

Point Clouds From Calibration to Classification

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Point Cloud Calibration and Orientation



- 3D color vs. mainly geometry
- Differences: vegetation, crane
- Piles of construction material
- DIM: stereo occlucion

Mandlburger et al.

• LiDAR: points between piles available



Point Cloud Change Detection

- 4 data sets taken at 4 different times
- Different modality RGB, nIR, photo/lidar, GSD, point density, shadow, ...
- Classified Lidar point clouds ground, building, vegetation





Computational Geometry – Point Cloud Legacy

- Design Process
 - Given: Point cloud $\mathbf{p}_i \in \mathbb{R}^3$, i = 1, ..., n
 - Find: surface s(u,v) closely interpolating p_i , i.e. minimize $f(s(u_i,v_i) p_i)$
 - NURBS (...) surface, patch layout based on curvature, curvature defined in each point





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 - NURBS (...) surface, patch layout based on curvature, <u>curvature defined in each point</u>
- Quality Inspection
 - Given: CAD model of a object, discretized as points m_i
 - Given: point cloud of the manufactured object, data points **d**_{*j*}
 - Find: transformation of \mathbf{d}_j onto \mathbf{m}_i , but no exact correspondence
 - Replace exact with approximate, iteratively determined correspondence: ICP



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 - Replace exact with approximate,
- Visualization
 - Given: Point cloud **p**_i
 - Find TIN with vertices \mathbf{p}_i that follows surface of object
 - No 2D solution, e.g. Delaunay criterion, but <u>localized processing</u> independent of overall shape





Point clouds

Computational Geometry

- Object centered (often)
- Point \mathbf{p}_i (x_i, y_i, z_i)
- Cartesian coordinate system
- No datum
- No attributes
- Error free (negligible errors)
- No measurement process

Geodesy and Geoinformation

- Billions of points
- Projected CS
- Random (0.5-30cm), systematic (up to meter), and many gross errors
- Attributes: color, accuracy, echo ID, FWF information, time, etc.
- Measurement process known
- Measurement along optical line of sight



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Data structures

- kD-tree appropriate for processing, nearest neighbor search, etc.
- octree appropriate for visualization (e.g. potree)
- Data structure for manuel editing, processing and visualization of point clouds?

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- Processing strategies parallelization tile wise processing
- Neighborhood optimal neighborhoods, parameter selection, etc.

10

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Calibration and orientation

- sensor modeling
- measurement process modeling sensor + medium/media + object
- observation error models

$$\mathbf{x}^{e}(t) = \mathbf{g}^{e}(t) + R_{n}^{e}(t) R_{i}^{n}(t) (\mathbf{a}^{i} + R_{s}^{i} \mathbf{x}^{s}(t))$$



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Applications

- land cover mapping
- topographic modeling
- indoor modeling
- engineering surveying
- deformation analysis
- change detection



Calibration of point clouds

Integrated calibration and orientation of lidar and image matching point clouds

- Where's the problem?
- Lidar point clouds are good within surfaces and for vegetation, not influenced by (sun) shadows
- Image matching point clouds are good on edges and have high resolution physical explanation: aperture size of current laser scanners vs. photogrammetric cameras
- Aim combine the advantages and exploit the differences
- Requirement precise geo-referencing
- Standard method independent bundle block adjustment and laser scanning strip adjustment



Flight block Melk (Austria)



Mandlburger et al.









Elevation differences with standard method



Mandlburger et al.









Mandlburger et al.

DSM generation from LiDAR and DIM



Mandlburger et al.

LiDAR/DIM data properties: vegetation penetration

- Vegetation: DIM=top of grass surface, LiDAR=penetrates grass layer
- Impenetrable surfaces: negligible height differences between DIM and ALS



Classification of point clouds

Point cloud classification

Principle: use measured and computed features to infer, which class a point belongs to (features selection?)





Classification of point clouds

Point cloud classification

- Principle: use measured and computed features to infer, which class a point belongs to (features selection?)
- Methods: manual decision trees, support vector machines, random forests, Markov chains, deep convolutional neural networks
- Considerations: transferability of rules (across missions, scales, etc.), number of classes, run time, amout of training data, representation of rarely occuring classes, classification accuracy



Change detection in point clouds

- A1: classify point clouds of different epochs + compare labels (proximity?)
- A2: compute geometric point cloud difference + classify changed points
- Problem 1
 change in class
 and change in
 geometry can be
 independent
- Problem 2 different data properties
- Problem 33D changes















PC CD

PC CD Method

- Exploit the power of machine learning
- Features for class and features for change
- 1. measurement process: echo ID, waveform attribute, etc.
- 2. local neighborhood: normal vector, roughness, etc.
- 3. approximate height (simple terrain model)
- 4. change indicators
 - distance to nearest point in PC of other epoch
 - point distribution feature evaluated at location of epoch 1 points with points of epoch 2



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 - distance to nearest point in PC of other epoch
 - point distribution feature evaluated at location of epoch 1 points with points of epoch 2
- Sample training data, learn model (e.g. random forests)
 apply model to detect all chang done (?)



2007



Stability

20 40

60

80 100

2015



16

PC CD ML





PC CD ML





Lost building							
New building and new ground							
New tree	2015	UG	CG	UB	NB	UT	NT
Lost tree	Ref_UG Ref_CG Ref_UB Ref_NB Ref_UT Ref_NT	48.3 0.9 0 0 0 0 0	0.5 10 0 0.2 0 0	0.1 0.1 16.5 0.1 0.3 0.1	0 0.1 0.2 4.6 0.2 0.1	0 0 0.9 0.1 11.1 1.1	0 0 0 0 1.1 1.6
Ground change in height	Sum EOC Corr Overall A	49.2 1.8 98.2 Accurac	10.8 6.9 93.1 zy: 92.0	17.1 3.6 96.4 5	5.3 12.4 87.6	13.2 15.9 84.1	2.7 42 58.0
Height (m) -5 5 12 16 18 20 >20 • Unchanged building • Lost building • New building • Unchanged tree • New tree • Lost tree • Unchanged ground • Changed ground	Total nur	nber of	points	s: 8,636	,900	Tran e	et al.

Conclusions

Many open point cloud research questions



References

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