A Survey of Simple Geometric Primitives Detection Methods for Captured 3D Data

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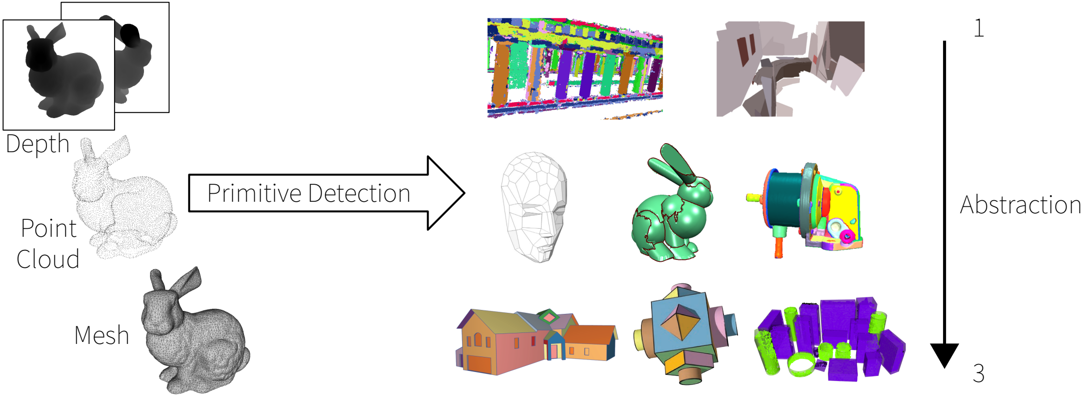
Context



Depth

Point Cloud

Mesh

Primitive Detection

1

Abstraction

3

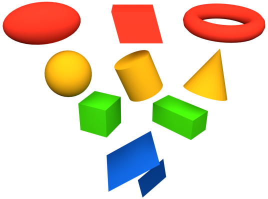
Captured 3D Data

High Level Model

Context

Geometric Primitives → Simple 3D Shapes

- **High-level** and **compact** description of complex objects, Visual summary
- **Simplification** of geometry and topology: Make subsequent analysis **easier**
- **Accurate** representation: Geometric **substitute**
- Spatial **relationships**



Context

Historical Background

- **1960s**: 3D capture
- **1972**: Polyhedron fitting [Shirai, 1972]
- **1975**: Cylinder fitting [Popplestone et al., 1975]
- **1982**: Parameter spaces [Hebert and Ponce, 1982]
- **1983**: Primitives shapes for object recognition [Oshima and Shirai, 1983]
- In this survey: 1998 - 2016

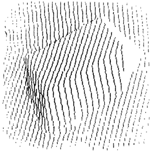


Fig.4. The center points of slits

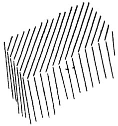


Fig.9. Recognition of rectangular prism

[Shirai, 1972]

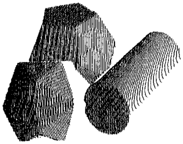


Fig. 4. Slit image of a scene.

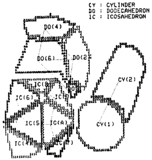


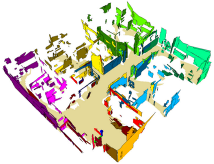
Fig. 9. The result of recognition.

[Oshima and Shirai, 1983]

Context

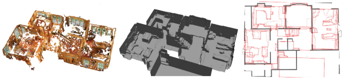
Applications

- **Robotics**: Scene tracking and mapping (SLAM)
- **Modeling**: Lightweight scene reconstruction
- **Shape Processing**: Bounding shapes
- **Rendering**: Level-of-details, occlusion, soft shadowing
- **Interaction**: Navigation space
- **Animation**: Control rigs, Skinning weights
- **Architecture**: Building modeling



[Lee et al., 2012]

[Décoret et al., 2003]



[Furukawa et al., 2009]

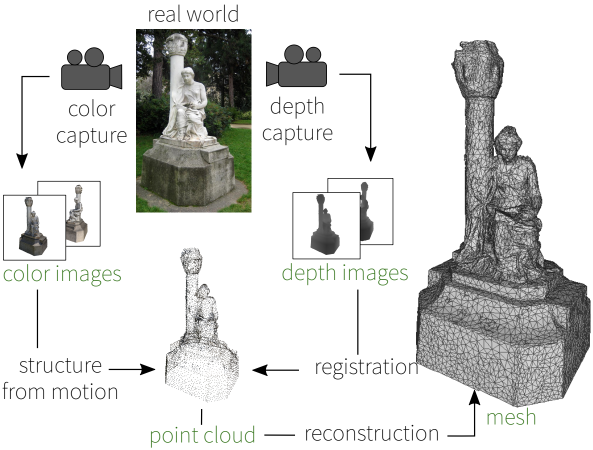
[Thiery et al., 2016]

Organization

- Background
- Theoretical Foundations
- Characterization
- Methods and Applications
- Metrics and Evaluation
- Discussion

Background

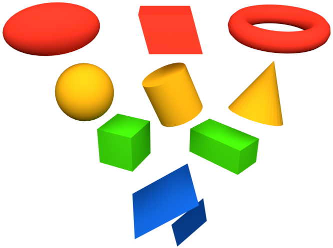
3D Data Acquisition



input for primitive detection

Background

Simple Geometric Primitives

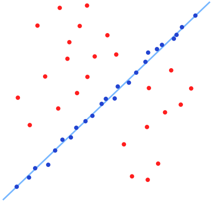


- **Limited number** of parameters
- **Convex**, **Symmetric**
- Basic shape that **can be assembled**
- **Trimmed** shape surfaces
  - **Surfaces** of objects, not volumes
  - **Trimming**: convex hull, connected components [Schnabel et al., 2007]
  - **Merge** patches [Biswas and Veloso, 2011]
  - **Compact** boundary curve

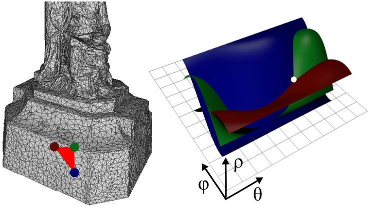
Theoretical Foundations

Three Categories

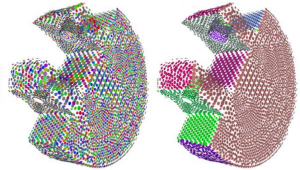
- Stochastic
  - RANSAC
  - Local statistics
- Parameter spaces
  - Hough transform
  - Clustering
- Clustering
  - Primitive growing
  - Automatic
  - Segmentation and fitting



RANSAC



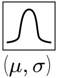
Plane Hough space

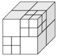


[Attene and Patanè, 2010]

Theoretical Foundations

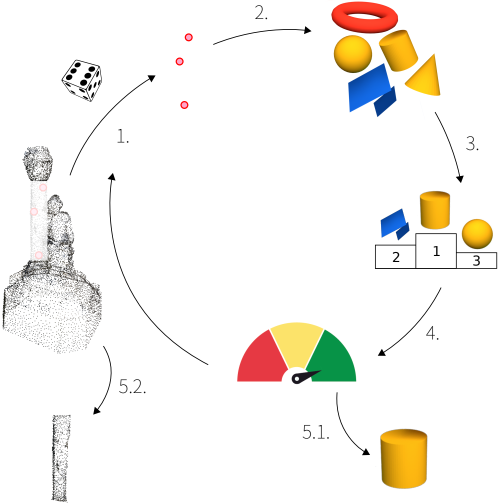
RANSAC [Schnabel et al., 2007]





Repeat N times ⚠

1. Random minimal set
2. Primitive shape fitting
3. **Shapes scores with all points** ⚠
4. Find best primitive
5. If score is high enough
    - 5.1. Keep primitive
    - 5.2. Remove inliers



Optimizations for speed and quality

⚠ dominates complexity

Theoretical Foundations

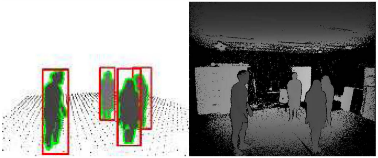
RANSAC

- Pros
    - Simple
    - General
    - Accurate
    - Robust to outliers
- Cons
    - Many parameters to tune
    - Dependent on a minimum set
    - No spatial consistency
    - Not reproducible

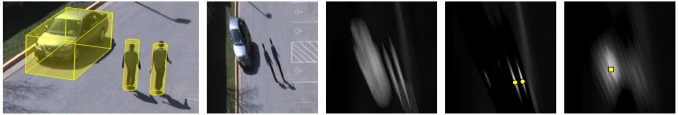
Theoretical Foundations

Local Statistics

- Occupancy probabilities
- Infer primitive parameters
- Bounding shapes



[Bagautdinov et al., 2015]



Occupancy Maps [Carr et al., 2012]

Theoretical Foundations

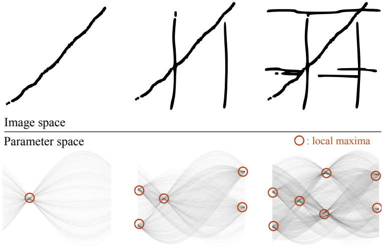
Local Statistics

- Pros
    - Application-specific
- Cons
    - Model-dependent

Theoretical Foundations

Hough Transform

- Shape parameter space
- Discretization, accumulation and vote [Hough, 1962]
- Line and circle detection [Ballard, 1981, Duda and Hart, 1972]
- Many variants for better performance

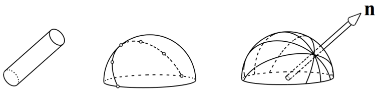


Hough line detection

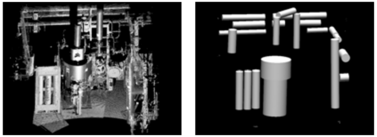
Theoretical Foundations

Hough Transform: In 3D

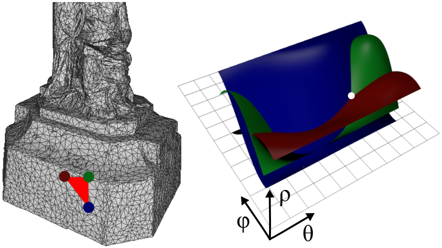
- Planes: spherical coordinates
- Cylinders: orientation, then position



Cylinder orientation detection



[Rabbani and Van Den Heuvel, 2005]



Plane Hough space

Theoretical Foundations

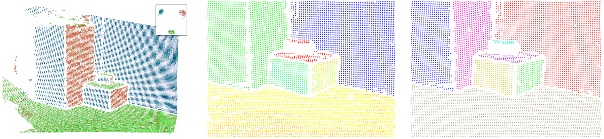
Hough Transform

- Pros
  - Handles missing data
  - Supports many model instances
  - Relatively robust to noise
- Cons
  - Unbounded space size
  - Dependent on parameter space quantization

Theoretical Foundations

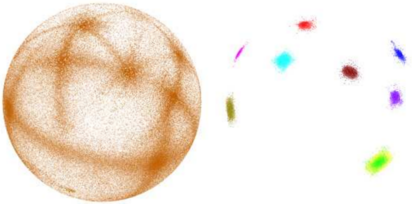
Clustering Parameter Spaces

- For planes: normal, distance to origin
- Step 1: Gauss sphere clustering
- Step 2: Threshold distance



(a) 3 Normal clusters (b) Distance space (c) 8 Plane clusters

[Holz et al., 2011]



Normal space clustering [Chen and Chen, 2008]

Theoretical Foundations

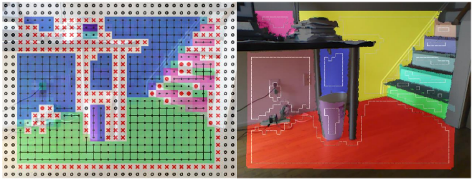
Clustering Parameter Spaces

- Pros
    - Robust to outliers
- Cons
    - Restricted to low dimensions

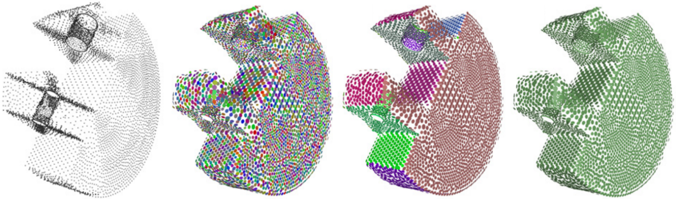
Theoretical Foundations

Primitive-driven Region Growing

- Connected component in 2.5D/3D data
- Propagation based on primitive heuristics
- Iterative neighbor merges



Agglomeration in depth images [Feng et al., 2014]



Hierarchical point cloud clustering [Attene and Patanè, 2010]

Theoretical Foundations

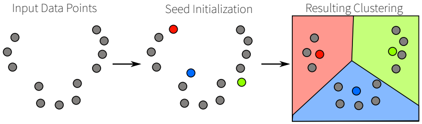
Primitive-driven Region Growing

- Pros
  - Meaningful segmentation
  - Spatial consistency
- Cons
  - Slow
  - Local
  - Sensitive to initial conditions (seeds)
  - Sensitive to noise
  - Sensitive to outliers

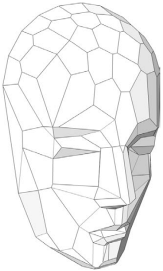
Theoretical Foundations

Automatic Clustering

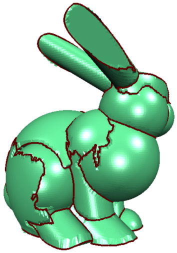
- Lloyd clustering: K-Means, Mean Shift
- Iterations of
  - Geometry partitioning (point assignment)
  - Shape fitting in each partition
- Random initialization
- “Variational Shape Approximation”



K-means clustering



[Cohen-Steiner et al., 2004]



[Wu and Kobbelt, 2005]

Theoretical Foundations

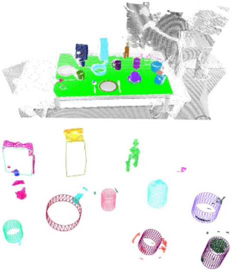
Automatic Clustering

- Pros
    - No prior on location
    - Few parameters
- Cons
    - Dependent on seeds
    - Sensitive to outliers
    - Can require numerous clusters (K-means)

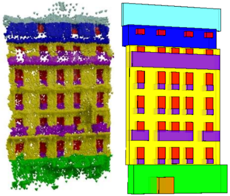
Theoretical Foundations

Segmentation: Primitive oblivious

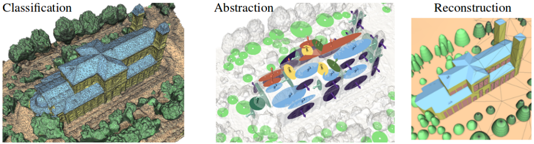
- Ignoring primitive shapes
- Region growing, flooding, classification
- Fitting primitives to segments
  (PCA, Least-Squares, Gradient Descent)



Geometry
[Rusu et al., 2009]



Rules
[Martinovic et al., 2015]



Semantics [Verdie et al., 2015]

Theoretical Foundations

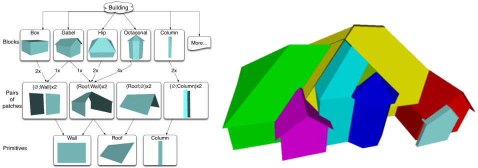
Segmentation

- Pros
  - Vast literature for segmentation
  - Tailored for application
- Cons
  - Can merge different primitives
  - Application-specific
  - Sensitive to noise
  - Sensitive to outliers

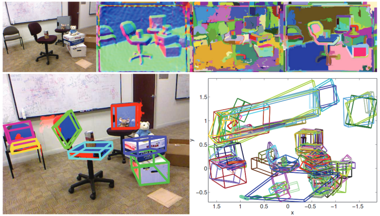
Theoretical Foundations

Assembling Primitives

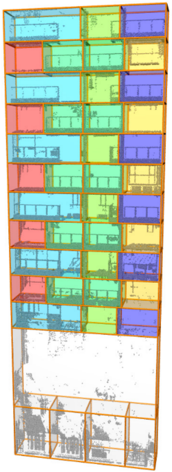
- Assemble detected shapes
- Bound objects, rooms, buildings
- Generate-and-test strategy



Hierarchical rules [Lin et al., 2013]



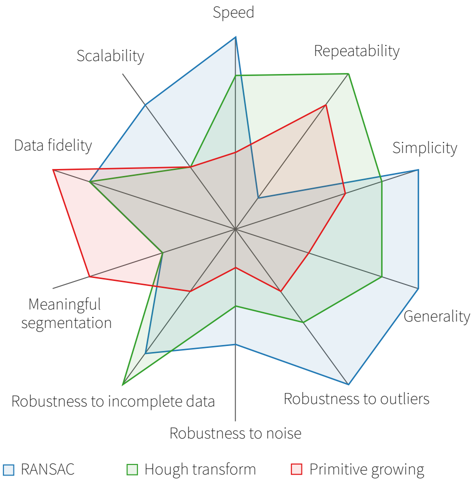
Box candidates [Jiang and Xiao, 2013]



[Shen et al., 2011]

Theoretical Foundations

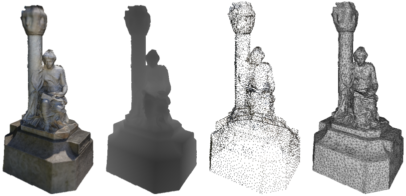
Comparison

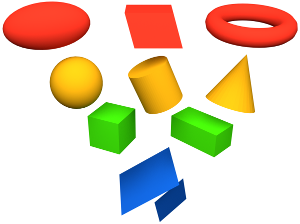


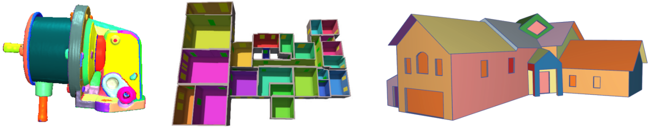
Characterization

Characteristics

- Data
- Detected primitives
- Detection Category
- Application context
- 14 properties





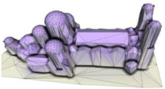


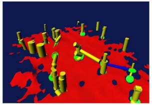
Characterization

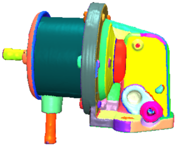
Application Context

- Individual objects
- Indoor scenes
- Outdoor scenes: urban or natural

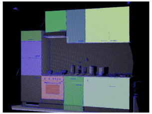

[Arikan et al., 2013]

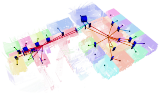

[Lafarge and Mallet, 2012]

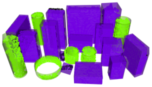

[Lalonde et al., 2006]

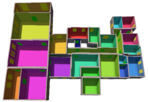

[Schnabel et al., 2007]


Generalized cylinder
[Zhou et al., 2015]


[Rusu et al., 2007]


[Ochmann et al., 2014]


[Goron et al., 2012]


[Ochmann et al., 2016]

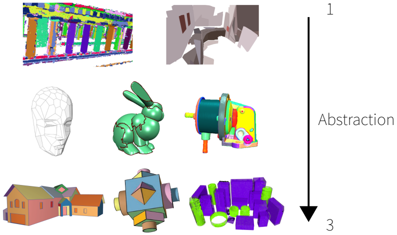
Characterization

Properties: Accuracy

- Data Fidelity
- Abstraction Level

Value	Characteristics
1	Approximating planes or bounding boxes
2	Planes fitting planar data only
3	Planes and primitives fitting all data

Data fidelity scale



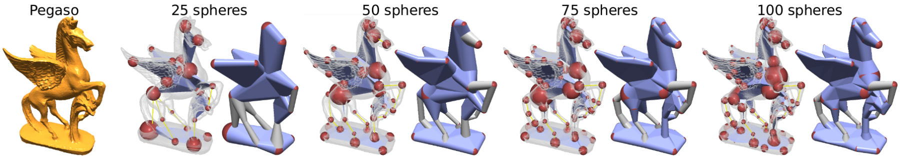
Level	Characteristics
0	Raw point cloud
1	Primitive patches
2	Full primitives
3	Assembled primitives

Abstraction scale

Characterization

Properties: Practicality

- Timing: online / offline
- Scalability
- Intuitive Tuning

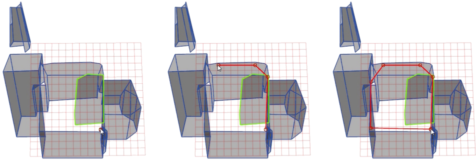


Controlling abstraction in Sphere-Meshes [Thiery et al., 2013]

Characterization

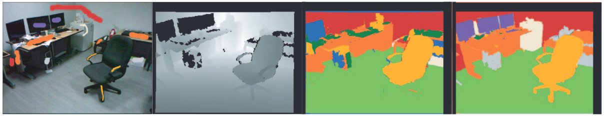
Properties: Practicality

- User Assistance



Manual fitting in O-Snap [Arikan et al., 2013]

User interaction in 3-Sweep
[Chen et al., 2013]

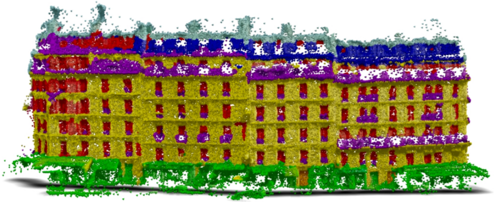


User strokes to fix segmentation [Shao et al., 2012]

Characterization

Properties: Practicality

- Learning Phase



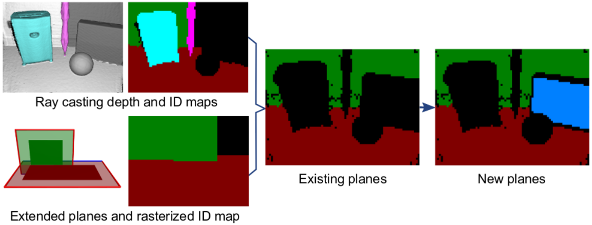
Facade labeling [Martinovic et al., 2015]

Database model matching
[Shao et al., 2012]

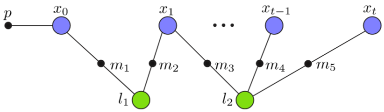
Characterization

Properties: Practicality

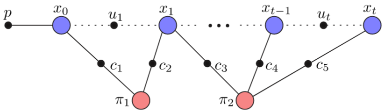
- Temporal Consistency



Plane tracking [Zhang et al., 2015]



Structure-from-motion (SFM)



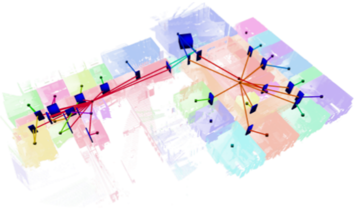
Planar SLAM

Planes in pose graph [Kaess, 2015]

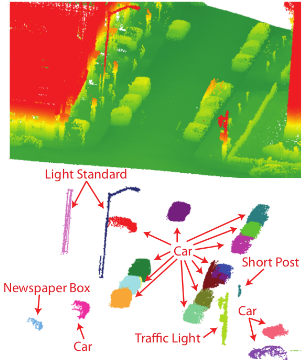
Characterization

Properties: Information

- Semantics
- Needs Extra Information
- Provides Meta Data



Relations between rooms
[Ochmann et al., 2014]

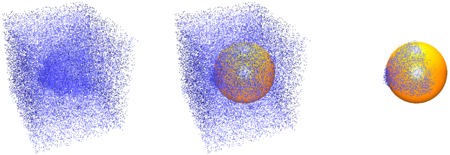


Semantics
[Golovinskiy et al., 2009]

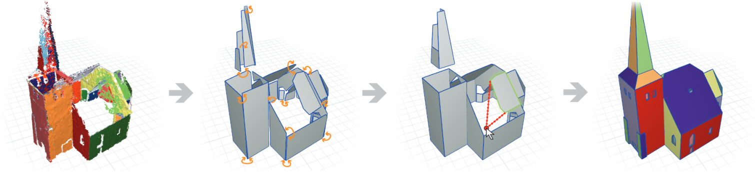
Characterization

Properties: Robustness

- Noise
- Outliers
- Incomplete Data

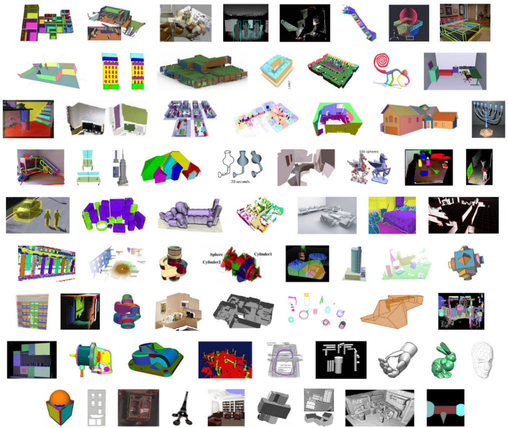


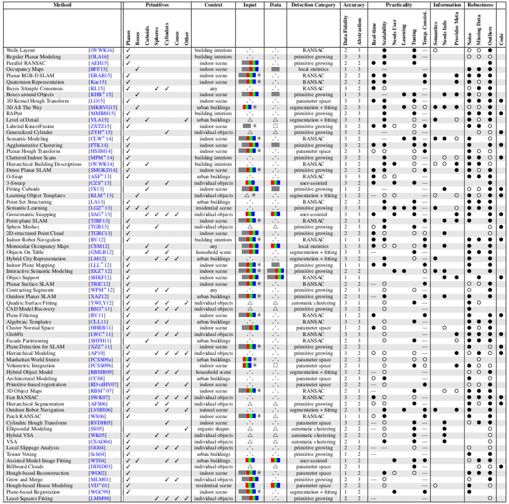
RANSAC [Schnabel et al., 2007]



Completion in O-Snap [Arikan et al., 2013]

Methods and Applications

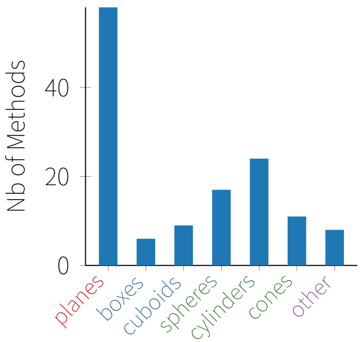




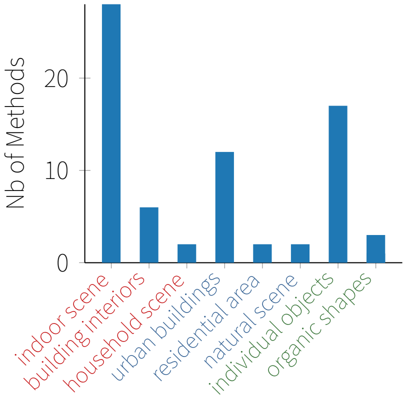
Method		Primitives							Context	Input	Data	Detection Category	Accuracy		Practicality						Information			Robustness			
		Planes	Boxes	Cuboids	Spheres	Cylinders	Cones	Other					Data Fidelity	Abstraction	Real-time	Scalability	Needs User	Learning	Tuning	Temp. Consist.	Semantics	Needs Info	Provides Meta	Noise	Missing Data	Outliers	Code
Walls Layout	[OVWK16]	✓							building interiors	∴	∴	RANSAC	2	3		●			●	—	○			○	○	●	
Regular Planar Modeling	[OLA16]	✓							building interiors	∴	∴	primitive growing	3	3		●			●	—				○	○	○	
Parallel RANSAC	[AEH15]	✓							indoor scene	▬🟥🟩🟦	∴	primitive growing	2	2	●	●			●							●	
Occupancy Maps	[BFF15]		✓						indoor scene	▬🟥🟩🟦	▬	local statistics	1	3		—				—				●	●	●	
Planar RGB-D SLAM	[ERAB15]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	2	●	●				●			●	●	●	●	
Quaternion Representation	[Kae15]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	2	●	●				●			●	●	○	●	
Bayes SAmple Consensus	[KL15]	✓			✓	✓			any	∴	∴	RANSAC	3	2	●	○				—				○	●	●	
Boxes around Objects	[KHB*15]		✓						indoor scene	▬🟥🟩🟦	▬	primitive growing	1	3		—		●	●	—		●	●	●	○	●	
3D Kernel Hough Transform	[LO15]	✓							indoor scene	∴	∴	parameter space	3	3	●	●			●	—				●	●	●	●
3D All The Way	[MKRVG15]		✓						urban buildings	🟥🟩🟦 *	∴	segmentation + fitting	2	3		●		●	○	○	●	●	●	○	○	●	
RAPter	[MMBM15]	✓							building interiors	∴	∴	primitive growing	2	3		●			●	—				●	●	●	●
Level of Detail	[VLA15]	✓		✓				✓	urban buildings	△	△	segmentation + fitting	3	3		●			○	—	●		○	●	○	●	
Labeled KinectFusion	[ZXTZ15]	✓							indoor scene	▬ *	□	primitive growing	3	2	●	●	○		○	●				●	●	○	
Generalized Cylinder	[ZYH*15]					✓			individual objects	△	△	primitive growing	3	2		—			○	—					○	○	●
Semantic Modeling	[CLW*14]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	3	2		—		●	●	—	●	●	○	●		○	
Agglomerative Clustering	[FTK14]	✓							indoor scene	▬🟥🟩🟦	▬	primitive growing	3	2	●	●			●	●				●		●	●
Planar Hough Transform	[HSSM14]	✓							indoor scene	▬🟥🟩🟦 *	∴	parameter space	2	3	○	○			○	●				●	○	○	
Cluttered Indoor Scans	[MPM*14]	✓							building interiors	∴	∴	primitive growing	3	2		●			○	—		○	○	●	●	○	●
Hierarchical Building Descriptions	[OVWK14]	✓		✓					building interiors	∴	∴	RANSAC	3	2		●	●		○	—	○	○	●	●	●	○	
Dense Planar SLAM	[SMGKD14]	✓							indoor scene	▬🟥🟩🟦 *	∴	primitive growing	2	2	●	●			○	●			●	●	○	●	
O-Snap	[ASF*13]	✓							urban buildings	∴	∴	RANSAC	3	3	●	○	○			—				●	●	●	
3-Sweep	[CZS*13]			✓		✓			individual objects	🟥🟩🟦	🟥🟩🟦	user-assisted	3	2	●		●		●	—						●	
Fitting Cuboids	[JX13]			✓					indoor scene	▬🟥🟩🟦	▬	primitive growing	1	2		—				—		●		○	○	●	●
Learning Object Templates	[KLM*13]		✓						individual objects	△ *	∴	segmentation + fitting	1	2	—	○	○			—	○		○	●	○	●	●
Point Set Structuring	[LA13]	✓							urban buildings	∴	∴	RANSAC	2	2		●			●	—				●	●	●	
Semantic Learning	[LGZ*13]	✓	✓	✓					residential scene	∴	∴	primitive growing	3	3		●	●	●	●	—	●		○	●	●	●	
Geosemantic Snapping	[SAG*13]			✓	✓	✓	✓		individual objects	🟥🟩🟦	🟥🟩🟦	user-assisted	3	3	●		●		●	—			●	●		●	●
Point-plane SLAM	[TJRF13]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	1		●				●		●	●	●		●	
Sphere Meshes	[TGB13]	✓			✓				individual objects	△	△	primitive growing	2	3	○	●			●	—						○	●
2D-structured Point Cloud	[TGRC13]	✓							indoor scene	▬🟥🟩🟦	∴	primitive growing	2	2	●	○			○	○		●				○	
Indoor Robot Navigation	[BV12]	✓							building interiors	▬🟥🟩🟦 *	∴	RANSAC	1	1	●	●				●				●	●	●	●
Monocular Occupancy Maps	[CSM12]			✓		✓			any	▬🟥🟩🟦	🟥🟩🟦	local statistics	1	3	●	○	○		○	●		●		●		●	
Objects On Table	[GMLB12]			✓		✓			household scene	▬🟥🟩🟦	∴	segmentation + fitting	3	3	—				●	—				●	●	●	
Hybrid City Representation	[LM12]	✓			✓	✓	✓		urban buildings	∴	∴	segmentation + fitting	3	2		●			○	—	●			●		●	
Indoor Plane Mapping	[LLL*12]	✓							indoor scene	▬🟥🟩🟦 *	▬	primitive growing	1	1	●	●				●				●		●	
Interactive Semantic Modeling	[SXZ*12]	✓							indoor scene	▬🟥🟩🟦 *	▬🟥🟩🟦	primitive growing	2	2			●	●		○	●	●		●		●	
Object Support	[SHKF12]	✓							indoor scene	▬🟥🟩🟦	▬🟥🟩🟦	RANSAC	1	1						—		●	●		●		●
Planar Surface SLAM	[TRIC12]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	2	—	○				●				○	○	●	
Contracting Segments	[WPM*12]	✓			✓	✓			any	∴	∴	primitive growing	2	1		○			○	—				○		●	
Outdoor Planar SLAM	[XAZ12]	✓							urban buildings	▬🟥🟩🟦 *	∴	primitive growing	2	1	—	●				●		●		●		●	
Quadric Surface Fitting	[YWLY12]	✓			✓	✓		✓	individual objects	△	△	automatic clustering	3	1		○			●	—				●	○		
CAD Model Recovery	[BSG*11]	✓			✓	✓	✓		individual objects	△	△	primitive growing	3	2		○				—				●			
Plane Filtering	[BV11]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	1	2	●					●				●		●	●
Algebraic Templates	[CLL11]	✓			✓	✓			urban buildings	∴	∴	RANSAC	3	3		○			●	—				●	●	●	
Cluster Normal Space	[HHRB11]	✓							indoor scene	▬🟥🟩🟦	∴	parameter space	1	2	●	○				—		○		●	○	●	
GlobFit	[LWC*11]	✓			✓	✓	✓		individual objects	∴	∴	RANSAC	3	3		○				—			●	●	●	●	●
Facade Partitioning	[SHFH11]			✓					urban buildings	∴	∴	RANSAC	2	3		○			●	—			○	●	●	●	
Plane Detection for SLAM	[XZZ*11]	✓							indoor scene	▬🟥🟩🟦 *	∴	primitive growing	2	2						—				●		○	●
Hierarchical Modeling	[AP10]	✓			✓	✓	✓	✓	individual objects	∴	∴	primitive growing	3	2	○	○			○	—			●	○	●	○	●
Manhattan World Stereo	[FCSS09a]	✓							urban buildings	🟥🟩🟦 *	∴	parameter space	2	2		○			○	○					○		
Volumetric Integration	[FCSS09b]	✓							indoor scene	🟥🟩🟦 *	□	parameter space	2	1		○			●	○			●	●	○	○	
Hybrid Object Model	[RBMB09]	✓			✓	✓	✓		household scene	∴	∴	segmentation + fitting	3	2	—	○				—				○	○	●	
Architectural Modeling	[CC08]	✓							urban buildings	∴	∴	parameter space	2	3	○	●				—				●		○	
Primitive-based registration	[RDvdHV07]	✓			✓	✓		✓	indoor scene	∴	∴	parameter space	2	2	—	○				●				○	○	●	
3D Object Maps	[RBM*07]	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	1	—				●			○	○	●	●	●	
Fast RANSAC	[SWK07]	✓			✓	✓	✓	✓	individual objects	∴	∴	RANSAC	3	2	●	○			○	—				●	●	●	●
Hierarchical Segmentation	[AFS06]	✓			✓	✓			individual objects	△	△	primitive growing	2	2	○	○			●	—				●	○	●	●
Outdoor Robot Navigation	[LVHH06]	✓				✓		✓	natural scene	∴	∴	segmentation + fitting	2	3		●		●		●	●		●	●		●	
Patch RANSAC	[WS06]	✓							indoor scene	▬🟥🟩🟦 *	△	RANSAC	1	1	○	●				●				●		●	
Cylindric Hough Transform	[RVDH05]					✓			indoor scene	∴	∴	parameter space	3	2	—	○			●	—		●		○	●	●	
Ellipsoidal Modeling	[SS05]							✓	organic shapes	△	△	automatic clustering	2	2	—	○			●	—		●				○	
Hybrid VSA	[WK05]	✓			✓	✓			individual objects	△	△	automatic clustering	2	2		○			●	—		●				○	
VSA	[CSAD04]	✓							individual objects	△	△	automatic clustering	2	1		●			●	—		●				○	
Local Slippage Analysis	[GG04]	✓			✓	✓	✓		individual objects	∴	∴	primitive growing	2	2	—	—			○	—				○		○	
Tensor Voting	[Sch04]	✓							urban buildings	∴	∴	primitive growing	1	2	—					—				●		●	
Assisted Model-Image Fitting	[WT04]	✓	✓			✓	✓		urban buildings	🟥🟩🟦	🟥🟩🟦	user-assisted	1	2			●		●	●				○	●	●	
Billboard Clouds	[DDSD03]	✓							individual objects	△	△	parameter space	2	1					●	—					○	○	●
Hough-based Reconstruction	[WO02]	✓							indoor scene	▬🟥🟩🟦 *	∴	parameter space	1	2		●	○		○	—				●	●	●	
Grow and Merge	[MLM01]	✓				✓	✓		individual objects	▬🟥🟩🟦	∴	primitive growing	2	3	—	○				—				○		●	
Hough-based House Modeling	[VD*01]	✓							residential scene	🟥🟩🟦	🟥🟩🟦	parameter space	2	2		○				—	○			●		○	
Plane-based Registration	[WGC99]	✓							indoor scene	▬🟥🟩🟦 *	∴	segmentation + fitting	1	2			●			●				●			
Least-Squares Fitting	[LMM98]				✓	✓	✓	✓	individual objects	▬🟥🟩🟦	∴	primitive growing	2	2	—					—						○	

Methods and Applications

Statistics



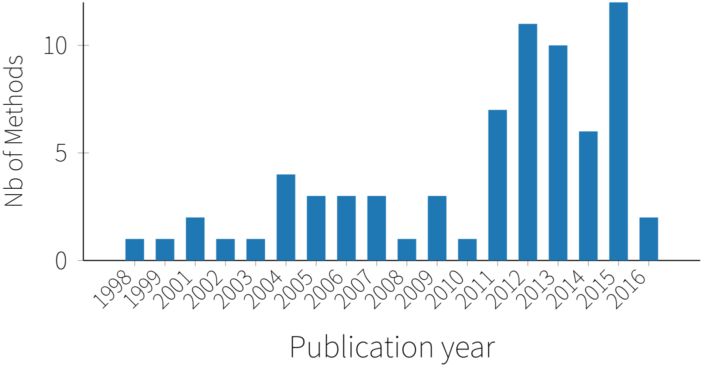
Detected primitives

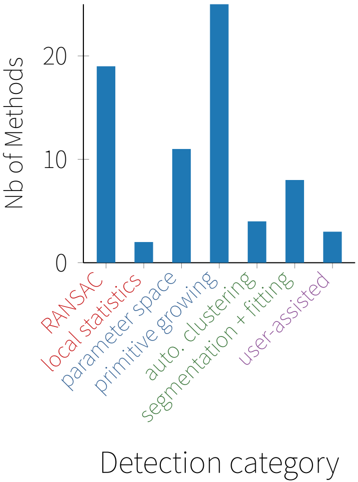


Application context

Methods and Applications

Statistics

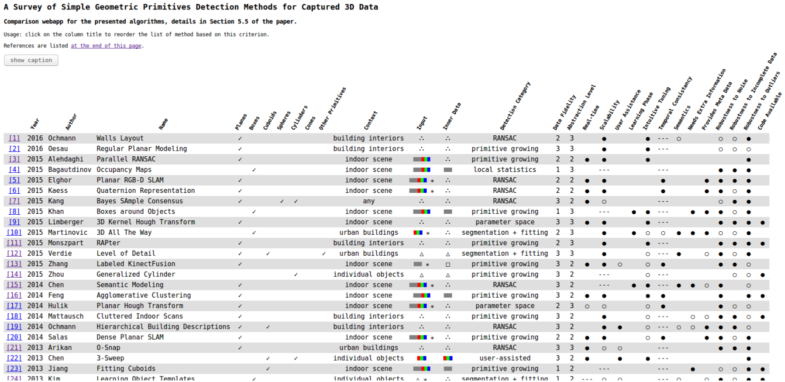




Methods and Applications

Web Application: Sort, Visual compendium, Links to methods, code and datasets

https://perso.telecom-paristech.fr/boubek/papers/GeoPrimFitSurvey/



A Survey of Simple Geometric Primitives Detection Methods for Captured 3D Data

Comparison webapp for the presented algorithms, details in Section 5.5 of the paper.

Usage: click on the column title to reorder the list of method based on this criterion.

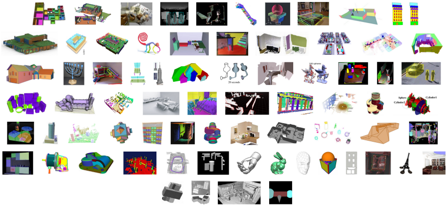
References are listed at the end of this page.

	Year	Author	Name	Planes	Boxes	Cuboids	Spheres	Cylinders	Cones	Other Primitives	Context	Input	Inner Data	Detection Category	Data Fidelity	Abstraction Level	Real-time	Scalability	User Assistance	Learning Phase	Intuitive Tuning	Temporal Consistency	Semantics	Needs Extra Information	Provides Meta Data	Robustness to Noise	Robustness to Incomplete Data	Robustness to Outliers	Code Available
[1]	2016	Ochmann	Walls Layout	✓							building interiors	∴	∴	RANSAC	2	3		●			●	---	○			○	○	●	
[2]	2016	Oesau	Regular Planar Modeling	✓							building interiors	∴	∴	primitive growing	3	3		●			●	---				○	○	○	
[3]	2015	Alehdaghi	Parallel RANSAC	✓							indoor scene	▬🟥🟩🟦	∴	primitive growing	2	2	●	●			●							●	
[4]	2015	Bagautdinov	Occupancy Maps		✓						indoor scene	▬🟥🟩🟦	▬	local statistics	1	3		---				---				●	●	●	
[5]	2015	Elghor	Planar RGB-D SLAM	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	2	●	●				●			●	●	●	●	
[6]	2015	Kaess	Quaternion Representation	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	2	2	●	●				●			●	●	○	●	
[7]	2015	Kang	Bayes SAmple Consensus	✓			✓	✓			any	∴	∴	RANSAC	3	2	●	○				---				○	●	●	
[8]	2015	Khan	Boxes around Objects		✓						indoor scene	▬🟥🟩🟦	▬	primitive growing	1	3		---		●	●	---		●	●	●	○	●	
[9]	2015	Limberger	3D Kernel Hough Transform	✓							indoor scene	∴	∴	parameter space	3	3	●	●			●	---				●	●	●	●
[10]	2015	Martinovic	3D All The Way		✓						urban buildings	🟥🟩🟦 *	∴	segmentation + fitting	2	3		●		●	○	○	●	●	●	○	○	●	
[11]	2015	Monszpart	RAPter	✓							building interiors	∴	∴	primitive growing	2	3		●			●	---				●	●	●	●
[12]	2015	Verdie	Level of Detail	✓		✓				✓	urban buildings	△	△	segmentation + fitting	3	3		●			○	---	●		○	●	○	●	
[13]	2015	Zhang	Labeled KinectFusion	✓							indoor scene	▬ *	□	primitive growing	3	2	●	●	○		○	●				●	●	○	
[14]	2015	Zhou	Generalized Cylinder					✓			individual objects	△	△	primitive growing	3	2		---			○	---					○	○	●
[15]	2014	Chen	Semantic Modeling	✓							indoor scene	▬🟥🟩🟦 *	∴	RANSAC	3	2		---		●	●	---	●	●	○	●		○	
[16]	2014	Feng	Agglomerative Clustering	✓							indoor scene	▬🟥🟩🟦	▬	primitive growing	3	2	●	●			●	●				●		●	●
[17]	2014	Hulik	Planar Hough Transform	✓							indoor scene	▬🟥🟩🟦 *	∴	parameter space	2	3	○	○			○	●				●	○	○	
[18]	2014	Mattausch	Cluttered Indoor Scans	✓							building interiors	∴	∴	primitive growing	3	2		●			○	---		○	○	●	●	○	●
[19]	2014	Ochmann	Hierarchical Building Descriptions	✓		✓					building interiors	∴	∴	RANSAC	3	2		●	●		○	---	○	○	●	●	●	○	
[20]	2014	Salas	Dense Planar SLAM	✓							indoor scene	▬🟥🟩🟦 *	∴	primitive growing	2	2	●	●			○	●			●	●	○	●	
[21]	2013	Arikan	O-Snap	✓							urban buildings	∴	∴	RANSAC	3	3	●	○	○			---				●	●	●	
[22]	2013	Chen	3-Sweep			✓		✓			individual objects	🟥🟩🟦	🟥🟩🟦	user-assisted	3	2	●		●		●	---						●	
[23]	2013	Jiang	Fitting Cuboids			✓					indoor scene	▬🟥🟩🟦	▬	primitive growing	1	2		---				---		●		○	○	●	●
[24]	2013	Kim	Learning Object Templates		✓						individual objects	△ *	∴	segmentation + fitting	1	2	---	○	○			---	○		○	●	○	●	●

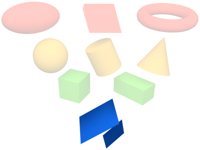
Methods and Applications

Survey

- 73 references from 1998 to 2016
- Communities: Graphics, Robotics, Vision, Image Processing
- Sorted by detected shapes
- Then by application context
- Grouped by theoretical foundation



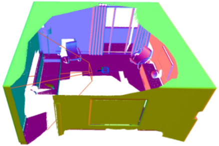
Methods and Applications



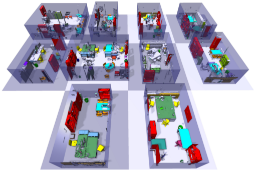
Planes: Indoor Scenes

- Region growing with **planar heuristics**
  - Unorganized 3D point clouds
  - Image structure: faster search for neighbors [Feng et al., 2014]
  - Slower than stochastic, but high quality, consistent
  - Sensitive to noise, but lower than outdoors

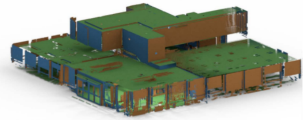
[Feng et al., 2014]



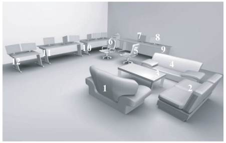
Plane matching and registration [Salas-Moreno et al., 2014]



Joint segmentation [Mattausch et al., 2014]

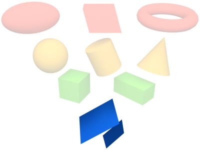


Regularized model [Monszpart et al., 2015]



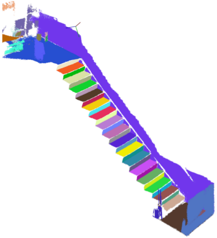
CAD model matching [Shao et al., 2012]

Methods and Applications

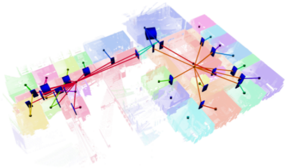


Planes: Indoor Scenes

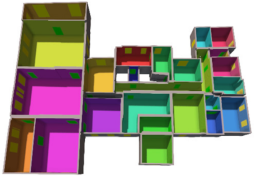
- RANSAC
  - Fast (for robotics)
  - Less consistent and accurate
  - Can be refined with time



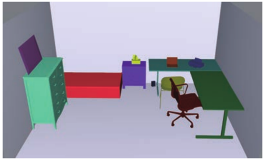
Planar SLAM
[Kaess, 2015]



Spatial relations
[Ochmann et al., 2014]



Floor plans
[Ochmann et al., 2016]

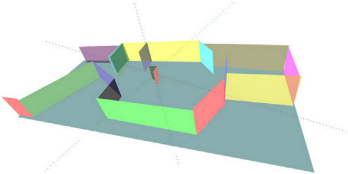


CAD models
[Chen et al., 2014]

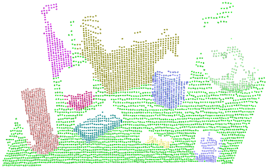
Methods and Applications

Planes: Indoor Scenes

- Parameter space
  - Hough transform for ”Manhattan” scenes [Limberger and Oliveira, 2015]
  - Only a few directions, stable
  - Simpler clustering of param space [Holz et al., 2011]



[Limberger and Oliveira, 2015]

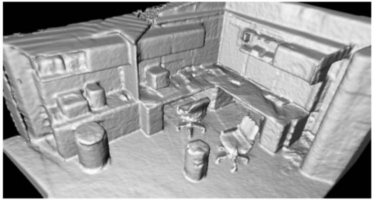


[Holz et al., 2011]

Methods and Applications

Planes: Indoor Scenes

- Segmentation
    - Watershed on range data [Whitaker et al., 1999]
    - Manual plane matching for registration



[Whitaker et al., 1999]

Methods and Applications

Planes: Outdoor Scenes

- Primitive growing
  - House models
  - Semantic labeling and plane assembly
  - Assembling is robust to missing data
  - Recover full house structure
  - Outdoor objects far from each other

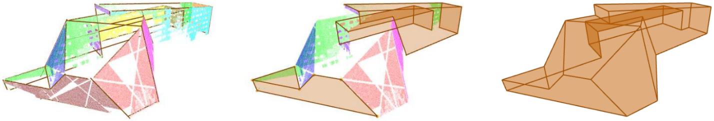
[Lin et al., 2013]

[Lin et al., 2013]

Methods and Applications

Planes: Outdoor Scenes

- Parameter space
  - Urban scene reconstruction
  - Normal-based clustering
  - Plane clipping
  - Buildings with regular planar parts

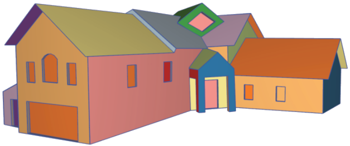


[Chen and Chen, 2008]

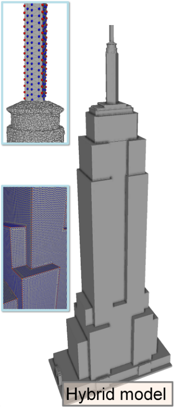
Methods and Applications

Planes: Outdoor Scenes

- RANSAC
  - House and building modeling
  - Planes intersections
  - RANSAC can miss planes → incomplete model



Interactive completion
[Arikan et al., 2013]

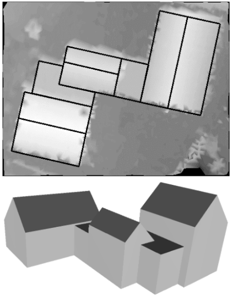


[Lafarge and Alliez, 2013]

Methods and Applications

Planes: Outdoor Scenes

- Hough transform
  - 3D models of buildings
  - Pre-segmentation with ground plans
  - Per-segment fitting
  - Followed by region growing



[Vosselman and Dijkman, 2001]

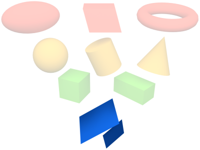
Methods and Applications

Planes: Individual Objects

- Hough transform
  - Simplified visualization of meshes
  - **Billboard Clouds**
  - Render few planar proxies

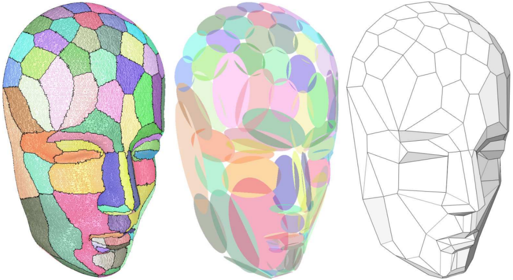
Original model (14K triangles) vs 20 billboards
[Décoret et al., 2003]

Methods and Applications



Planes: Individual Objects

- Automatic clustering
  - **Variational Shape Approximation**
  - K-means on polygonal mesh
  - Accurate, consistent results
  - Requires fixed number of patches

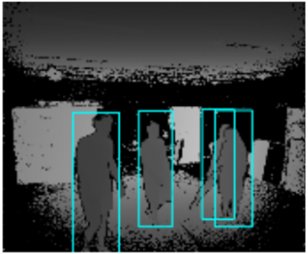


62K triangles to 110 planar patches
[Cohen-Steiner et al., 2004]

Methods and Applications

Bounding Boxes and Cuboids: Indoor Scenes

- Stochastic
  - Person identification from depth maps
  - Local statistics on floor
  - Robust to occlusions



[Bagautdinov et al., 2015]

Methods and Applications

Bounding Boxes and Cuboids: Indoor Scenes

- Assembled planes
  - Boxes around objects
  - Candidate generation and activation
  - Robust to missing faces

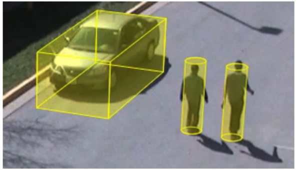
[Jiang and Xiao, 2013]

[Khan et al., 2015]

Methods and Applications

Bounding Boxes and Cuboids: Outdoor Scenes

- Stochastic
  - Detect vehicles and pedestrians
  - Occupancy maps on floor
  - Specific to application, sensitive to data

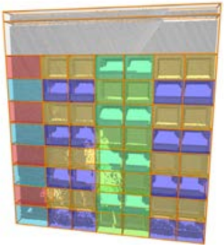


[Carr et al., 2012]

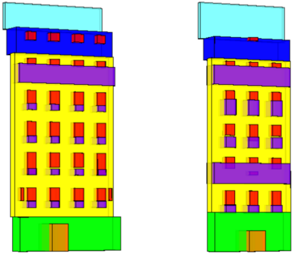
Methods and Applications

Bounding Boxes and Cuboids: Outdoor Scenes

- Segmentation
  - Facade splitting
  - Fit boxes to semantic components
  - Architectural priors, regular facades
  - Meaningful representation



Assembling planes
[Shen et al., 2011]

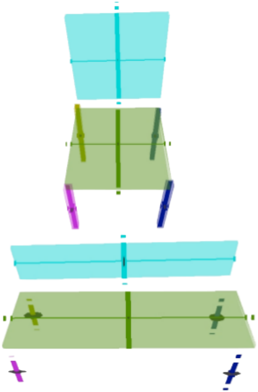


Semantic labeling
[Martinovic et al., 2015]

Methods and Applications

Bounding Boxes and Cuboids: Individual Objects

- Assembled planes
    - 3D shape templates
    - Cuboids from grown planar patches
    - Consistent across object instances
    - Deformation of template parts

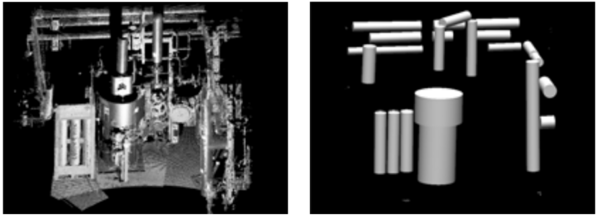


[Kim et al., 2013]

Methods and Applications

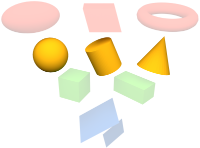
Spheres, Cylinders, Cones: Indoor Scenes

- Hough transform
    - Cylinder parameter space
    - Industrial setups
    - Robust to occluded parts
    - Match cylinders and register views [Rabbani et al., 2007]



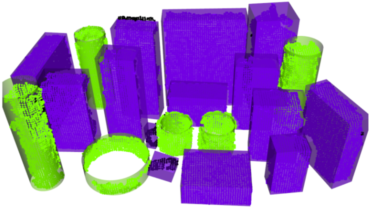
[Rabbani and Van Den Heuvel, 2005]

Methods and Applications



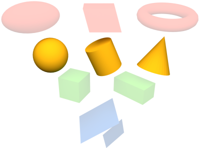
Spheres, Cylinders, Cones: Indoor Scenes

- Segmentation
  - Identify objects on table
  - Simple model for household robots
  - Connected components in 2D table space
  - Hybrid model for accuracy



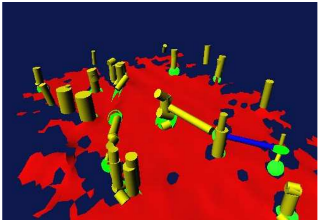
[Goron et al., 2012]

Methods and Applications

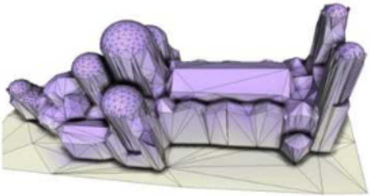


Spheres, Cylinders, Cones: Outdoor Scenes

- Segmentation
  - Classify natural elements / buildings
  - Fit cylinders for trees, cables, columns / spheres for domes
  - Semantic interpretation



Robot in natural environment
[Lalonde et al., 2006]



City modeling [Lafarge and Mallet, 2012]

Methods and Applications

Spheres, Cylinders, Cones: Outdoor Scenes

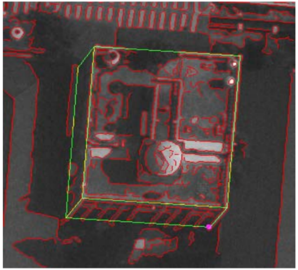
- RANSAC
    - High level model of buildings
    - Hierarchical assembly, decomposition
    - Genericity of RANSAC for revolution shapes

[Chen et al., 2011]

Methods and Applications

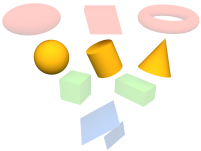
Spheres, Cylinders, Cones: Outdoor Scenes

- User assisted
  - Aerial images
  - Select primitive type, approximate fit
  - Auto refined



[Wang and Tseng, 2004]

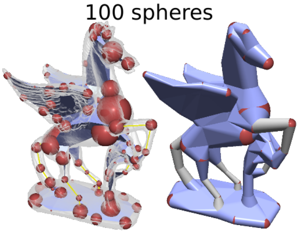
Methods and Applications



Spheres, Cylinders, Cones: Individual Objects

- Primitive growing
  - Object parts, meaningful segmentation
  - Separated by geometric heuristics

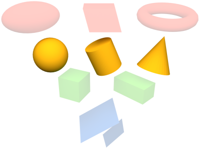
Mechanical parts
[Attene and Patanè, 2010]



Sphere mesh [Thiery et al., 2013]

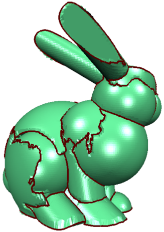
Generalized cylinder
[Zhou et al., 2015]

Methods and Applications

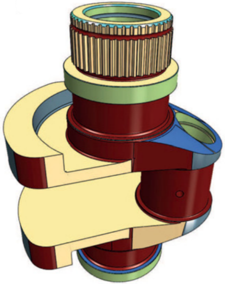


Spheres, Cylinders, Cones: Individual Objects

- Automatic clustering
  - Clusters naturally separate parts
  - Iterations of triangle assignment, primitive fitting
  - Extending VSA to more complex, fewer shapes

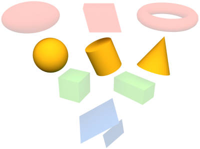


Hybrid VSA
[Wu and Kobbelt, 2005]



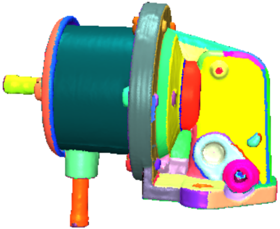
Quadric fitting
[Yan et al., 2012]

Methods and Applications

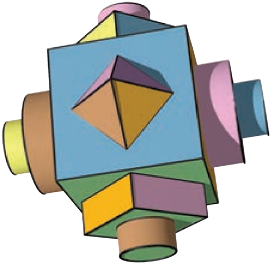


Spheres, Cylinders, Cones: Individual Objects

- RANSAC
  - Mechanical models
  - Need connected component

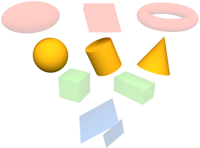


[Schnabel et al., 2007]



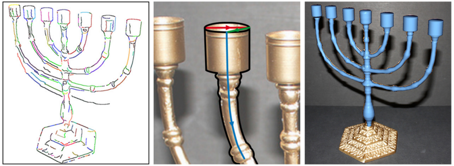
Regularization with Globfit
[Li et al., 2011]

Methods and Applications

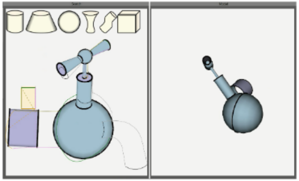


Spheres, Cylinders, Cones: Individual Objects

- Interactive methods
  - Single RGB view: 3-Sweep
  - Draw strokes, auto snapped to edges
  - Stroke semantics
  - Regular models but no automation



3-Sweep [Chen et al., 2013]

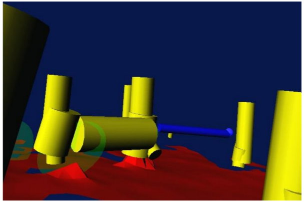


Geo-semantic strokes
[Shtof et al., 2013]

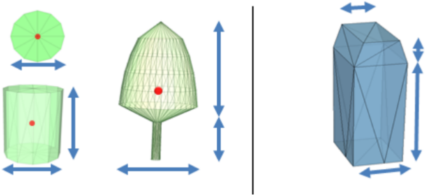
Methods and Applications

Ellipsoids, Tori, Parallelepipeds: Outdoor Scenes

- Segmentation
  - Bounding ellipsoids for organic objects, vegetation
  - Parallelepipeds for building superstructures
  - Usually no clear boundary



Natural elements
[Lalonde et al., 2006]

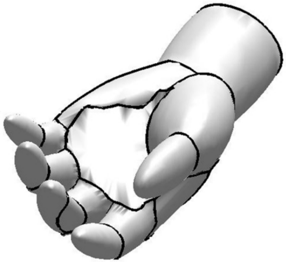


Urban elements [Verdie et al., 2015]

Methods and Applications

Ellipsoids, Tori, Parallelepipeds: Individual Objects

- Automatic clustering
    - Fit ellipse patches to organic shapes
    - Far from input but meaningful
    - Light modeling of complex shapes

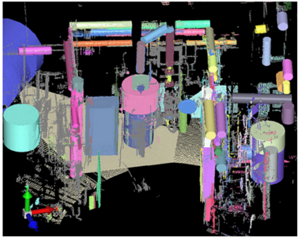


Ellipse VSA
[Simari and Singh, 2005]

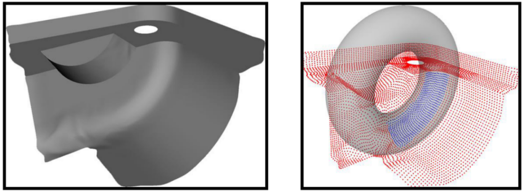
Methods and Applications

Ellipsoids, Tori, Parallelepipeds: Individual Objects

- Tori
  - Industrial environments and objects



Parts of objects, elbows
[Rabbani et al., 2007]



Blends between parts [Attene and Patanè, 2010]

Metrics and Evaluation

Evaluation Metrics

- Sum of Squared Differences (SSD)
  For primitives S_i, $i \in [0, N]$ gathering inliers P_j^i, $j \in [0, M]$, the fitting error is
  $$\epsilon = \sum_{i=0}^{N} \sum_{j=0}^{M} \left\| P_j^i - \mathrm{proj}(P_j^i, S_i) \right\|^2$$
  where $\mathrm{proj}(P_j^i, S_i)$ is the projection, i.e. closest point, of point P_j^i on its shape S_i

- Hausdorff distance
  For two sets of points $a \in A$ and $b \in B$,
  $$H_{AB} = \max_{a \in A} \{ \min_{b \in B} \ d(a, b) \}$$

Metrics and Evaluation

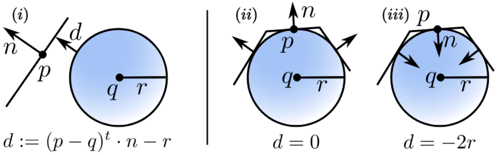
Processing Metrics

- Quadric Error Metric (QEM) [Garland and Heckbert, 1997]

  For a vertex v and N planes P_i, $i \in [1, N]$ with normals p_i, $i \in [1, N]$:

$$\epsilon = \sum_{i=1}^{N} \mathrm{dist}(v, p_i)^2 = \sum_{i=1}^{N} (p_i^T v)^2 = v^T \left(\sum_{i=1}^{N} p_i p_i^T\right) v = v^T Q v$$

- Spherical Quadric Error Metric (SQEM) [Thiery et al., 2013]

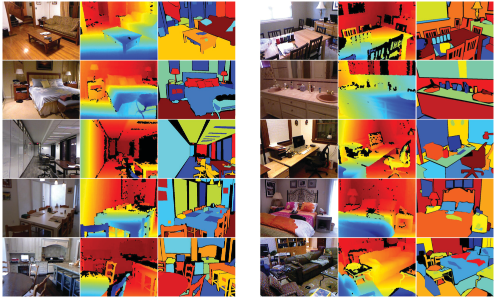


Distance from a sphere to oriented planes
[Thiery et al., 2013]

Metrics and Evaluation

Reproducibility: Online publication of

- Implementation (19 papers)
- Labeled datasets (11 papers)

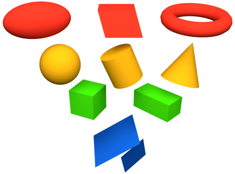


NYU Depth Dataset V2 [Silberman et al., 2012]

CGAL

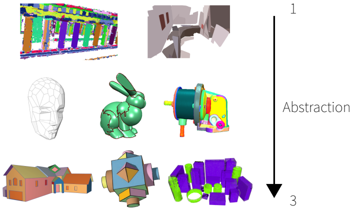
pointcloudlibrary

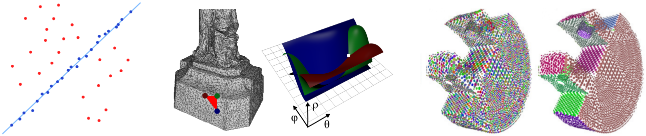
Discussion



Concluding Remarks

- Simple geometric shapes as **building blocks**
- **Simplified tool** for 3D data analysis
- **Faster and accurate** processing
- Multiple **detection paradigms**
- **Application-oriented** classification

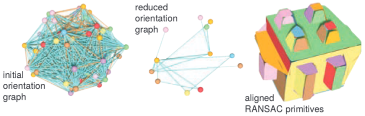




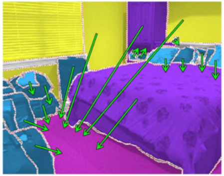
Discussion

Spatial Reasoning

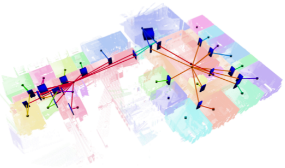
- Enrich data through **structural information**
- Qualitative and quantitative **knowledge of spatial locations**
- Graph of **geometric relations**
- Hierarchical **adjacency**
- Room **connectivity**
- But: only post-detection



GlobFit [Li et al., 2011]



[Silberman et al., 2012]

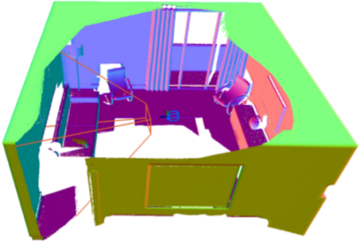


[Ochmann et al., 2014]

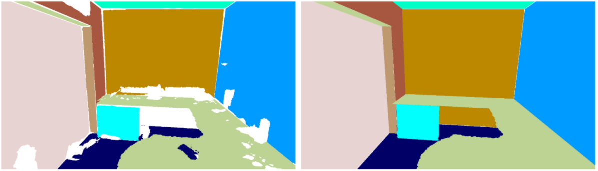
Discussion

Research Challenges: Model

- **Completeness**
- Consistency



Dense Planar SLAM
[Salas-Moreno et al., 2014]



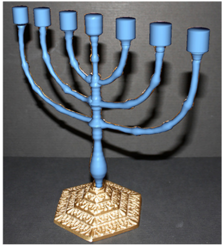
Plane extrapolation from 3D Lite (5h per scene)
[Huang et al., 2017]

Discussion

Research Challenges: Interpretation

- Semantics
- **Functional** behavior, **Constraints**, Visibility
- **Parametric** primitives

Generalized Cylinder
[Zhou et al., 2015]

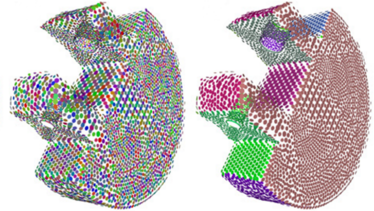


3-Sweep
[Chen et al., 2013]

Discussion

Research Challenges: Processing

- **Parallel** execution [Oesau et al., 2016]
- **Compressed** representations
- Primitives for **capture**
- **Multiscale**

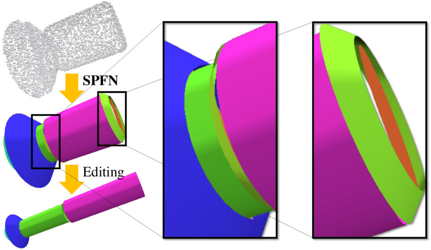


Model hierarchy
[Attene and Patanè, 2010]

Discussion

Research Challenges: Deep Learning

- **Detect** primitives
- Primitives as **features**
- Geometry of DNN



Supervised Fitting (based on PointNet++)
[Li et al., 2019]

A Survey of Simple Geometric Primitives Detection Methods for Captured 3D Data

Adrien Kaiser, Jose Alonso Ybanez Zepeda, Tamy Boubekeur

COMPUTER GRAPHICS *forum*

`https://perso.telecom-paristech.fr/boubek/papers/GeoPrimFitSurvey/`

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