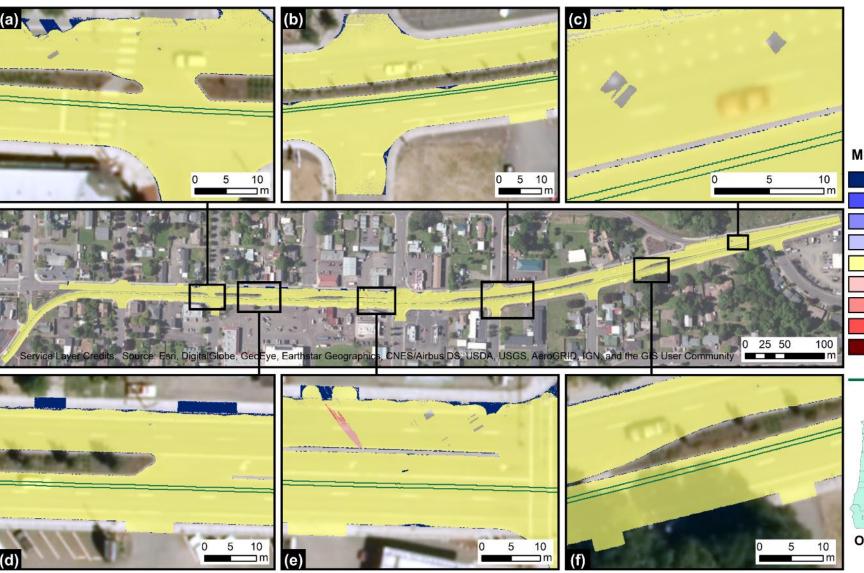


Avg speed: ~40 mph # of points: ~111 million

Processing Time: 243 s



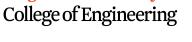
Accuracy Analysis



Model Difference (m) False negative < -0.025 -0.025 ~ -0.015 -0.015 ~ -0.005 -0.005 ~ 0.005 0.005 ~ 0.015 0.015 ~ 0.025 > 0.025 False positive

Scanner trajectory





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Cell size: 0.15 m

Class

Recall: 99.31% Precision: 97.01% F1 score: 98.14%

Model

RMSE:

Min:

Max

-0.032 m 0.033 m 0.003 m

F1 score: Harmonic mean of precision and recall

(Che et al., under review) ¹⁸

LidarTools





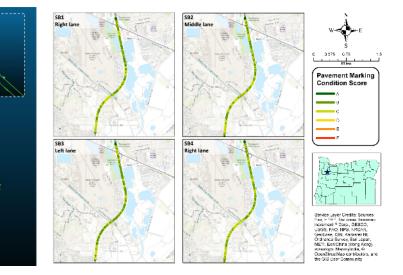
Oregon State University College of Engineering



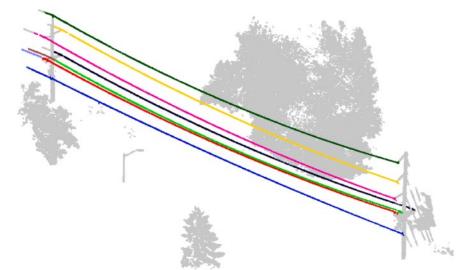
More Applications

Oregon State University College of Engineering

Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and Retroreflectivity Assessment Image: Additional Contraction (presented by ODOT last year) and tothy ODOT last year) and Retroreflectivity As



Powerline Extraction

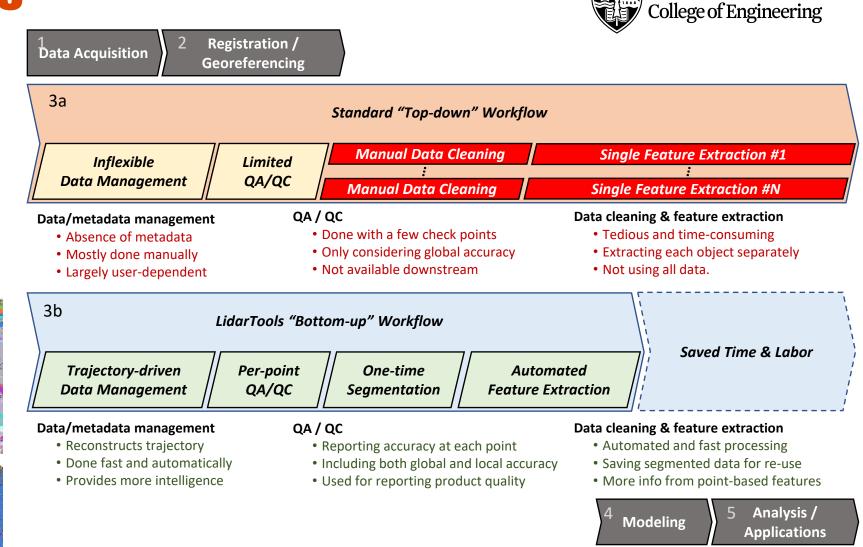


Final Takeaways

- LidarTools
 - Easy to use
 - Fast & automated
 - High Compatibility
 - (LAS/LAZ extra bytes)
 - Much more to come







EZdataMD, LLC

Oregon State University

Acknowledgement









Sign up for Beta Testing:

https://lidartools.com/join-beta-testing/

Contact:

EZDataMD@gmail.com CHEE@oregonstate.edu Michael.Olsen@oregonstate.edu

Reference

Che, E., & Olsen, M. J. (2018). Multi-scan segmentation of terrestrial laser scanning data based on normal variation analysis. *ISPRS journal of photogrammetry and remote sensing*, *143*, 233-248.
Che, E., & Olsen, M. J. (2019). An Efficient Framework for Mobile Lidar Trajectory Reconstruction and Mo-norvana Segmentation. *Remote Sensing*, *11*(7), 836.
Che, E., Jung, J., & Olsen, M. J. (2019). Object recognition, segmentation, and classification of mobile laser scanning point clouds: A state of the art review. *Sensors*, *19*(4), 810.
Che, E., Olsen, M.J., Jung, J., (under review). Efficient Segment-based Ground Filtering and Adaptive Road Detection from Mobile Lidar Data. International Journal of Remote Sensing, *104*, pp.88-100.
Xu, S., Wang, R. and Zheng, H., 2017. An optimal hierarchical clustering approach to segmentation of mobile lidar point clouds. *arXiv preprint arXiv:1703.02150*.
Yang, B. and Dong, Z., 2013. A shape-based segmentation method for mobile laser scanning point clouds. *ISPRS journal of photogrammetry and remote sensing*, *81*, pp.19-30.
Jung, J., Che, E., Olsen, M. J., & Parrish, C. (2019). Efficient and robust lane marking extraction from mobile lidar point clouds. *ISPRS journal of photogrammetry and remote sensing*, *147*, 1-18.
Olsen, M. J., Parrish, C., Che, E., Jung, J. (2019). Pavement Marking Reflectivity Evaluation Through Radiometric Calibration of the Leica P40 Terrestrial Laser Scanner. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, 333-339.
Che, E., Olsen, M. J., Parrish, C. E., & Jung, J. (2019). Pavement Marking Refroeflectivity Estimation and Evaluation using Mobile Lidar Data. *Photogrammetric Engineering & Remote Sensing*, *85*(8), 573-583.
Jung, J., Che, E., Olsen, M. J., Parrish, C. Zud, Automated and efficient powerline extraction from laser scanning data using a voxel-based subsampling with hierarchical approach. *ISPRS Journal of*

Photogrammetry and Remote Sensing, 163, pp.343-361.