FIG WORKING WEEK 2017

BIM FOR SURVEYORS

Helsinki Finland Sunday 28 May 2017

Efficient point cloud segmentation techniques to support BIM or GIS

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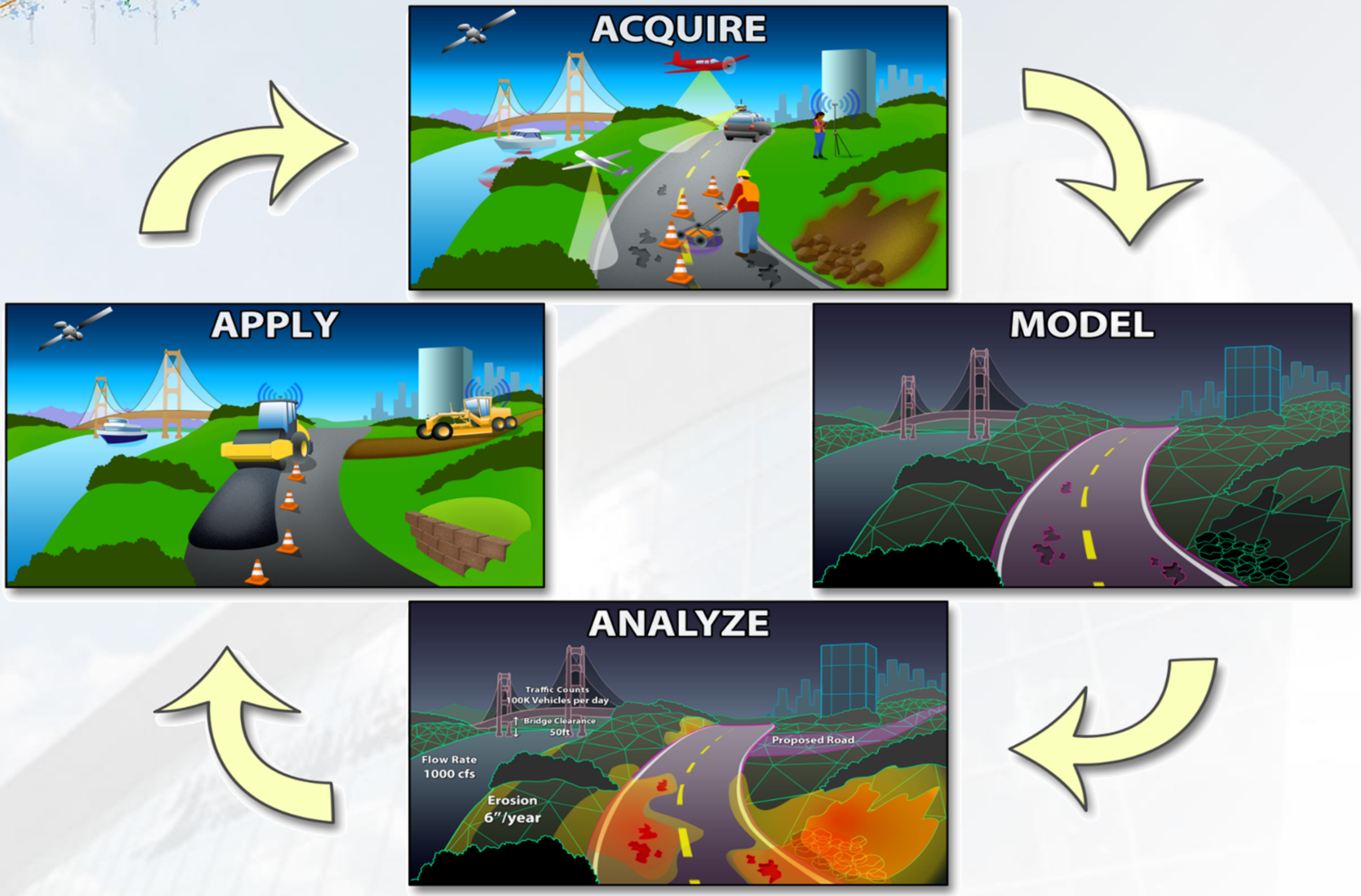
Contributions by:
Hamid Mahmoudabadhi and Ezra Che, Oregon State University

Image data: Ezra Che

Oregon State University

About me

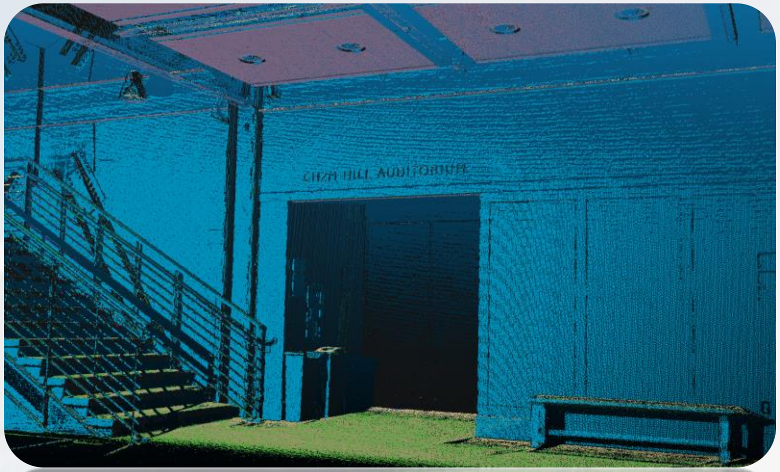
- Associate Professor of Geomatics
  School of Civil and Construction Engineering
  Oregon State University
- Editor-in-Chief, Journal of Surveying Engineering, ASCE
- Co-Chair, IAG Subcommission 4.2
  Geospatial Mapping and Engineering
- Technical Implementation Director
  NSF NHERI Rapid Center
- PhD. University of California, San Diego
  Research: lidar to model seacliff erosion
- MS and BS, University of Utah, liquefaction hazard mapping
- Primary Research Interests: Geomatics, lidar, 3D modeling, GIS, GNSS, scientific visualization, computational programming, coastal geomorphology, earthquakes, landslides, and other geo-hazards.

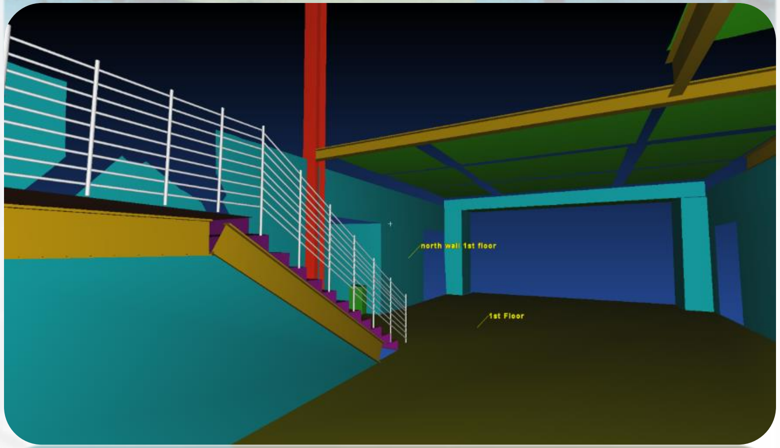


Source: NCHRP Synthesis 446

Outline

- Data acquisition
- Error Sources
- Data processing
- Segmentation Approaches
  - Manual
  - Semi-Automatic
  - Automatic
- Modeling Considerations
- Research Highlights
- Additional Resources





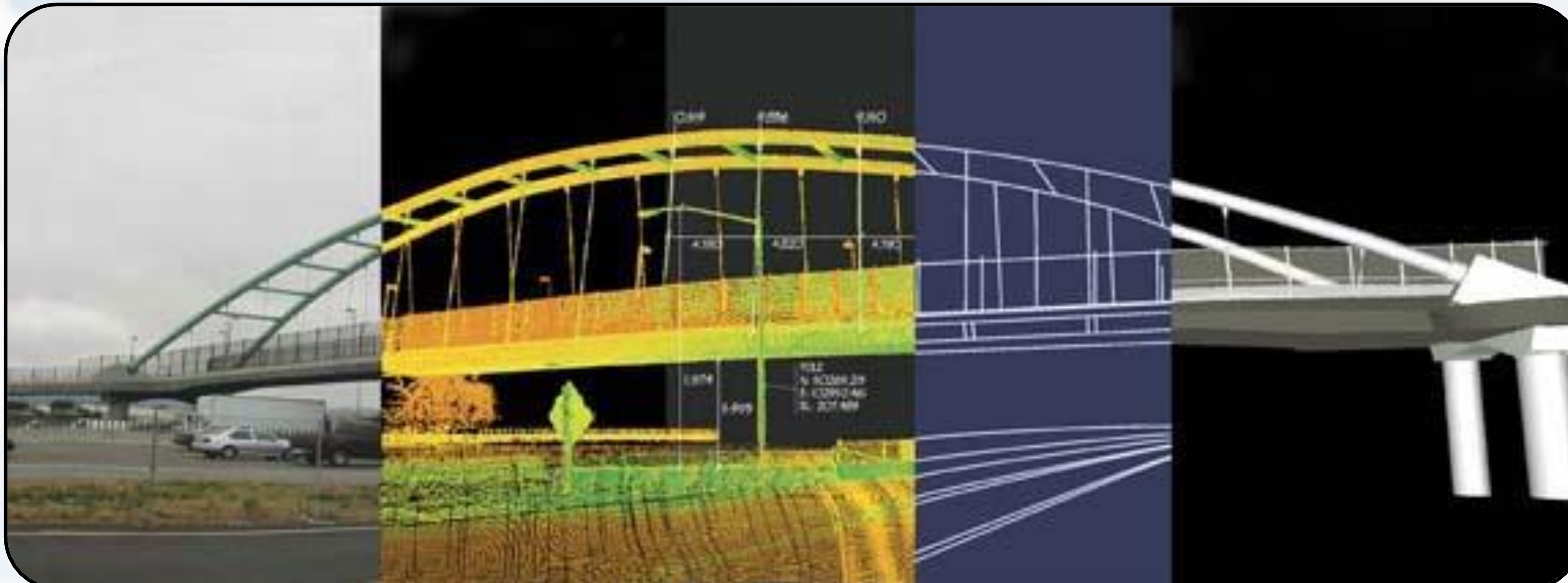
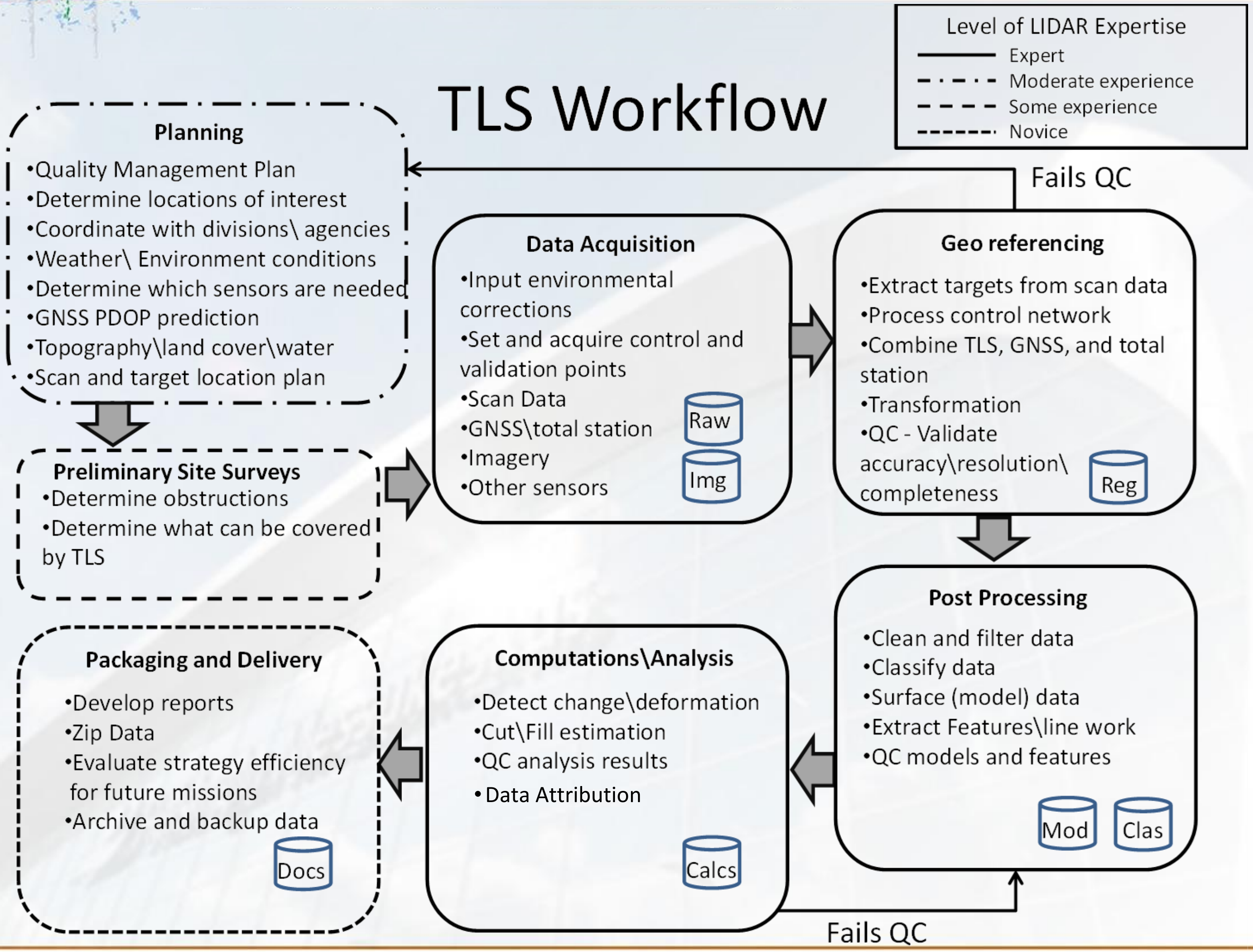


Photo Scan Vector Solid Objects

Image by Ron Singh, Oregon DOT

TLS Workflow



Modified from NCHRP Report #748

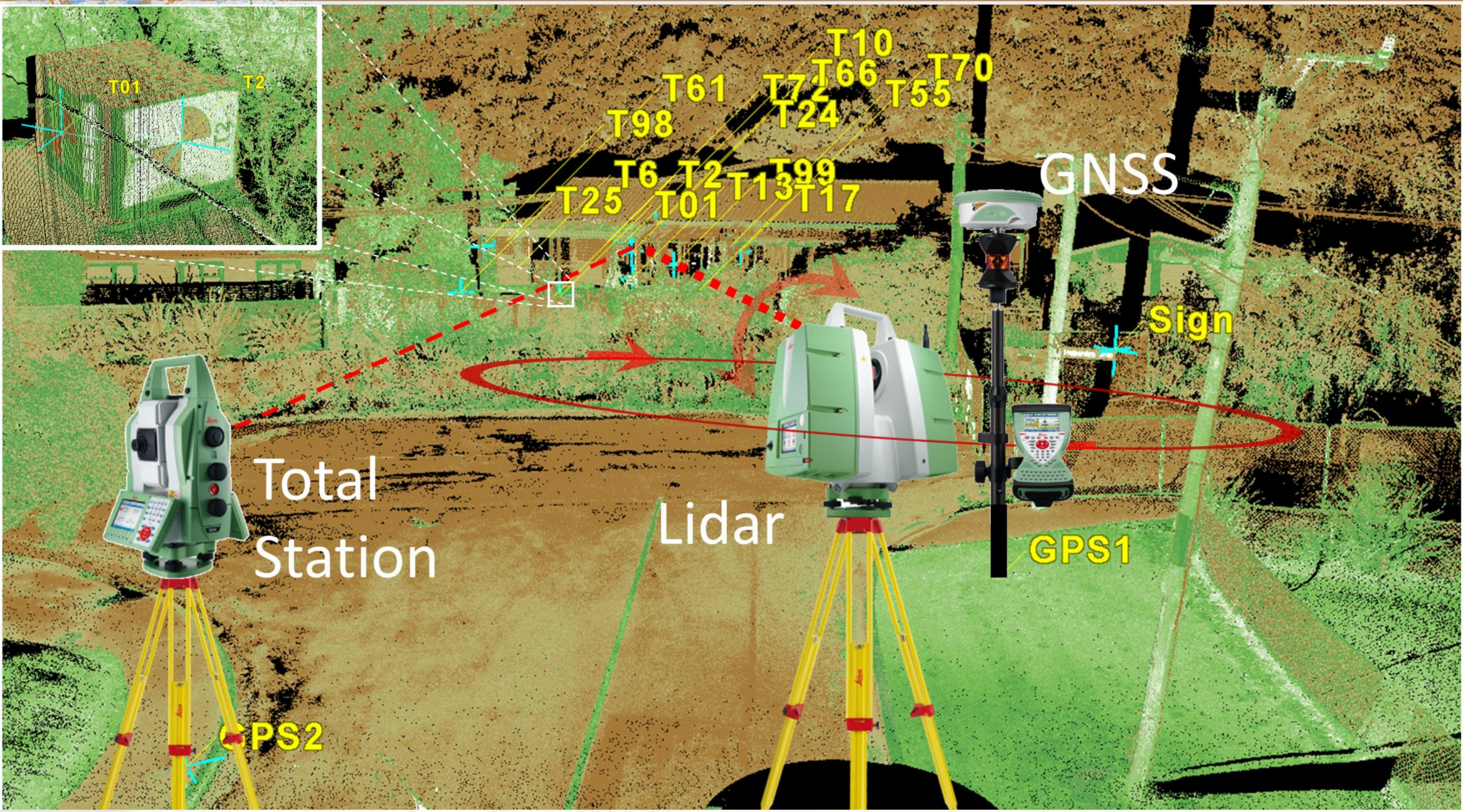


Image from Olsen & Gillins, 2015

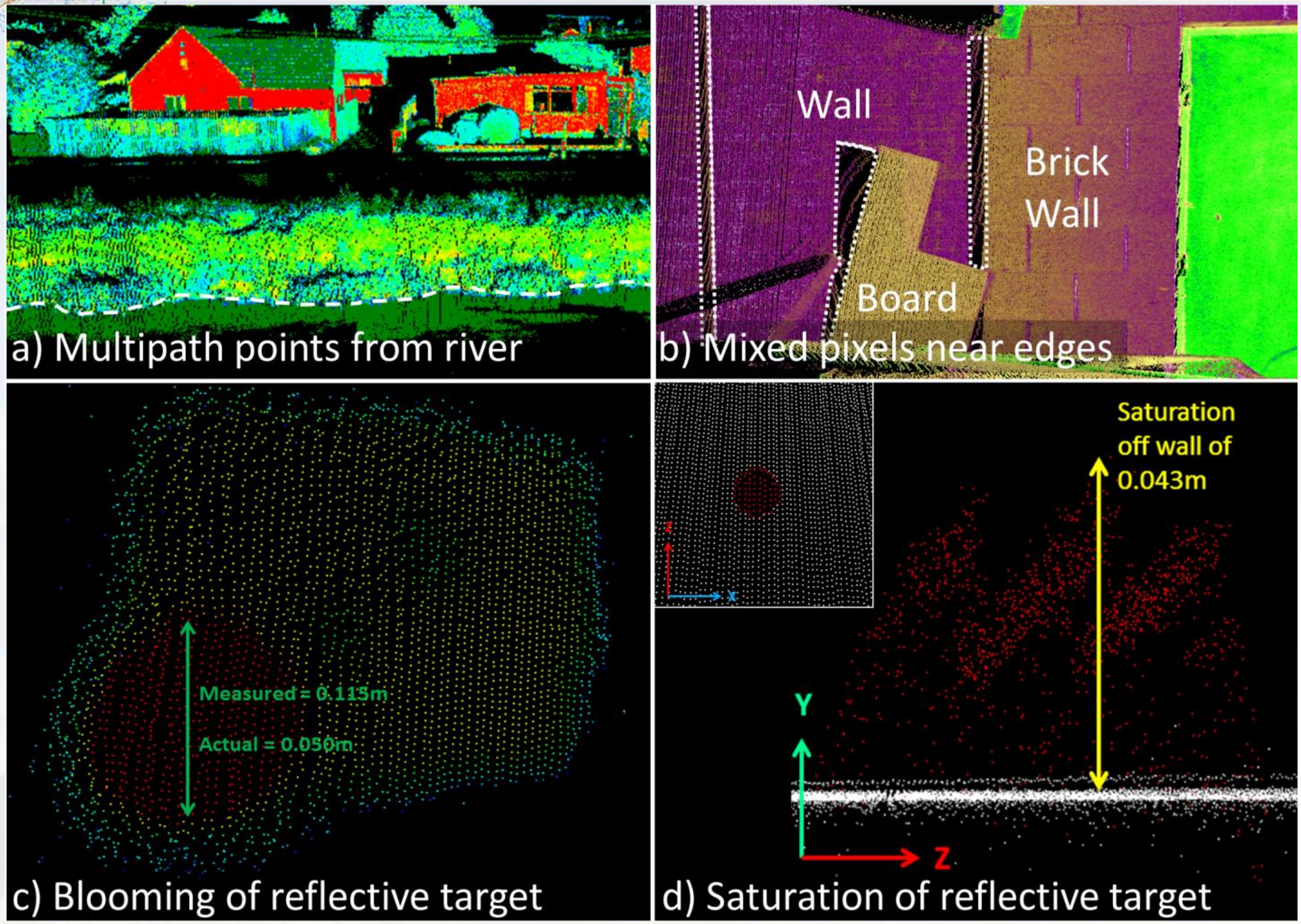
Key Points

- Survey accuracy (especially local) directly affects model accuracy
- High quality acquisition of field data is critical for reliable results and efficient extraction/modeling
- Understand and determine Level of Accuracy \Detail Requirements before planning survey
- Maintain balance of complete coverage versus “modelling” the object later from partial data
- You will never capture 100%. 80% is easy to do, but it is hard to fill in small shadows. Ultimately, you will need to interpolate. Avoid shadows on important objects or complex objects.

Overall factors influencing accuracy

- Ability to determine range
- Ability to determine angles (H&V)
- Spot size on target (i.e. distance from target)
- Geometric arrangement (angle of incidence)
- Material type and reflectivity
- Platform stability
- Geo-referencing methodology (e.g. IMU, GPS, etc.)
- DTM or CAD modeling technique
- Data transfer errors (e.g. digit truncation!!)
- Parallax between photograph and lidar data – use intensity

Is the model or the point cloud more accurate?



a) Multipath points from river

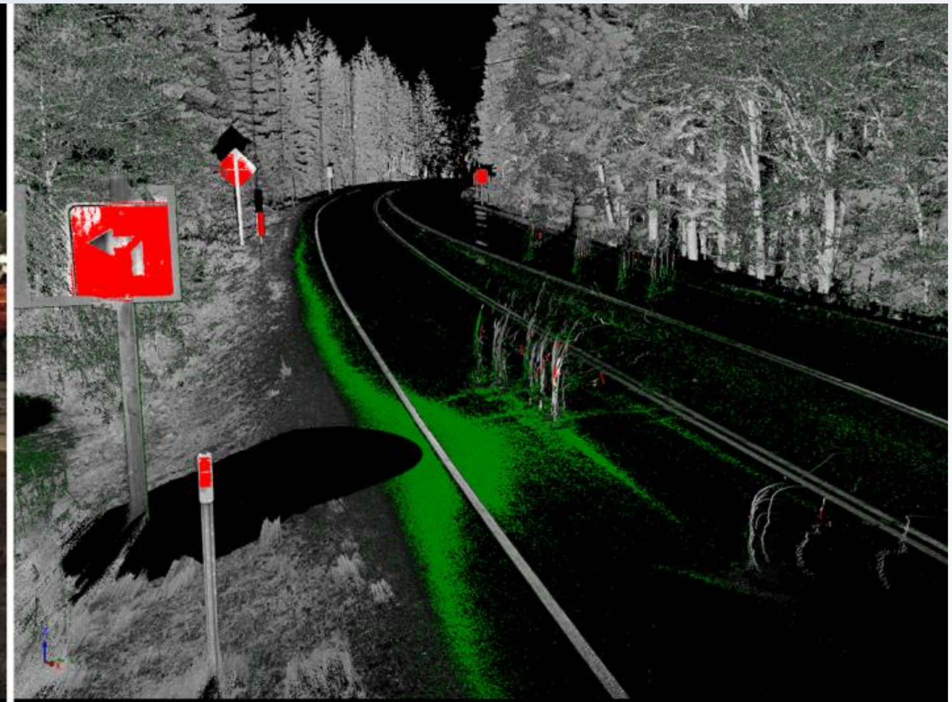
b) Mixed pixels near edges

c) Blooming of reflective target

d) Saturation of reflective target

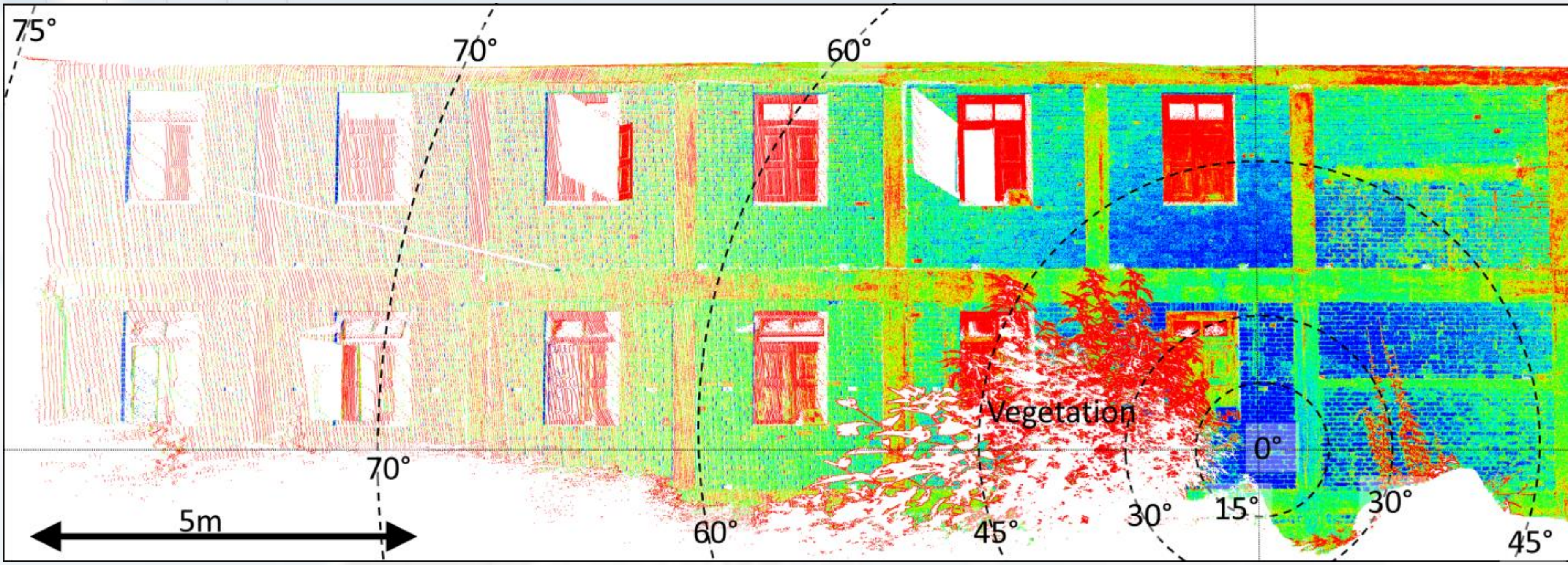
Figure from Olsen, M.J. (Accepted). Chapter 8, Terrestrial laser scanning, Surveying Engineering Manual, ASCE.

e) RGB misalignments on trees



f) Data loss on wet, dark pavement

Figure from Olsen, M.J. (Accepted). Chapter 8, Terrestrial laser scanning, Surveying Engineering Manual, ASCE.

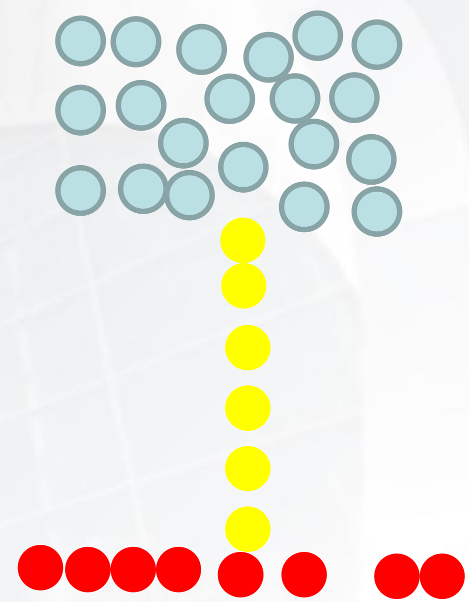


- Data quality degrades with obliqueness to the surface
  - Position
  - Intensity
  - Resolution

Figure from Olsen, M.J. (Accepted). Chapter 8, Terrestrial laser scanning, Surveying Engineering Manual, ASCE.

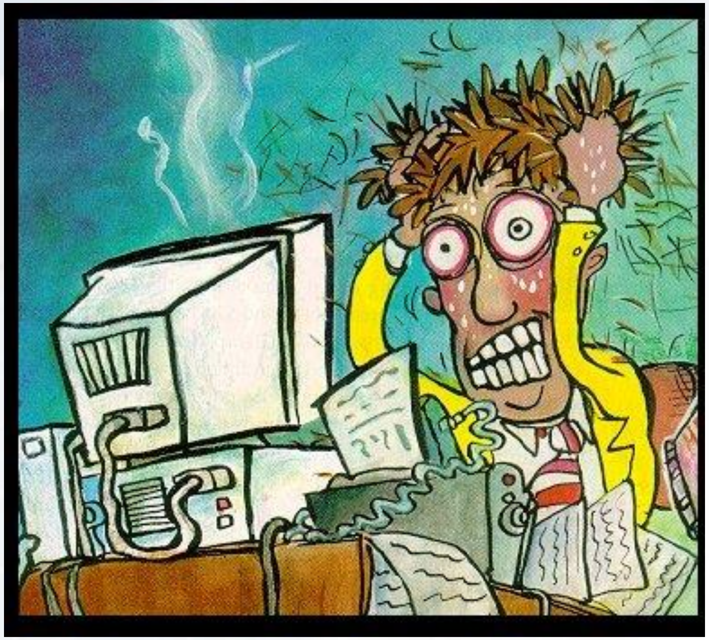
Cleaning/Filtering/Classifying

- Polygons
- Range, intensity, XYZ filters
- Plane filters (above, below)
- Full waveform
- Ground filtering
- Minimum Separation
- Random
- Select and "Delete"
- Some software masks data rather than deletes

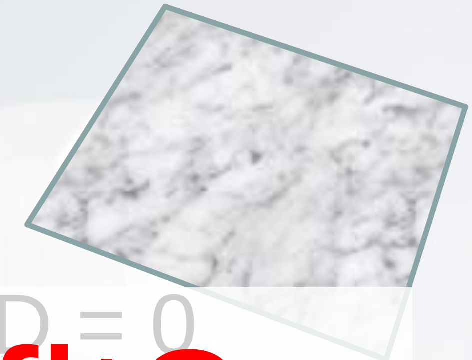


Segmentation Approaches

- Manual
  - Tedious & Frustrating
- Semi-Automatic
  - Isolate an object of interest
  - Fit object to cluster of points
- Automatic
  - Often require a lot of fine tuning of parameters (e.g. tiling)
  - Be prepared for manual cleanup



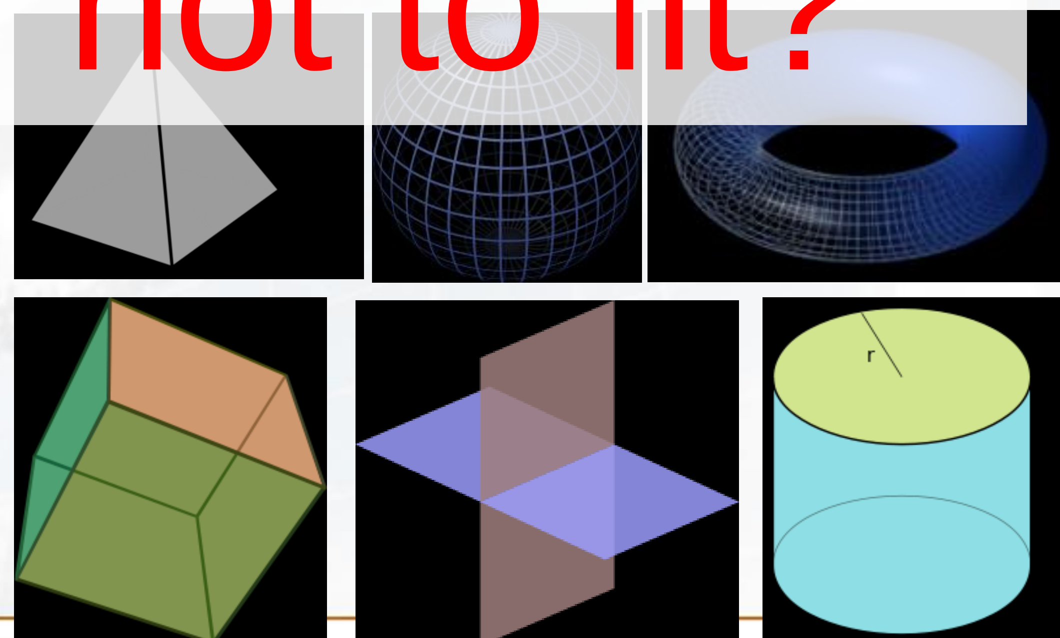
Mathematically defined, Geometric Primitives



- points
- lines and line segments
- planes
- circles and ellipses
- triangles and other polygons
- spline curves
- spheres
- cubes or boxes
- toroids
- cylinders
- pyramids
- teapot

$$Ax + By + Cz + D = 0$$

To fit or not to fit?



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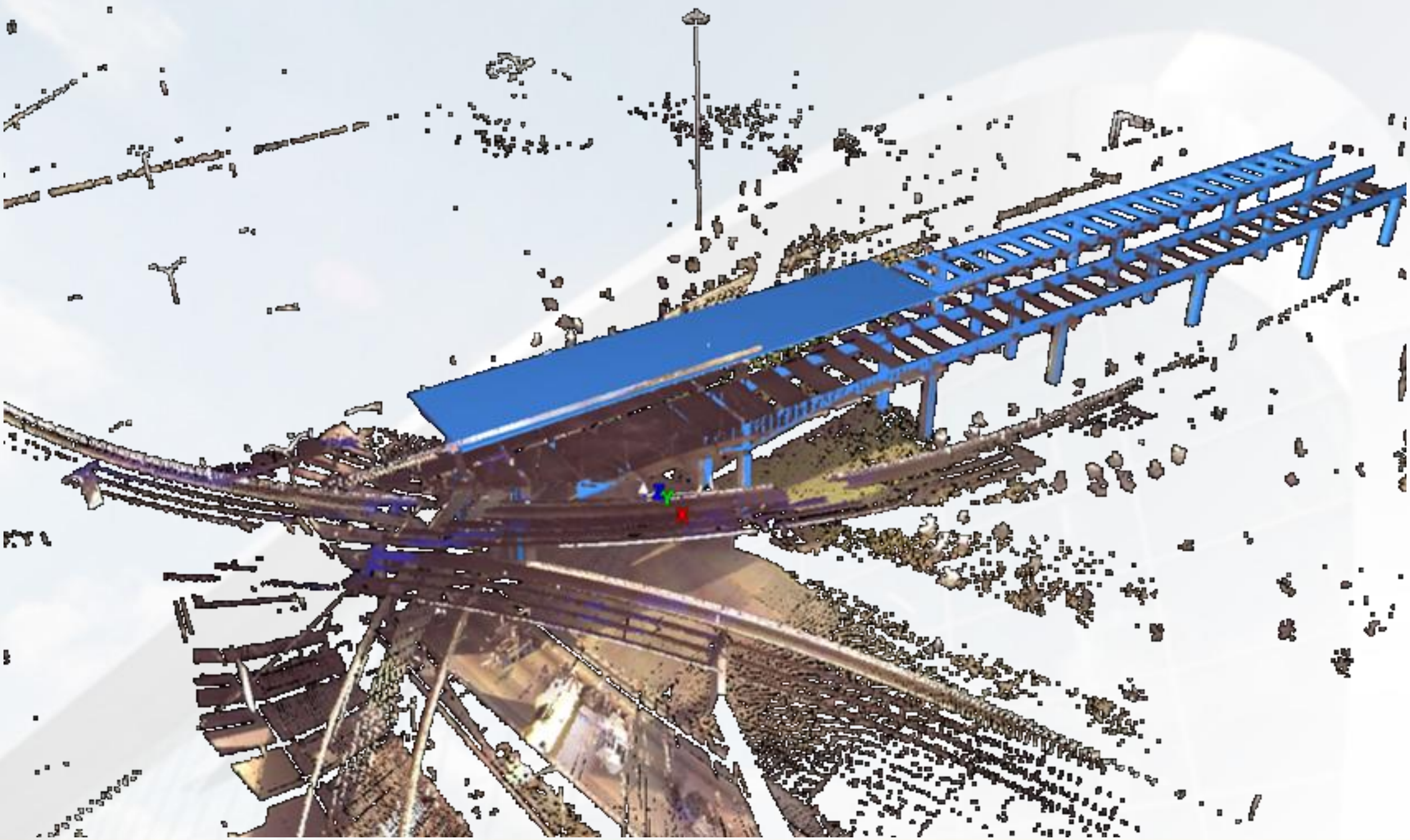

Logan Allendar
Torger Torgerson

Oregon State University

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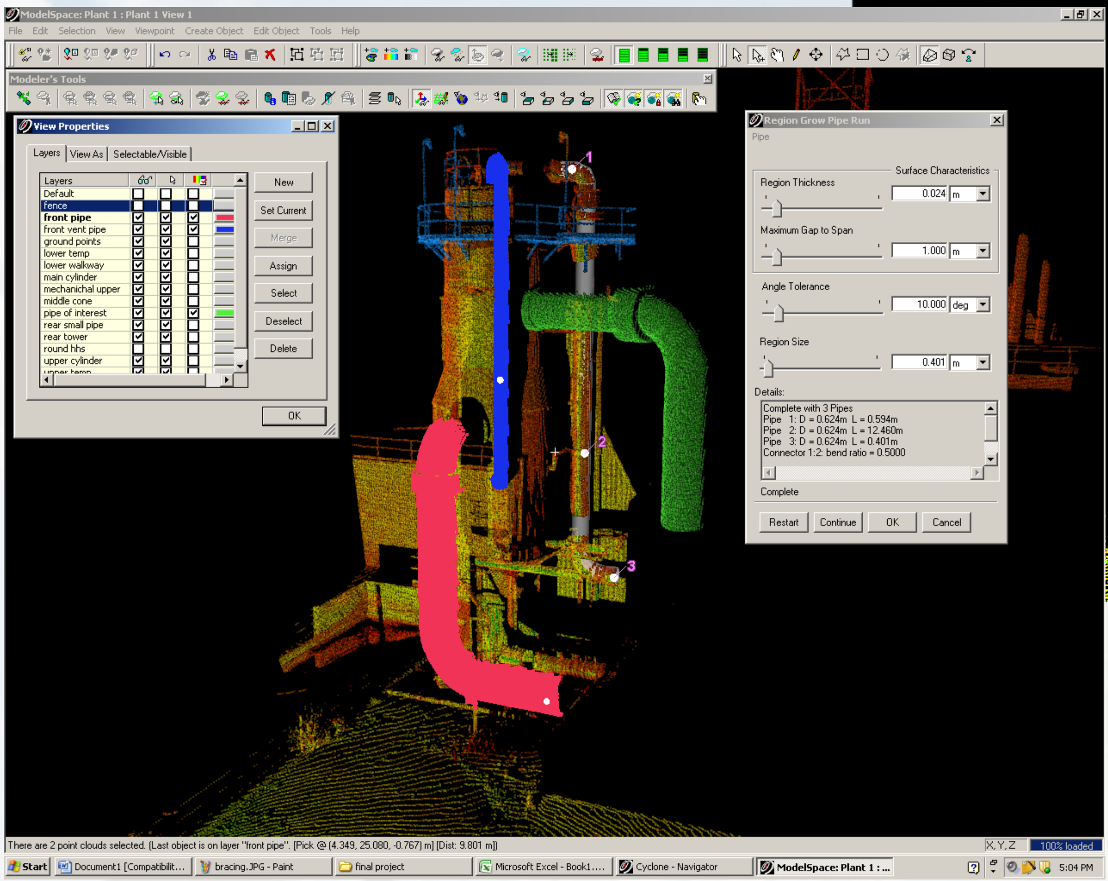

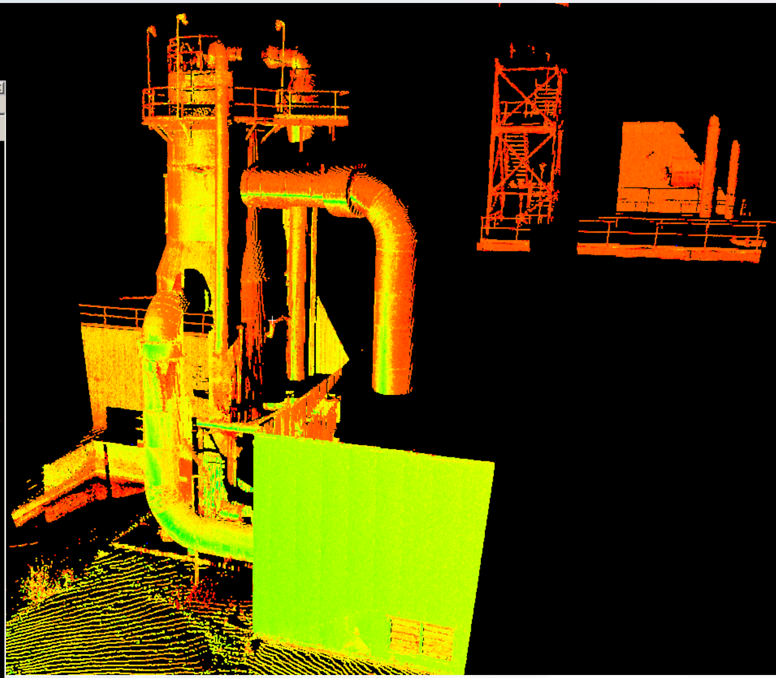

Pipe Modeling
in Leica Cyclone:
Autodetect, Pipe Run

Caution: Scale dependent. Need to seed a typical pipe diameter for best results.

Image: Logan Allendar and Torger Torgerson

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BIM FOR SURVEYORS

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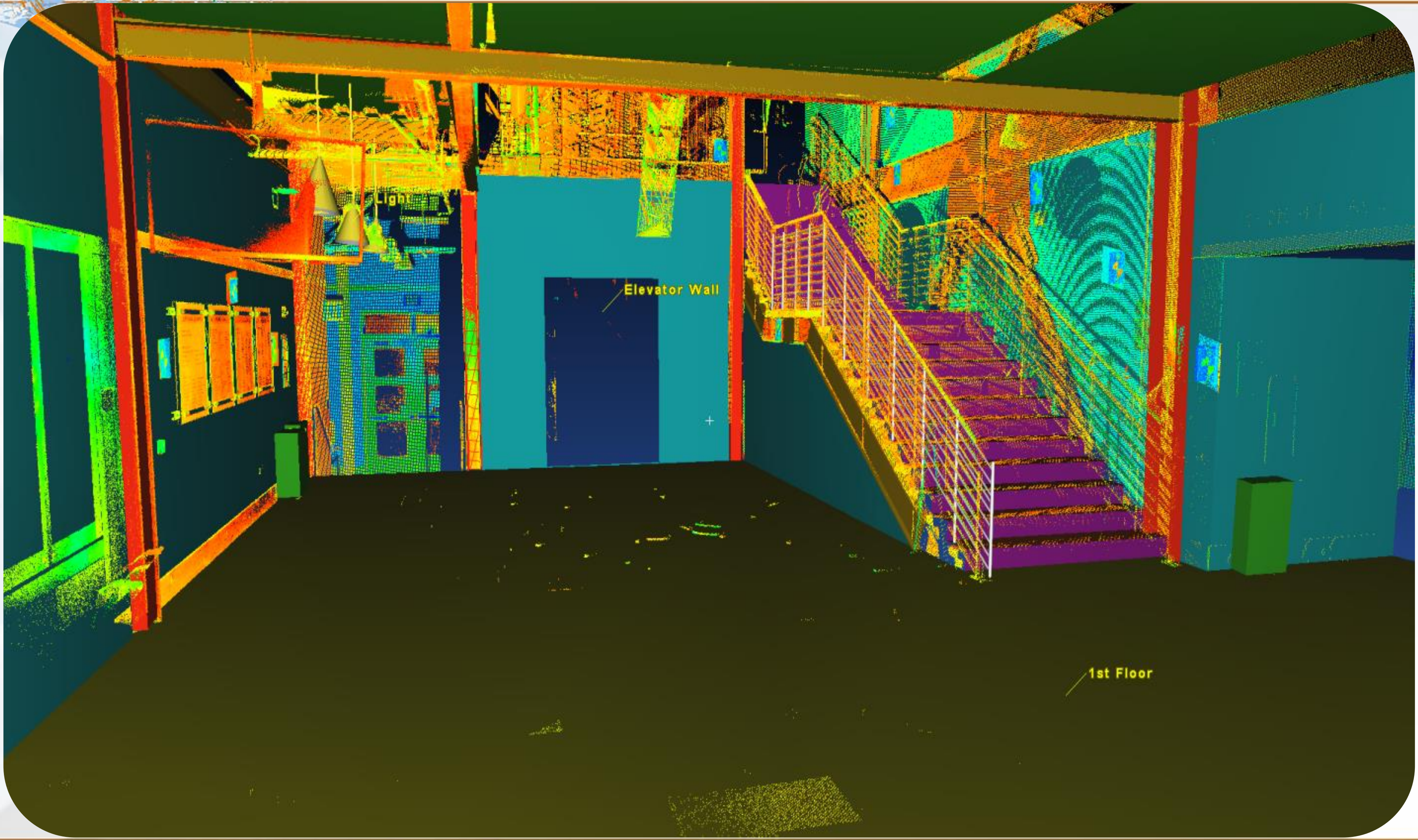

Image: Michael Dennis

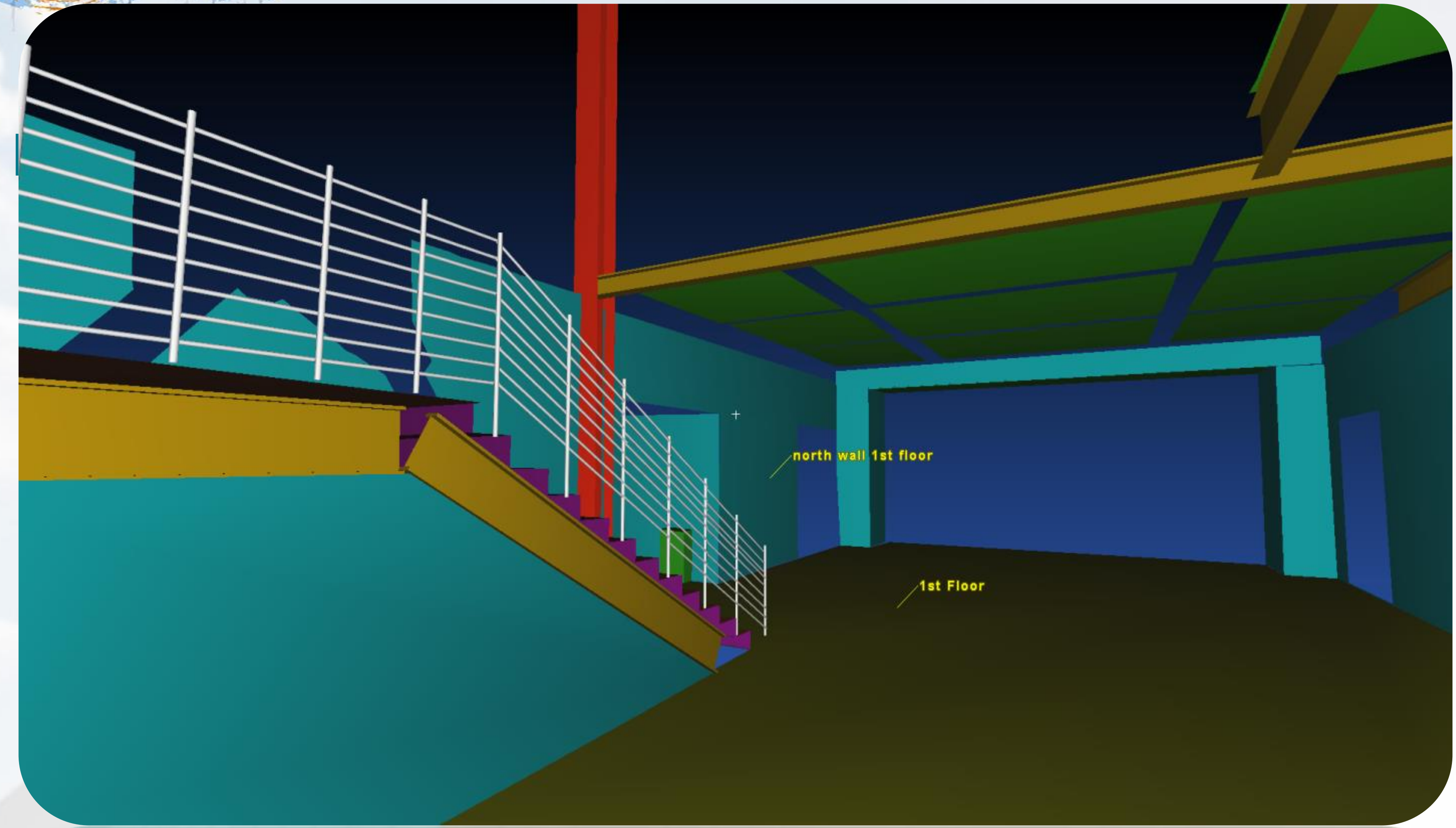

Image: Michael Dennis

Object ID	Object type	Location	*Model dimensions		Section from plans	AISC dimensions		Error with respect to AISC		Section from model	AISC dimensions		Error with respect to AISC	
			d	bf		d	bf	d	bf		d	bf	d	bf
6580	Column	1st floor, by monitor	29.3	22.8	W10X22	25.9	14.6	13.1%	56.1%	W12X53	30.7	25.4	-4.7%	-10.2%
65A0	Column	1st floor, NE corner of elevator	29.8	23.9	W10x45	25.7	20.4	16.2%	17.3%	W12X53	30.7	25.4	-3.0%	-5.9%
65AC	Beam	1st floor, by rear entrance	34.8	12.5	W14x22	34.8	12.7	0.0%	-1.6%	W14x22	34.8	12.7	0.0%	-1.6%
65C6	Beam	1st floor, by main doors	34.1	19.9	W10x22	25.9	14.6	31.6%	36.3%	W14X43	34.8	20.3	-2.0%	-2.1%
65D4	Beam	1st floor, cross beam above stairs	21.6	16.8	W10x22	25.9	14.6	-16.6%	15.0%	W8X28	20.5	16.6	5.5%	1.1%
66DC	Beam	1st floor, by hanging sculpture	44.1	15.5	W14x22	34.8	12.7	26.7%	22.0%	W18X35	45.0	15.2	-1.9%	1.7%
6776	Column	1st floor, at elevator and stairs	19.4	14.6	W8X24	20.1	16.5	-3.7%	-11.6%	W8X24	20.1	16.5	-3.7%	-11.6%
6B28	Column	1st & 2nd floor, SE corner elevator	21.3	19.5	W8X24	20.1	16.5	5.7%	18.1%	W8X40	21.0	20.5	1.6%	-4.9%
6879	Beam	2nd floor, north wall	58.7	21.6	W24X76	60.7	22.8	-3.3%	-5.4%	W24X76	60.7	22.8	-3.3%	-5.4%
68A6	Beam	2nd floor, base atrium balcony	37.8	13.3	W10X22	25.9	14.6	45.9%	-8.9%	W16X26	39.9	14.6	-5.2%	-8.9%
695B	Beam	2nd floor, east side atrium	52.3	16.0	W21X50	52.8	16.6	-1.0%	-3.5%	W21X50	52.8	16.6	-1.0%	-3.5%
68AE	Column	1st & 2nd floor, north wall	32.9	35.6	W14X132	37.3	37.3	-11.9%	-4.7%	W14X90	35.6	37.3	-7.5%	-4.7%
							Minimum	**-16.6%**	**-11.6%**			**Minimum**	**-7.5%**	**-11.6%**
							Maximum	**45.9%**	**56.1%**			**Maximum**	**5.5%**	**1.7%**
							Mean	**8.6%**	**10.8%**			**Mean**	**-2.1%**	**-4.2%**
							Std deviation	**±18.7%**	**±20.7%**			**Std deviation**	**±3.4%**	**±4.0%**

Table by Michael Dennis
(OSU, NGS-NOAA)

Automated Approaches

Type	Advantages	Limitations	Example Algorithms	Reference
Geometric	Generic - Function with any point cloud, most widely available. Works well in urban environments where well defined features are prominent	Computationally costly, require finely-tuned parameters, limited to small datasets, sensitive to variable point density and data gaps common in TLS data.	RANSAC (Random Sampling and Consensus)	Fischler and Bolles (1981), Schnabel et al. (2007).
			Hough Transform	Hough (1962), Ballard and Brown (1982), Vosselman (1999), Maas and Vosselman (1999), Rabbani (2006)
			Region Growing (based on proximity, slope, curvature, and surface normal) from a seed location	Ballard and Brown (1982), Rabbani et al. (2007), Pu et al. (2006), Moussa and El-Sheimy (2010)
			Detecting Surface Discontinuities	Wang and Shan (2009)
			K-Means Clustering	Chehata et al. (2008)
			Voxelation	Douillard et al. (2011)
			Curvature	Son and Kim (2015)
			Multi-scale morphological analysis	Bradu and Lague (2012), Rodriguez-Caballero et al. (2016)
			Fuzzy Parameters in relative height differentials	Biosca and Lerma (2008)
			Tensor voting of normal vector clusters	Lin and You (2006)
			Support Vector Machine classification of the DTM	Serna and Marcotegui (2014)
Color	Enables application of Computer Vision and Image Processing algorithms, some objects are readably segmentable by color	Color information not always available in point cloud, Obtaining high quality images with scans can sometimes be time consuming, Color not sufficient alone to distinguish multiple objects - some features can have more than one color, others can share the same color.	Spectral filtering	Lichti (2005)
			Graph theory segmentation and union (also considers normals)	Strom et al. (2010)
			Mean shift smoothing algorithm to cluster sections of images followed by PCA for classification.	Sok and Adams (2010)
			Superpixel clustering (SLIC) followed by normal vector evaluation through SVM. A k-nearest neighbor algorithm is utilized for refinement.	Mahmoudabadi et al. (2013)
Intensity	Inherent property of laser scan data, intensity helps distinguish contracts between surfaces that may not be distinguished by geometry alone. Computationally efficient.	Intensity values are affected by a variety of factors. Requires radiometric calibration for optimal results.	Conditional Random Field to classify buildings, low vegetation, tree, natural ground, and asphalt.	Niemeyer et al. (2012)
			Full waveform analysis the of the intensity amplitude, the cross-section per illuminated area, and the backscatter coefficient followed by a SVM classifier.	Mallet et al. (2011)
Data Structure	Efficient and enables exploitation of computer vision and image processing algorithms.	Requires a structure point cloud	Scan line segmentation followed by surface growing process between adjacent scan lines	Jiang and Bunke (1994), Hoover et al. (1996), Sithole and Vosselman (2003), Sithole (2005)
			Calculations of gradients from the range image followed by region growing image segmentation	Gorte (2007)
			Smoothed surface normal and range panorama analysis	Zeibak and Filin (2009)
			Mean-shift algorithm to segment Intensity, Range, Surface normals, and True Color Channel panoramas.	Barnea and Filin (2013)
			Extraction of trees using range, intensity, LUV, and HSV color panoramas	Barnea and Filin (2012)
			Use of computer vision algorithms to segment based on HDR color, normalized intensity, range, and normal components represented as 2D panoramas.	Mahmoudabadi et al. (2016)

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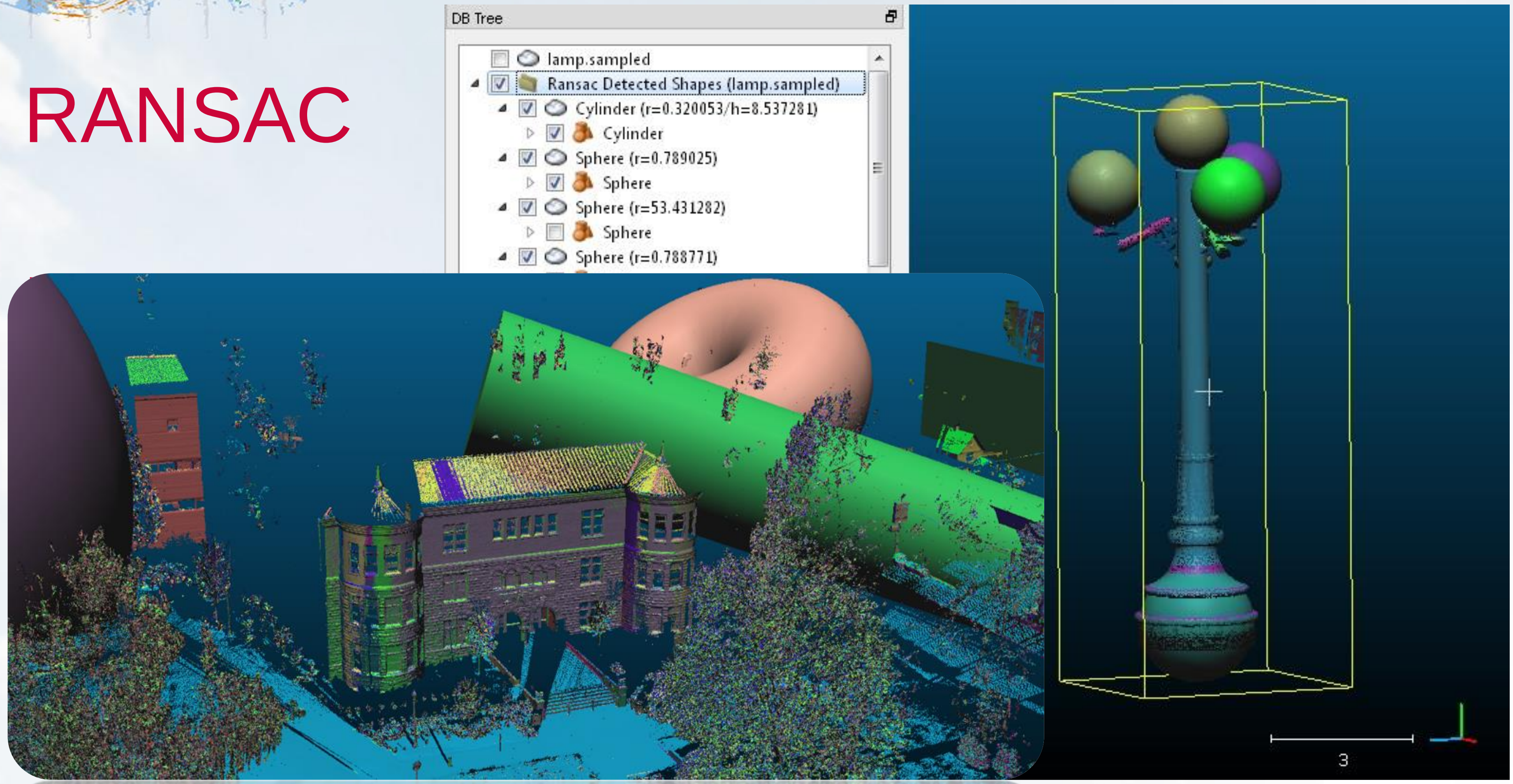
Semi-Automated\Automated cloud segmentation challenges

- Usually complex, computationally costly
- Require finely-tuned parameters & sensitive to parameters
- Laborious when applied to broader and larger datasets
- Fit the points to mathematical models – not all objects have regular geometric shape
- Many techniques developed for small datasets (few million points)
- Quality Control is still often a manual process

RANSAC



http://www.cloudcompare.org/doc/wiki/index.php?title=File:Cc_qRansacSD_result.jpg

CAD/BIM considerations

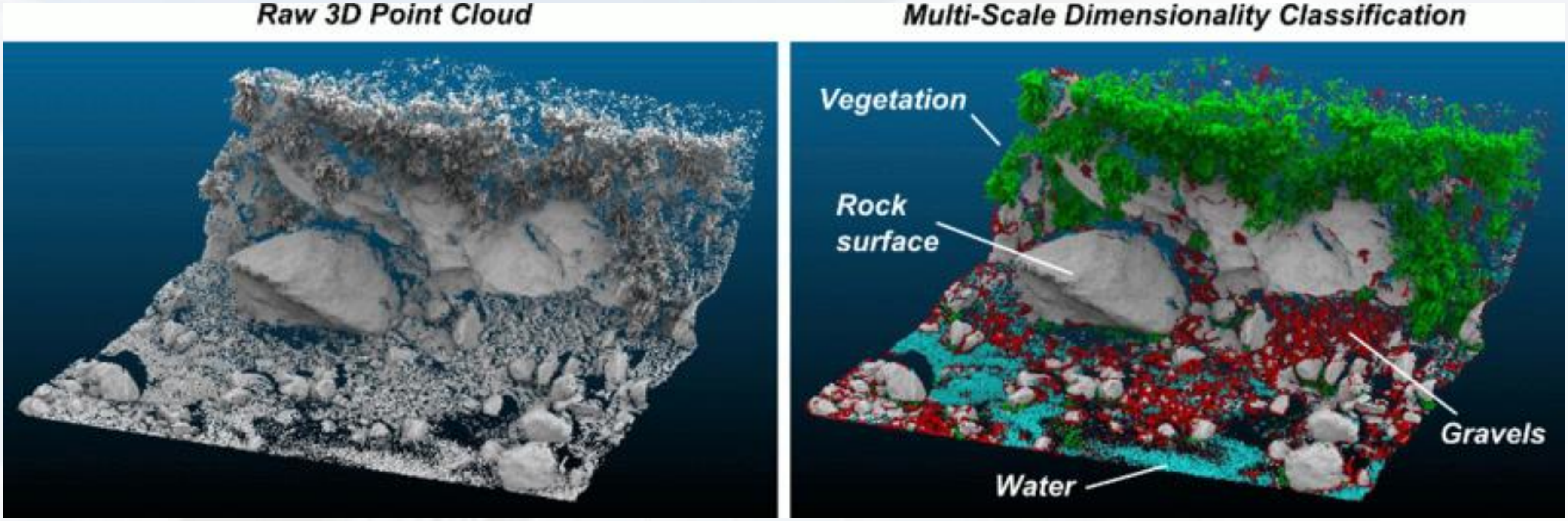
- Simple geometric shapes (minimal storage, easy interaction)
- Real world is not simple (deflections)
- Constraints (e.g., horizontal, vertical, or meet at 90 degrees).
- Data interoperability hurdles
- Data coverage can enable very accurate modeling (e.g., plane defined by 1E6 points versus few points by traditional methods)
- Software enables point cloud viewing\modeling in CAD\BIM

Generic modeling considerations

- To fit or not to fit
- Increased data = increased computation time
- Engineering software may not be able to handle it
- Increased smoothing removes noise, but removes features
- Too much smoothing removes wanted features
- Orders of magnitude increase in manual processing time for better and better (higher resolution\reduced artifacts) models
- Suggest iterative approach. Start with a “crude model” , clean it, do calculations\evaluation, then keep cleaning, repeat calculations and see how much things change.

Canupo

•Brodu, N. and Lague, D., 3D Terrestrial LiDAR data classification of complex natural scenes using a multi-scale dimensionality criterion : applications in geomorphology, *ISPRS journal of Photogrammmetry and Remote Sensing*, 68, p. 121-134, 2012.



- http://www.cloudcompare.org/doc/wiki/index.php?title=CANUPO_(plugin)
  https://geosciences.univ-rennes1.fr/spip.php?article1284&lang=fr

Efficient Segmentation

Mahmoudabadi, H., **Olsen, M.J**., & Todorovic, S., (2016). "Efficient point cloud segmentation utilizing computer vision algorithms." *Journal of Photogrammetry and Remote Sensing*, 119C, 135-150, doi: 10.1016/j.isprsjprs.2016.05.015

Objectives:

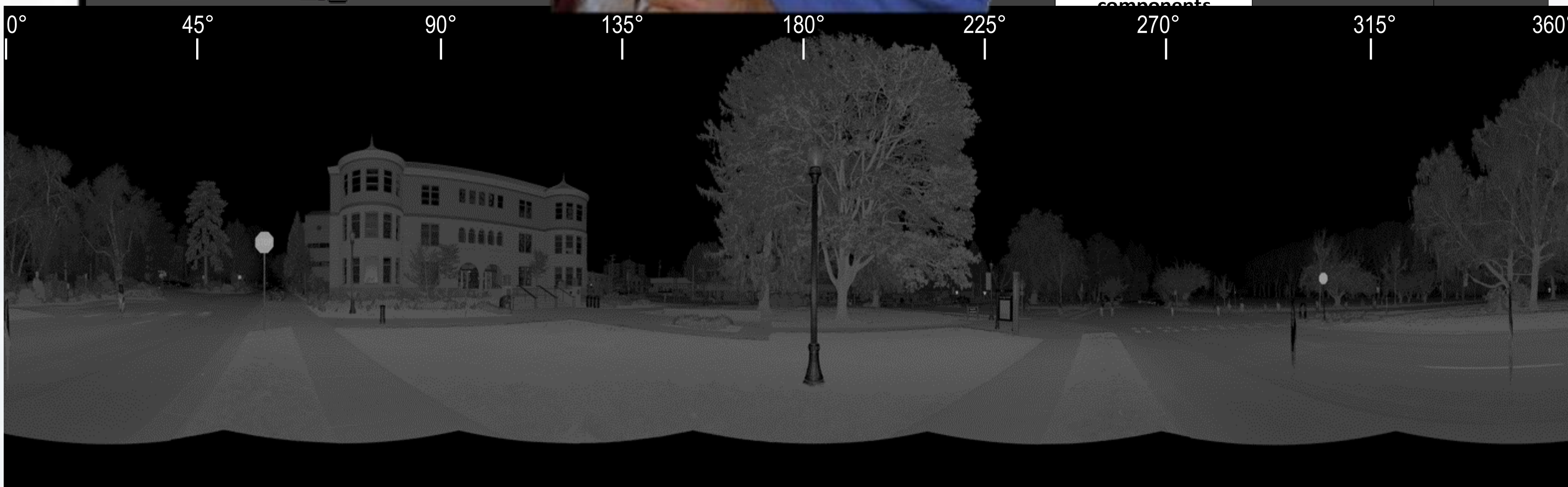
- Apply image processing and computer vision to segment dense, large, 3D point clouds

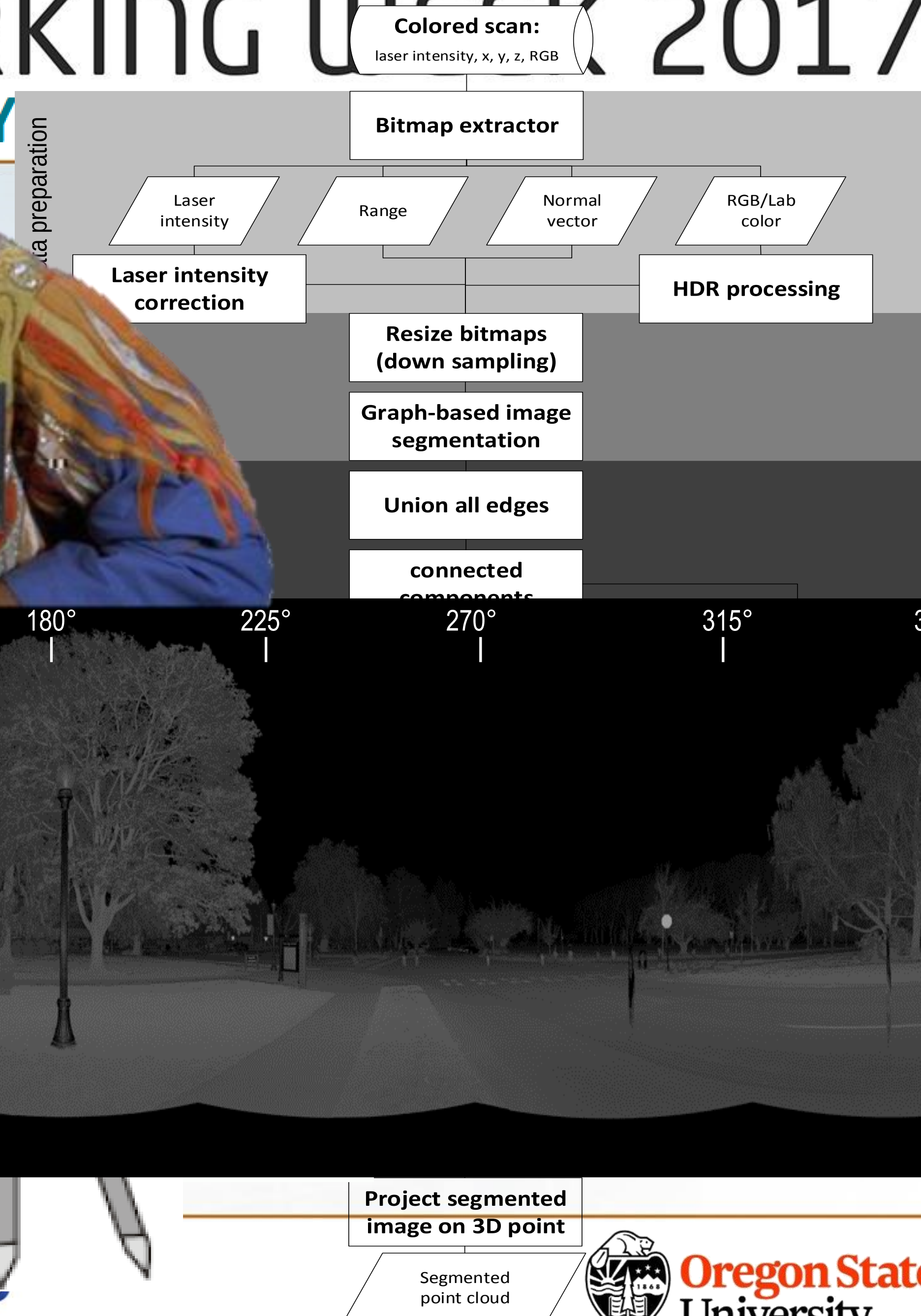
- Implement HDR photography to improve digital images and consequently segmentation results.

- Derive an empirical correction formula to improve segmentation performance.

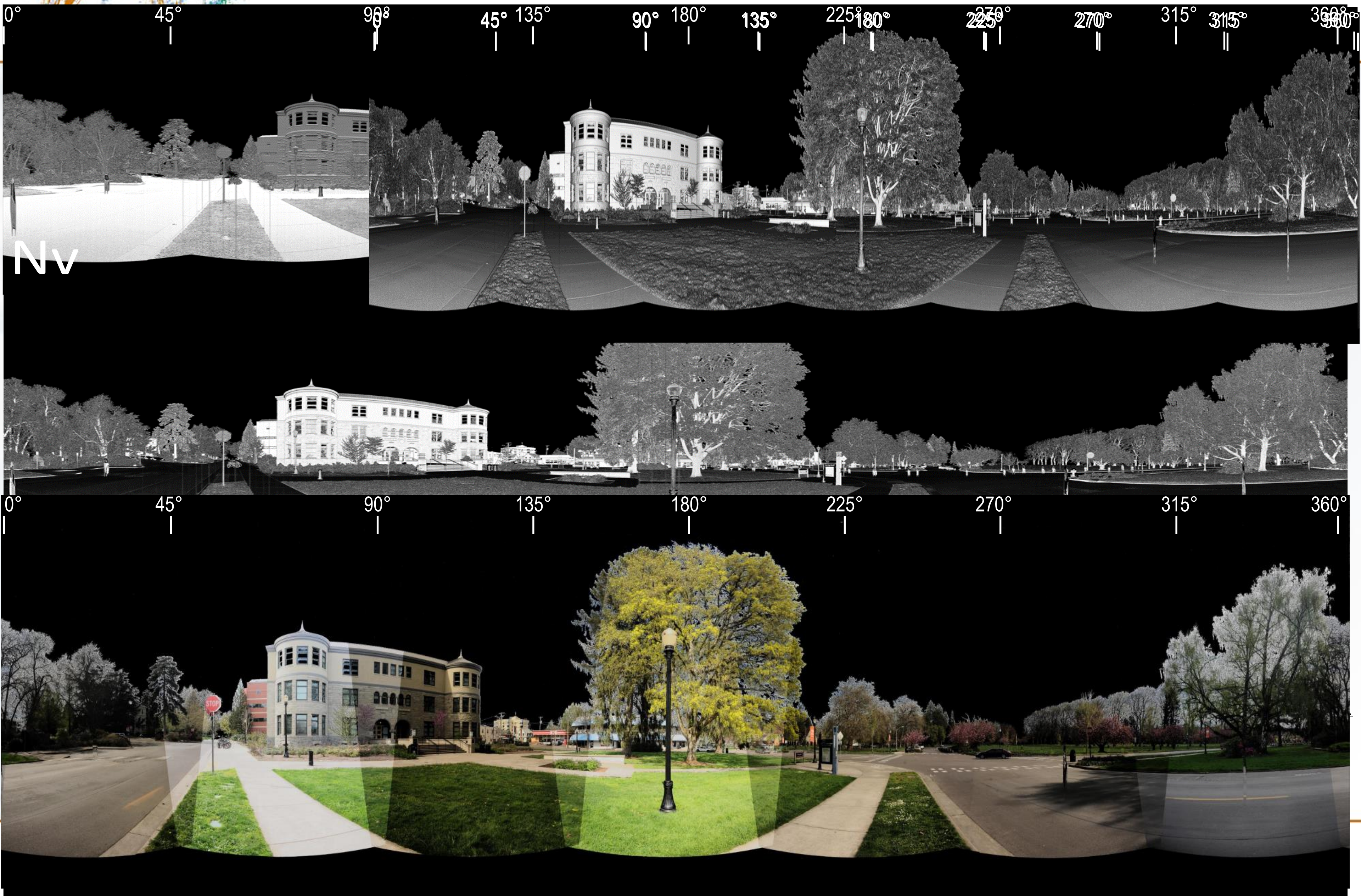
Methodology

2D Panoramic Image Map



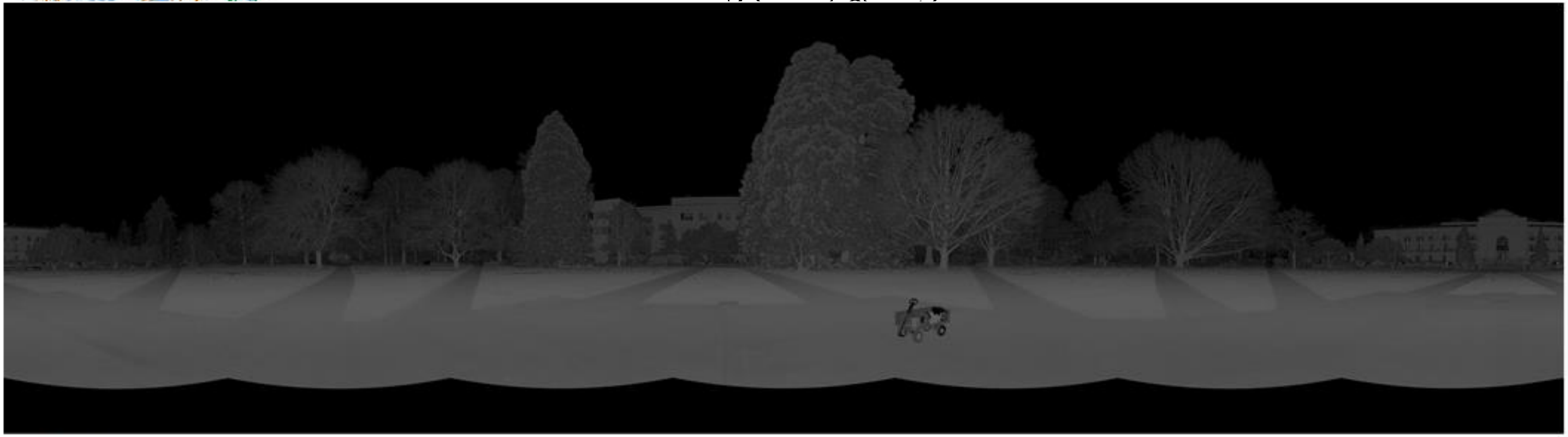


PIMP my scans:



Data improvement 1 - Laser intensity correction

$$log(\frac{L \times \rho}{\ldots})$$



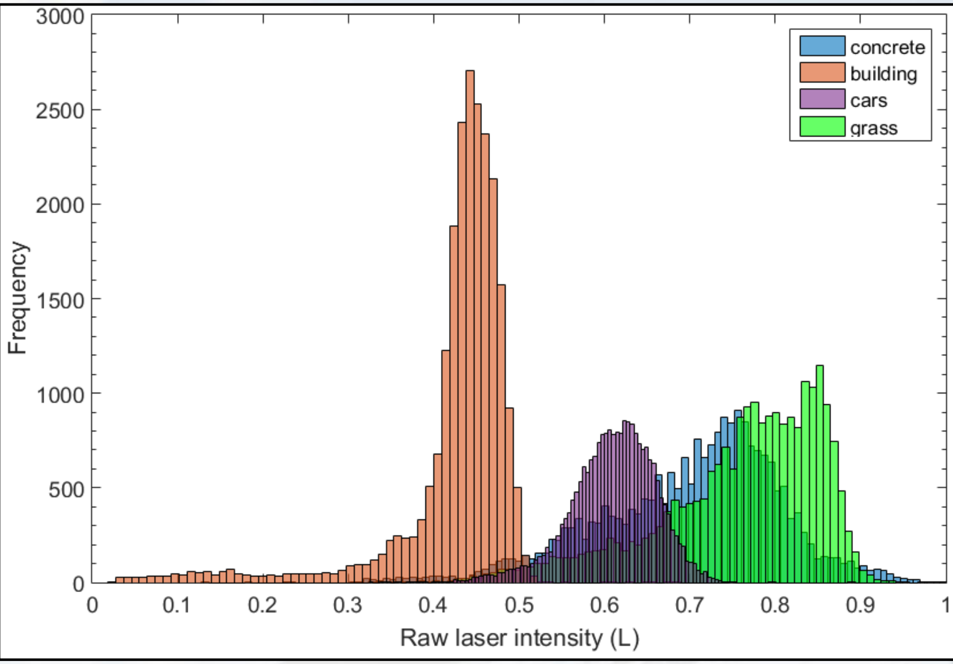
A) L PIMP

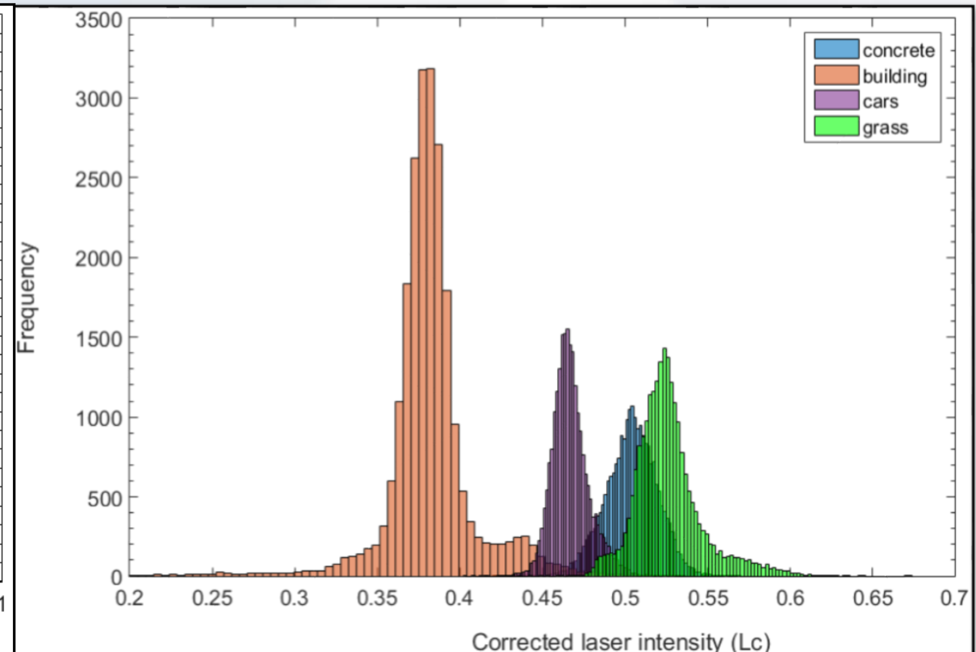
B) Lc PIMP

geospatial software

University

Data improvement 1 - Laser intensity correction (B)





Review of Techniques: Kashani, A., **Olsen, M.J.**, Parrish, C.E., & Wilson, N. (2015). "A review of lidar radiometric processing: from ad hoc intensity correction to rigorous radiometric calibration," *Sensors*, 15(11), 28099-28128; doi: 10.3390/s151128099

Data improvement 2 – HDR vs automatic mode

A) RGB PIMP

B) HDR PIMP

C) RGB PIMP

D) HDR PIMP

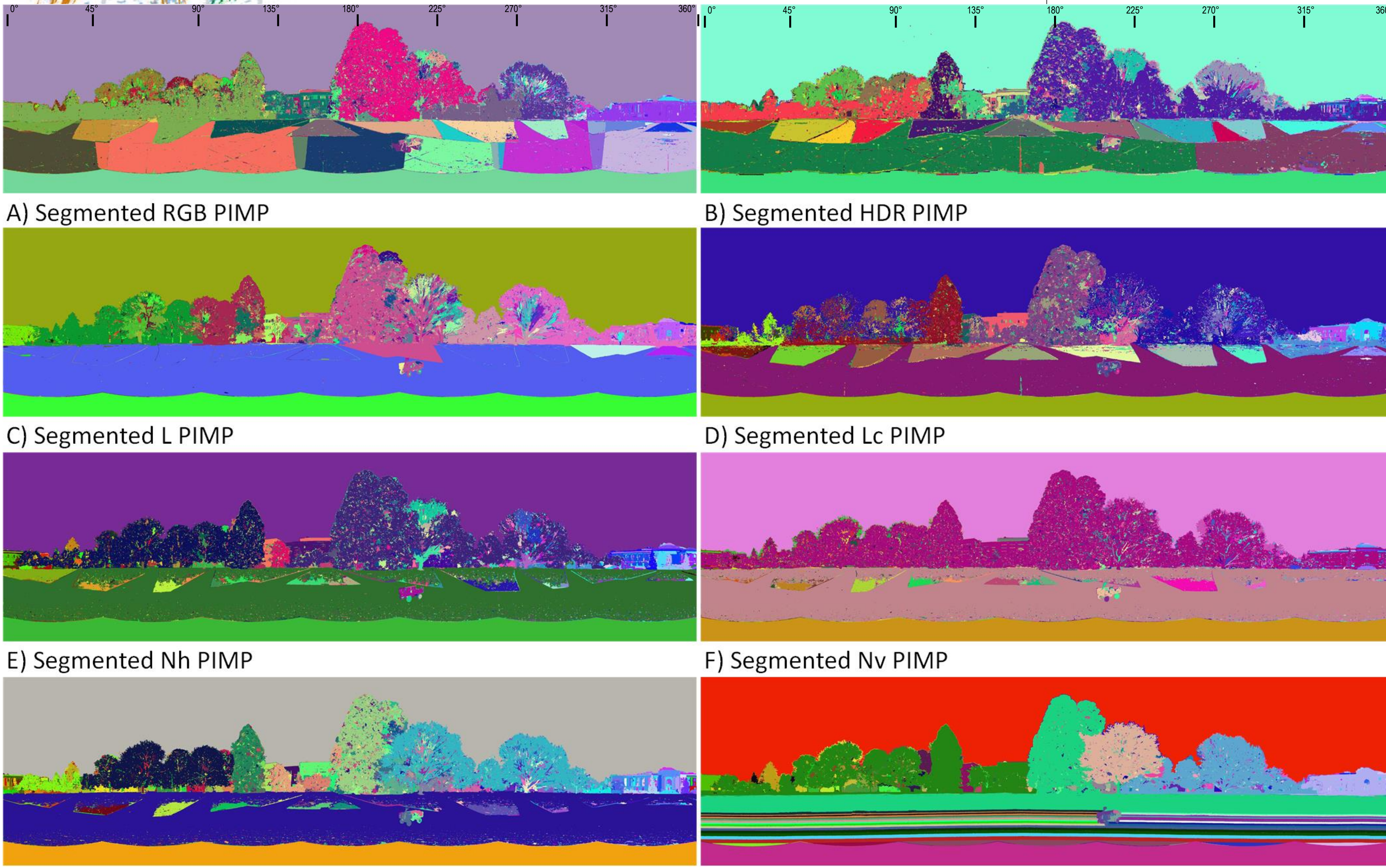
E) RGB PIMP

F) HDR PIMP

G) RGB PIMP

H) HDR PIMP

Colored scan:
laser intensity, x, y, z, RGB



A) Segmented RGB PIMP

B) Segmented HDR PIMP

C) Segmented L PIMP

D) Segmented Lc PIMP

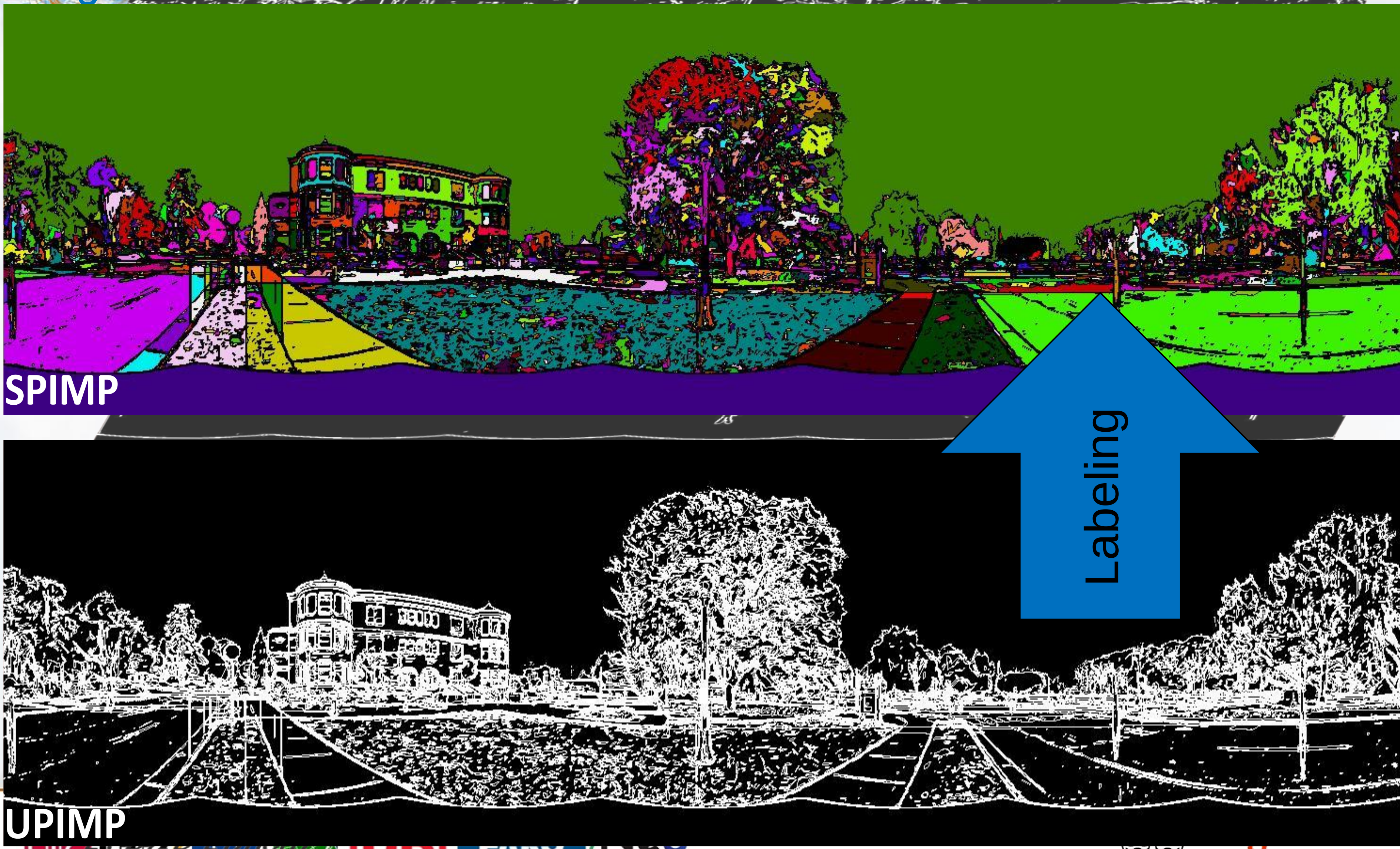
E) Segmented Nh PIMP

F) Segmented Nv PIMP

G) Segmented β PIMP

H) Segmented ρ PIMP

Integra



Merging

$$V_{ik} = [\mu_{ik} \quad \sigma_{ik}] \qquad k = 1, \cdots, K$$

K = number of input PIMPs

N = number of segments

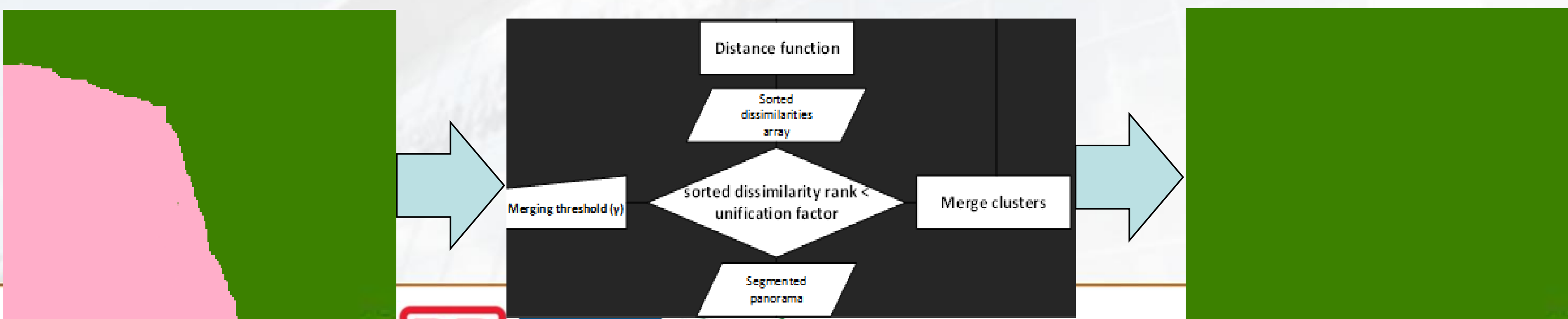
W = Weight vector (in this research all 1)

D = sparse matrix of (δ_{ij})

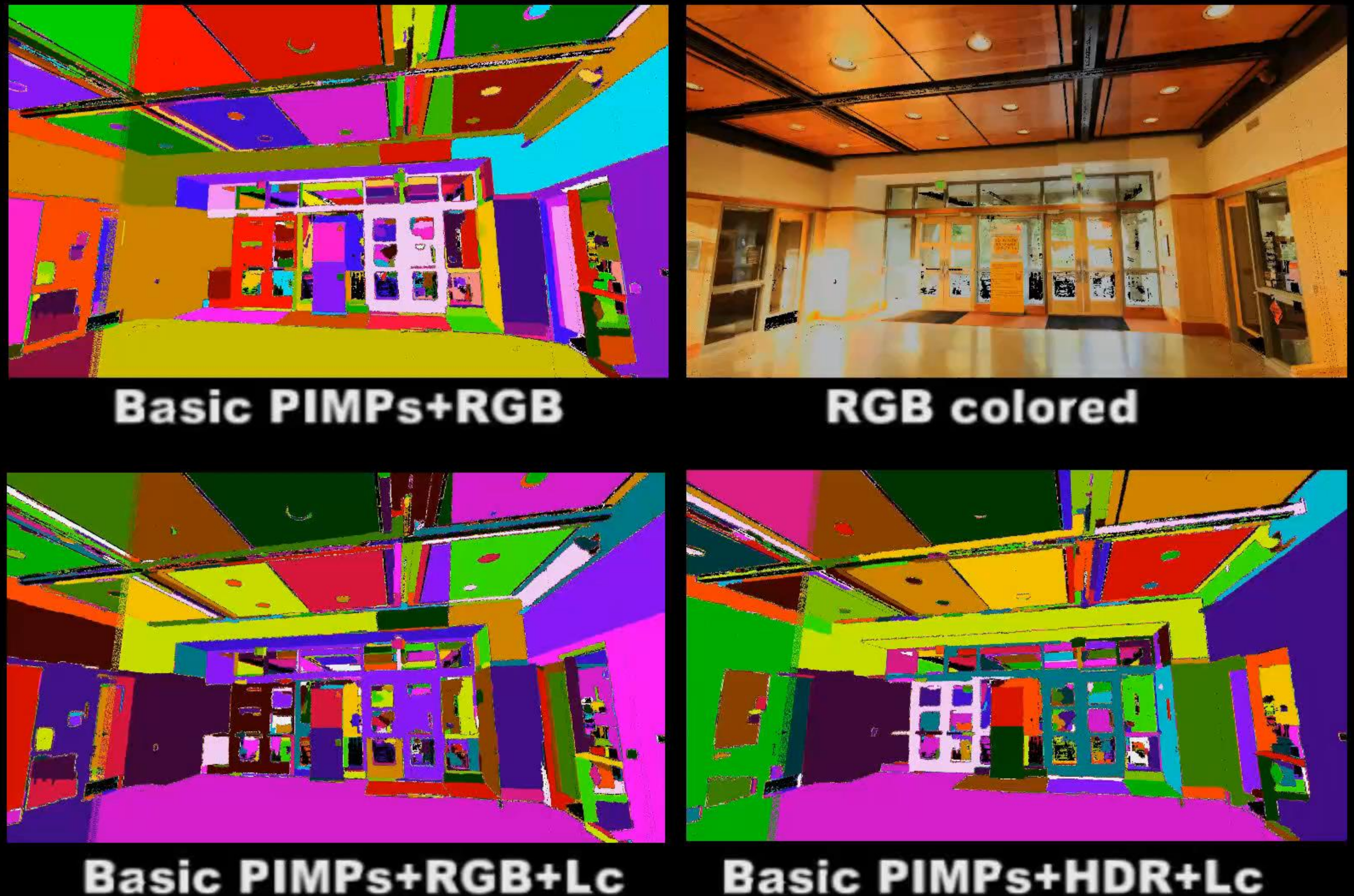
γ = merging threshold

$$\delta_{i,j} = \sum_{k=1}^{K} W_k \cdot \| V_{i_k} - V_{j_k} \|$$

$$\max(\| D \|) = \frac{N(N-1)}{2}$$



Evaluate data improvement



A) RGB PIMP B) Basic PIMPs (Nn, Nv, ρ, β)+ RGB C) Basic PIMPs + HDR D) Basic PIMPs + HDR + Lc

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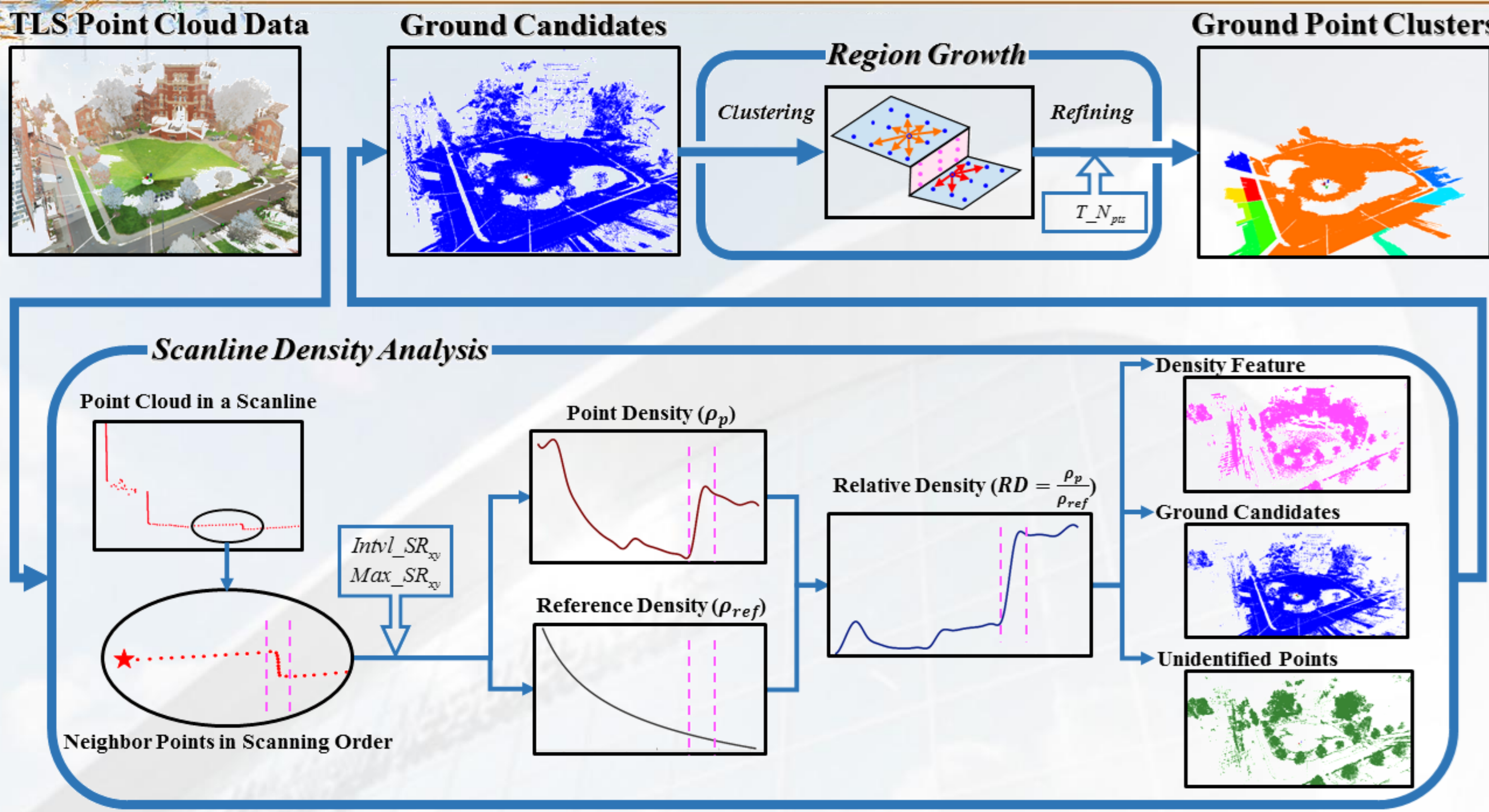


Che, E., & **Olsen, M.J.,** (2017). “Fast Ground Filtering for TLS data via ScanLine Density Analysis,” *ISPRS Journal of Photogrammetry and Remote Sensing,* 129, 226-240, http://dx.doi.org/10.1016/j.isprsjprs.2017.05.006.

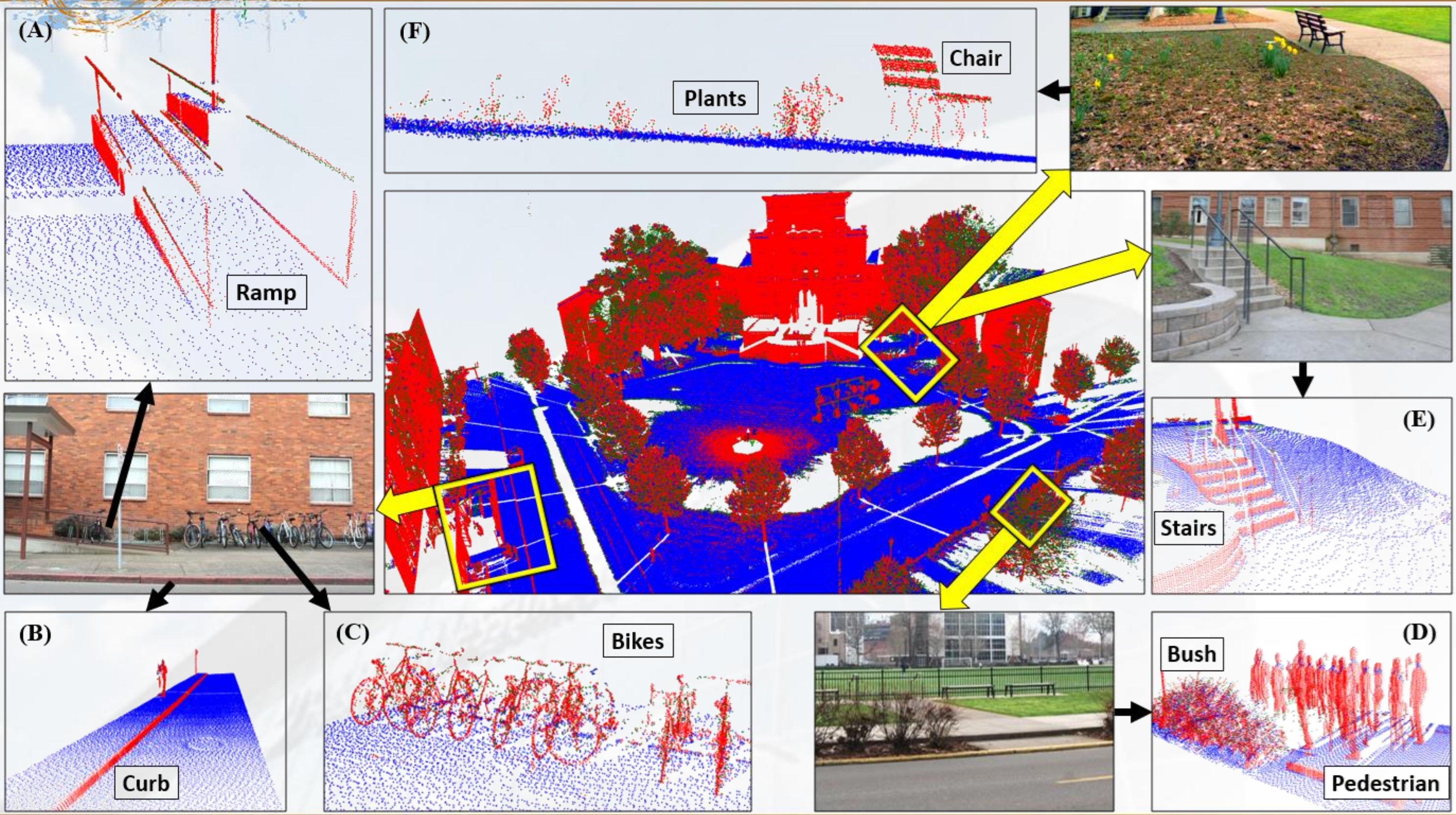


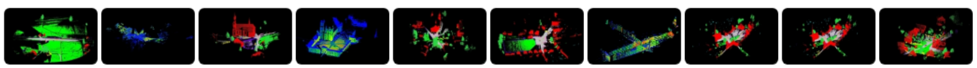
Image: Che & Olsen, 2017

Semantic3d.net

Large-Scale Point Cloud Classification Benchmark

home data results submit FAQ people login sign up

Welcome to the Large-Scale Point Cloud Classification Benchmark!



3D point cloud classification is an important task with applications in robotics, augmented reality and urban planning. Recent advances in Machine Learning and Computer Vision have proven that complex real-world tasks require large training data sets for classifier training. At the same time, until now there were no data sets for 3D point cloud classification which would be sufficiently rich in both object representations and number of labelled points. For example, the well-known Oakland data set contains less than 2 million labelled points. Another popular data set, the NYU benchmark, provides only indoor scenes. Finally, both Sydney Urban Objects data set and the IQmulus & TerraMobilita Contest use a 3D Velodyne LIDAR mounted on a car which provides much lower point density than a static scanner. The same counts for the Vaihingen3D airborne benchmark.

This benchmark closes the gap and provides the largest known labelled 3D point cloud data set of natural scenes with over 3 billion points in total. It also covers a range of diverse urban scenes: churches, streets, railroad tracks, squares, villages, soccer fields, castles to name just a few. The point clouds we provide are scanned statically with state-of-the-art equipment and contain very fine details. Our goal is to help data-demanding methods like deep neural nets to unleash their full power and to learn richer 3D representations than it was ever possible before.

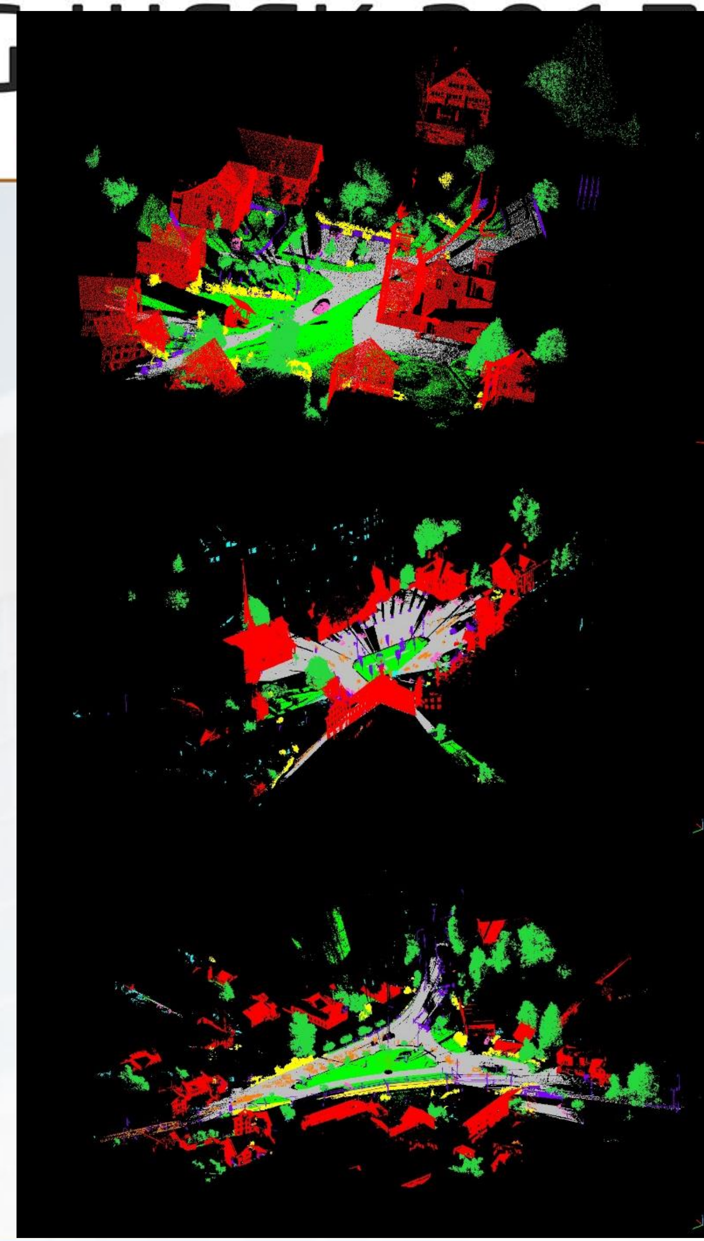
What do we provide?

We have created a framework for the fair evaluation of semantic classification in 3D space. In this framework we provide:

- A large set of point clouds with over **one billion** of labelled points.
- Ground truth, hand-labelled by professional assessors.
- A common evaluation tool providing the established intersection-union measure along with the full confusion matrix.

Change Log

- 11.01.2016: The Point Cloud Classification website is online.

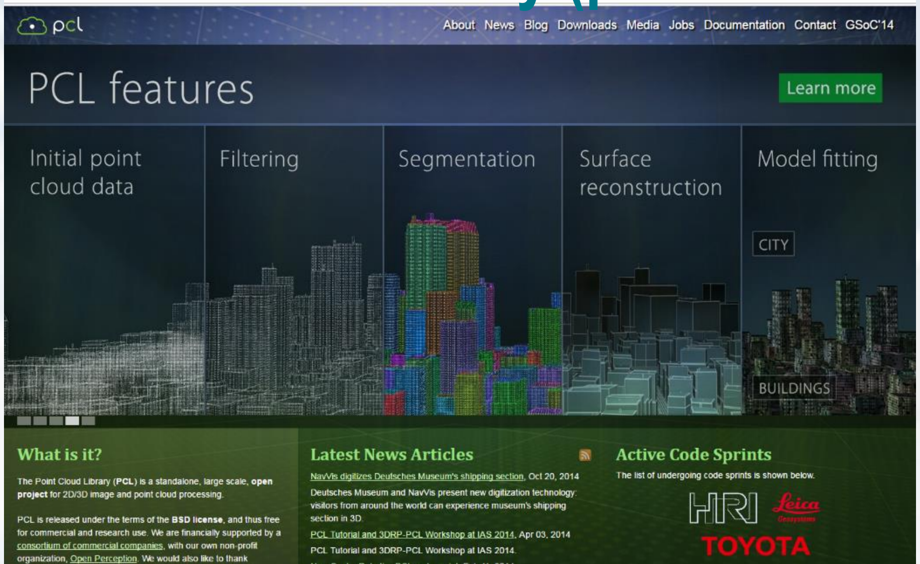


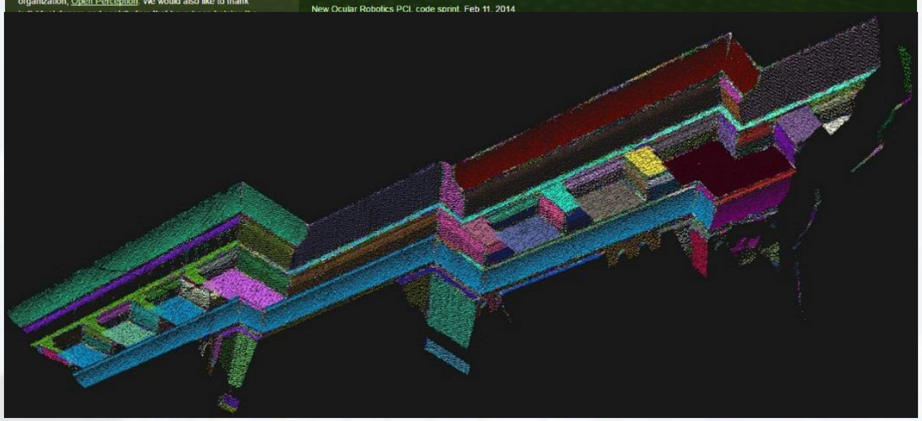
Images: Semantic3d.net

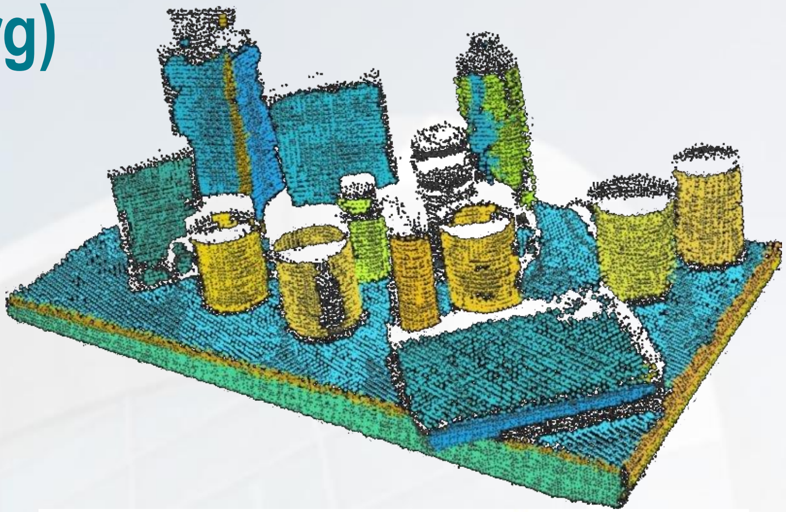
Classification Accuracy Confusion Matrix

PREDICTED / ACTUAL	Ground	Vehicle	Vegetation	Building
Ground	90%	1%	9%	0%
Vehicle	3%	87%	8%	2%
Vegetation	7%	12%	75%	3%
Building	0%	0%	6%	95%

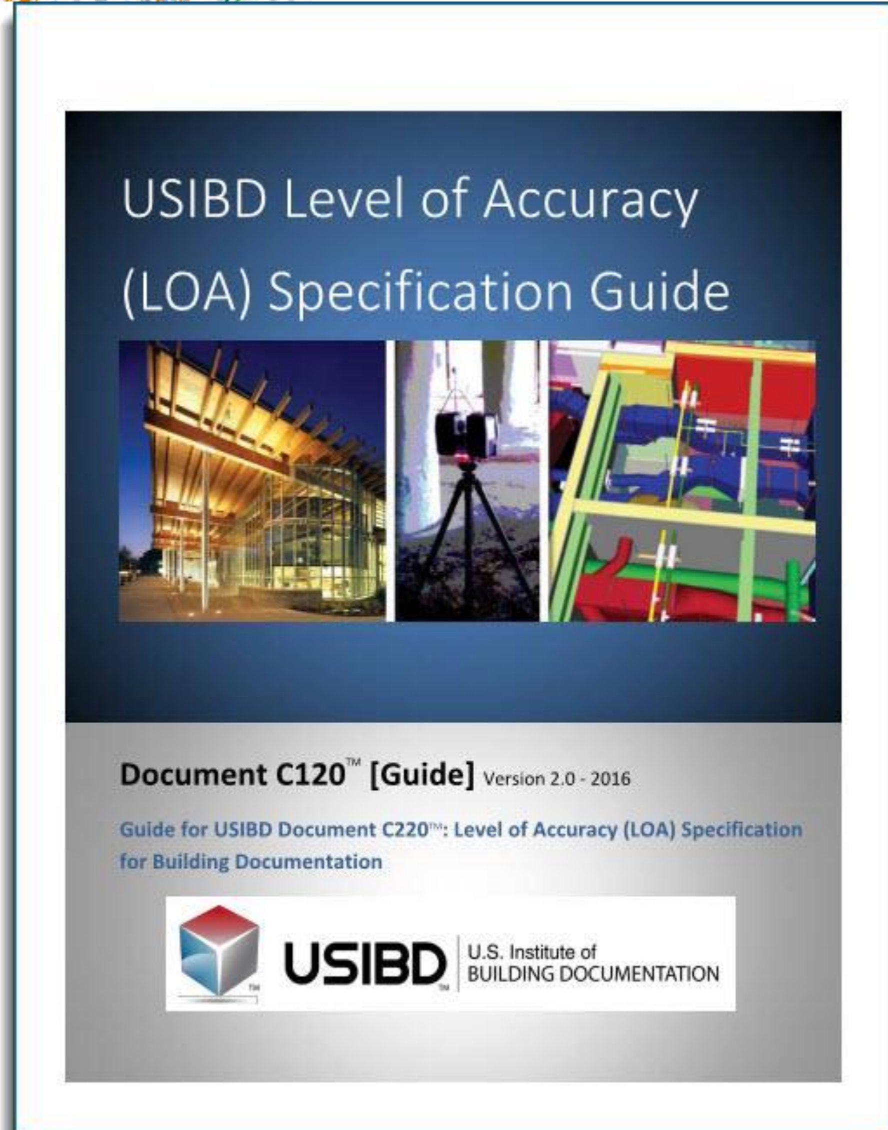
Point Cloud Library (pointclouds.org)







Images from
http://pointclouds.org



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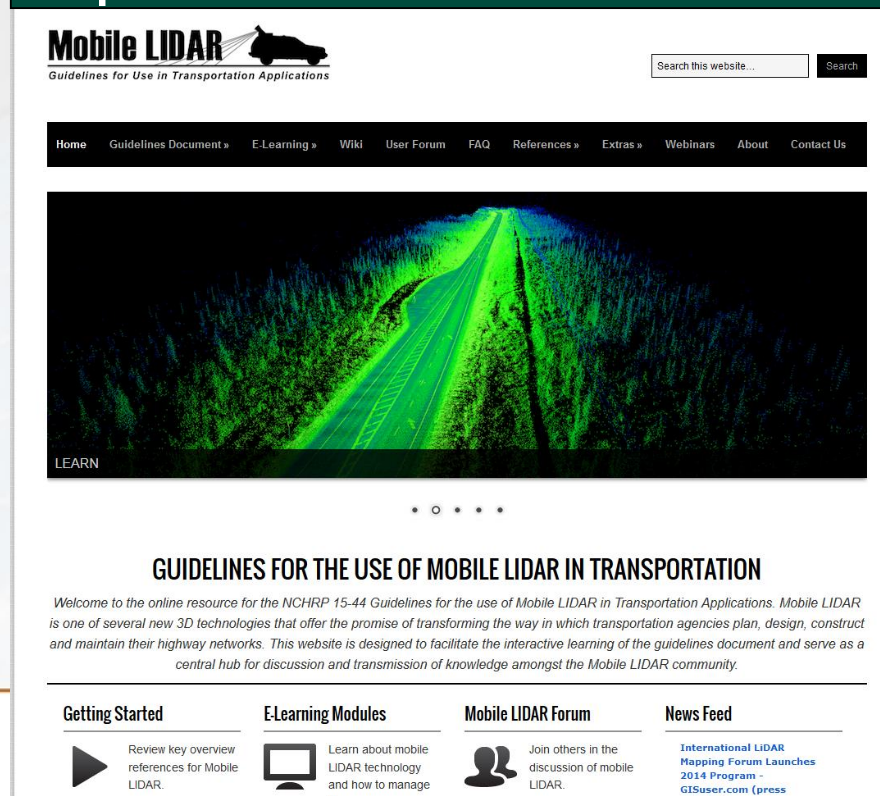
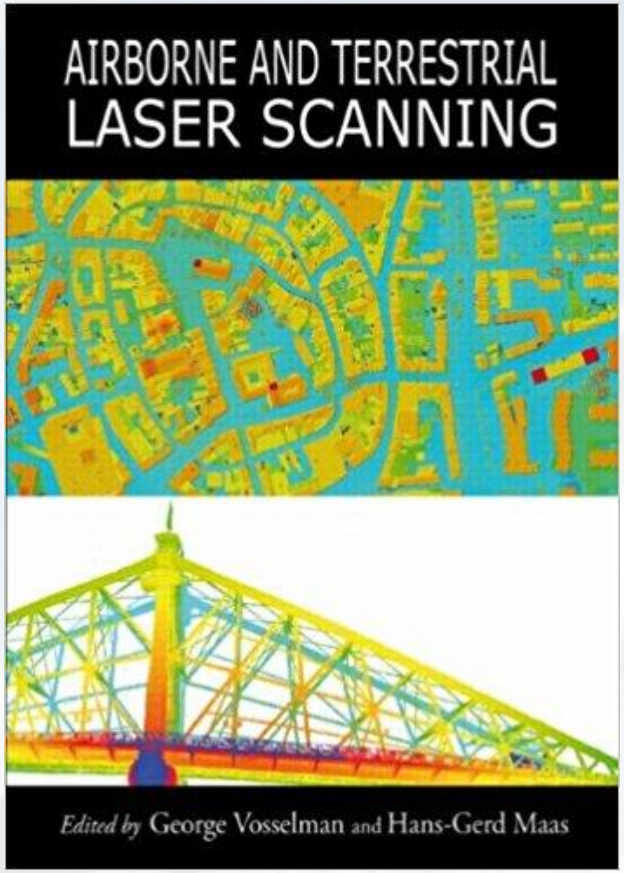
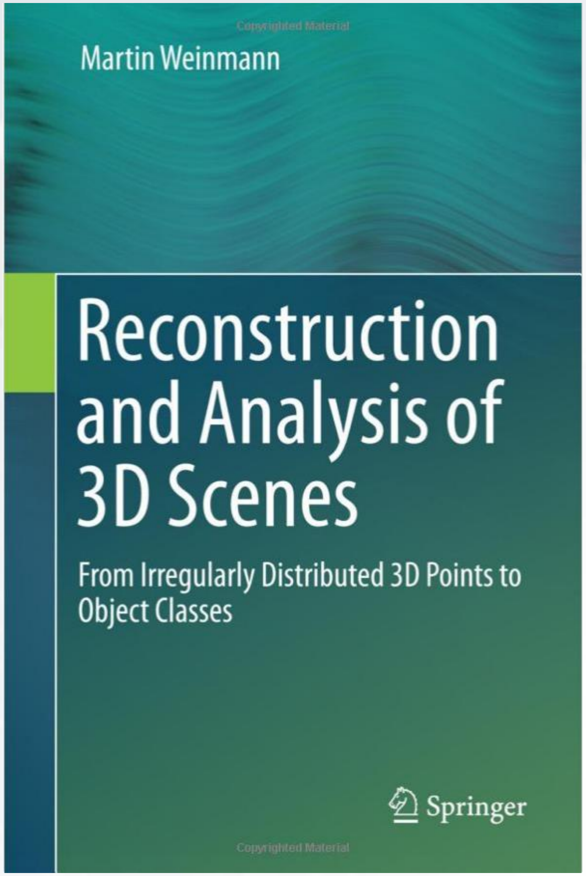
http://learnmobilelidar.com



Recommended Reading





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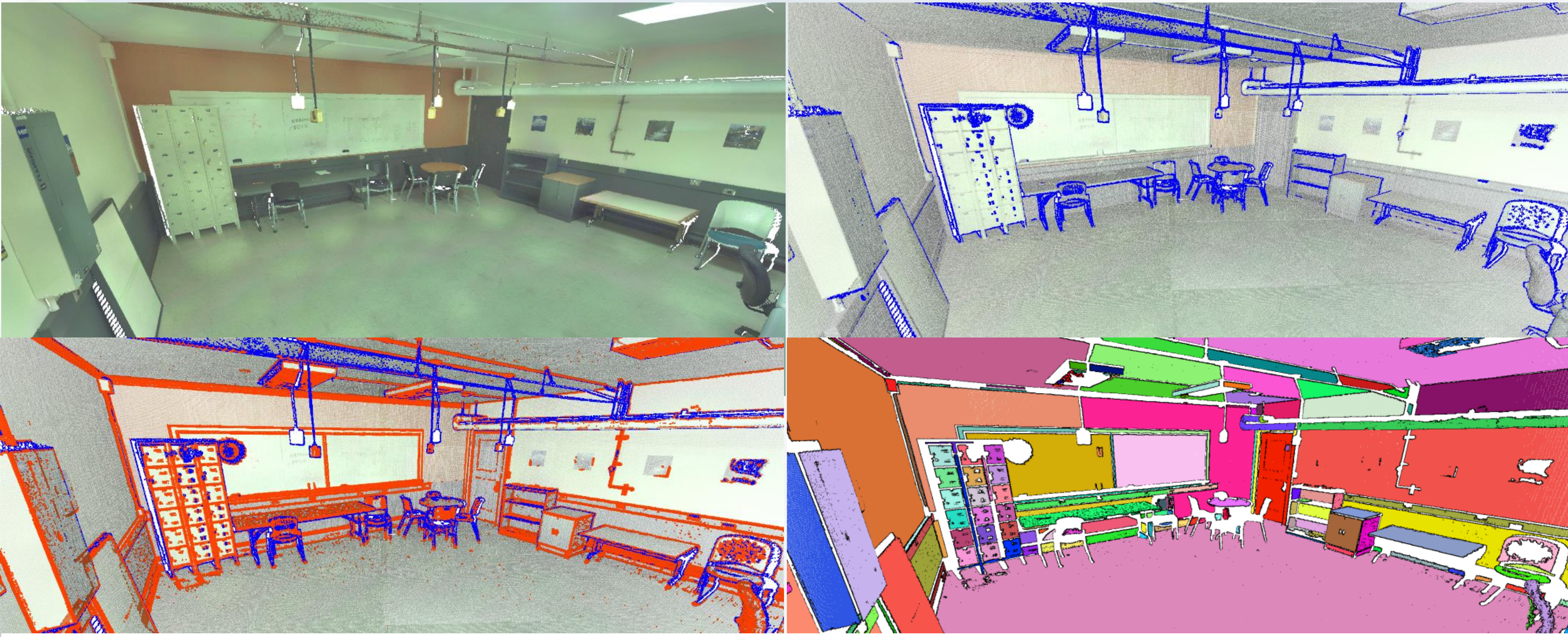

Che, E.,* and **Olsen, M.J.,** (2017). "Fast Edge Detection and Segmentation of Terrestrial Laser Scans through Normal Variation Analysis," *ISPRS Geospatial Week, Laser Scanning '17, Wuhan, China*

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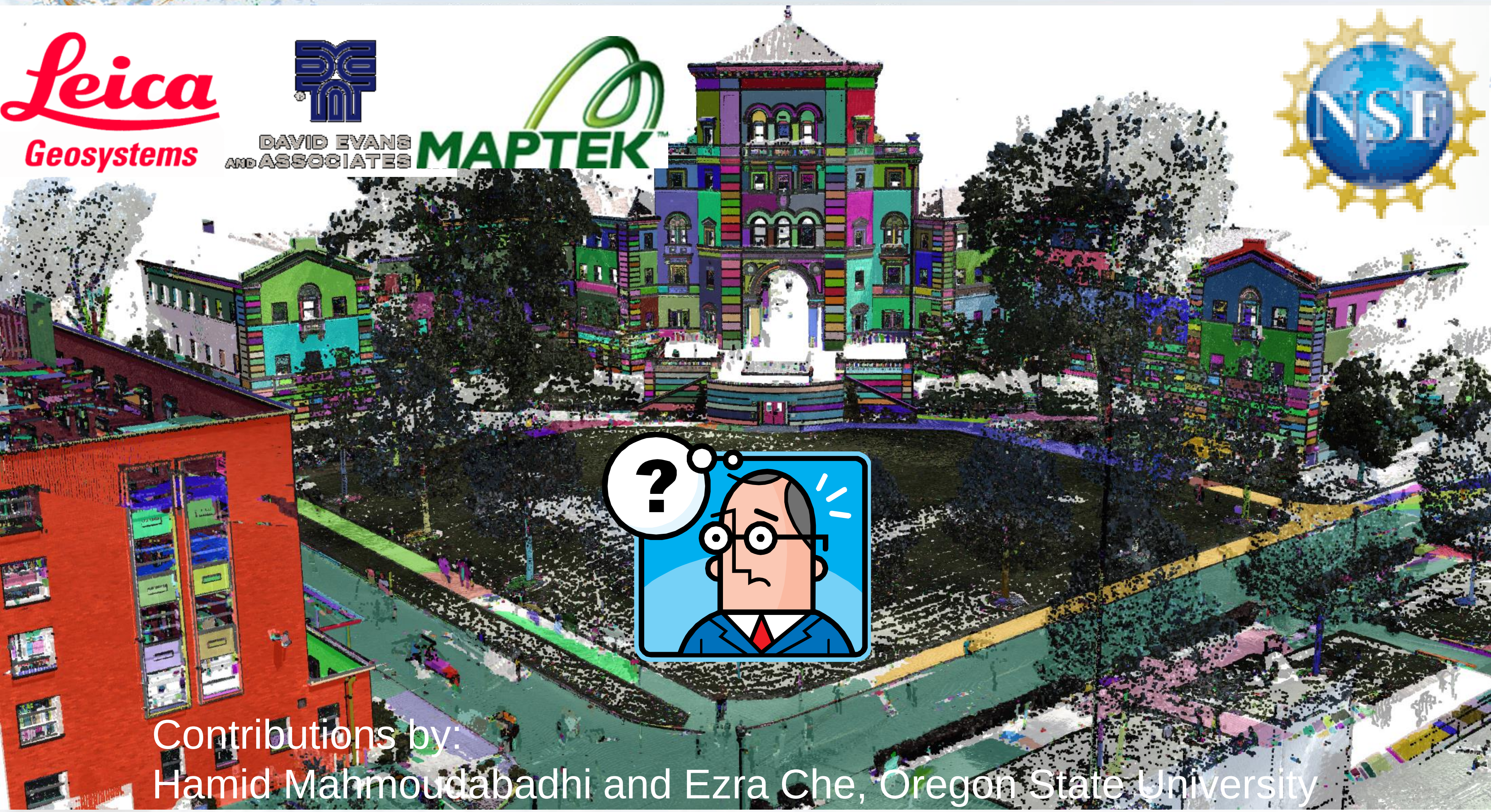

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