2018 U.S. EPA International Decontamination R&D Conference
Durham, North Carolina, May 8–10, 2018

Mapping the Great Indoors:
Spatial context through indoor maps

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May 10, 2018

Smart Cities

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What is a smart city?

11 ideas & 15 definitions[1]

- Wired city
- Intelligent city
- Sustainable city, etc.

"City designed to facilitate information exchange and data analysis"

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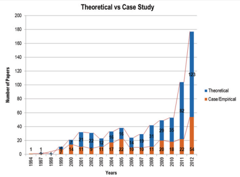
Interest in smart cities on the rise

Studies 1994-2012[1]

- Asia (49%)
- Europe (36%)
- North America (9%)



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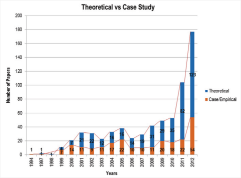


But what about indoors?

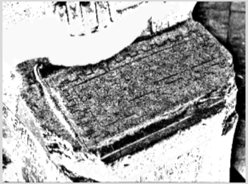
Observations

- City, not building, scale
- City-dwellers spend 90% of time indoors[2]
- 2D floor plans remain prevailing paradigm . . . since **ancient times**

Innovation of indoor maps through the ages

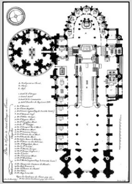
3000 BC
Girsu [3]

2150 BC
Ningirsu Temple [4]

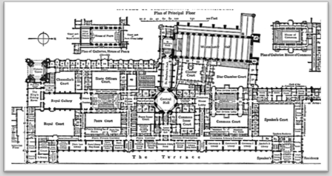


210 AD
Forma Urbis Romae [5]

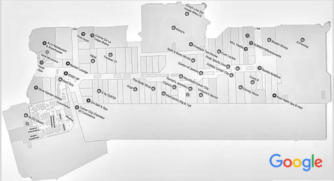
1700
Saint-Denis Abbey [6]



1800s
House of Parliament, Westminster, England [7]



2017
Westfield Shopping Mall, Culver City [8]



Mapping the "Great Indoors"

> "A bargain is struck in which technology giveth and technology taketh away."
>
> — Neil Postman, Technopoly

The Past → The Future

Blueprints/CAD	Manual measurements	Modeling by hand
⇓	⇓	⇓
3D building models	3D remote sensing	Automation
Indoor modeling standards	**Indoor reality capture**	**Automated data conversion**

Building modeling standards

- Standards driven by ($$$) potential return on investment

Industry Foundation Classes (IFC)

Architecture, engineering, & construction (AEC)

- Supports BIM data
- Interior & exterior
- Extremely fine details
- Level of *development*

City Geography Markup Language (CityGML)

Urban-scale GIS including emergency management

- Buildings & surroundings
- Mostly exterior
- Level of *detail*

Indoor Geography Markup Language (IndoorGML)

Indoor positioning & navigation

- Building interiors
- Topology, not geometry
- Integrates w/ CityGML & IFC

Indoor considerations for IFC and CityGML

- BIM-GIS integration already existing & improving
  - Facilities Information Spatial Data Model (FISDM)
  - Safe Software's Feature Manipulation Engine (FME)
- Indoor cartographic features are lacking
  - BIM/IFC: uses level of development
  - CityGML: single indoor LOD

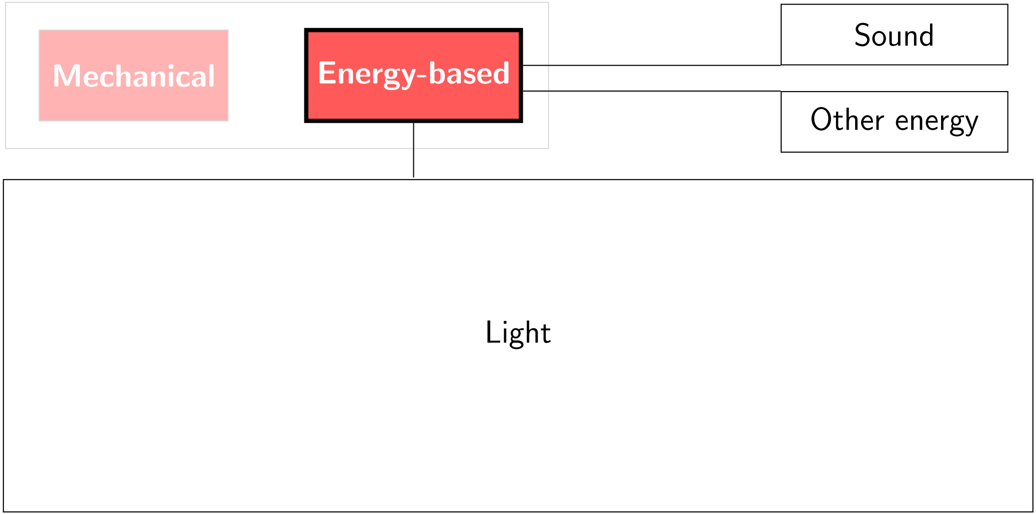
Indoor reality capture

- Reality capture
  - Marketing term for non-technical audience
  - Really just *remote sensing* . . . *close-range remote sensing*
- Why capture reality?
  - Measurements ⇒ basic building blocks of models
  - Many buildings have only 2D drawings, if any
  - Capture *as-is* condition . . . buildings change with time

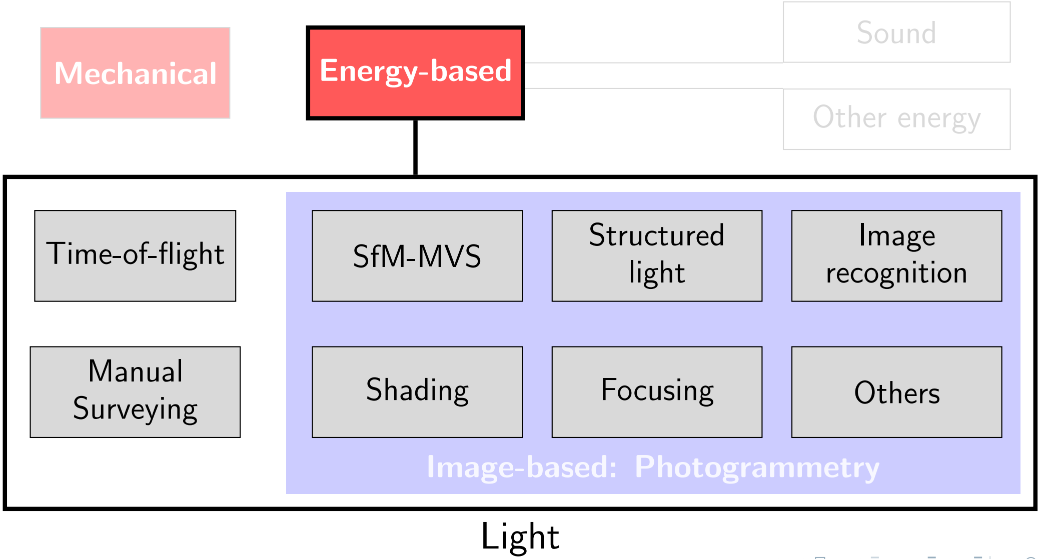
Measurement methods

- Mechanical
- Energy-based

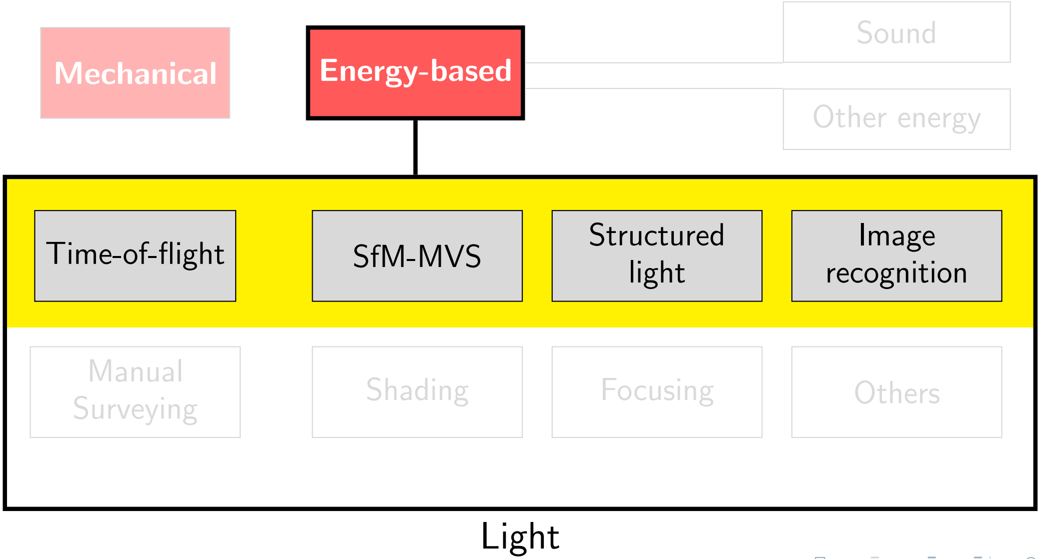
Measurement methods



Measurement methods



Measurement methods

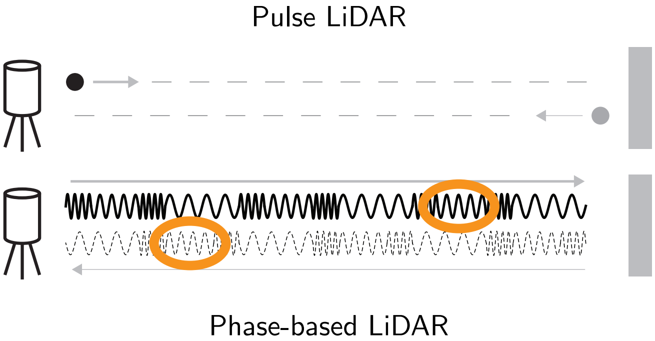


Top 3 reality capture techniques

Light detection and ranging

More common name for ToF; uses speed of light $\Rightarrow$ distance

- LiDAR or "laser scanning"
- Distance $\approx (c \times t)/2$
- Pulse vs. phase-based

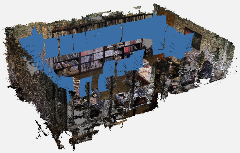


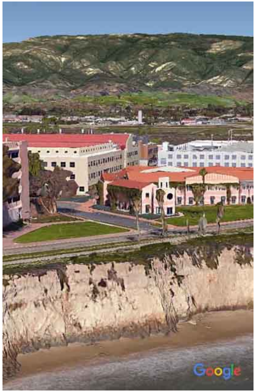
Top 3 reality capture techniques

SfM-MVS

Derives 3D structure from sets of overlapping 2D images

- Structure-from-motion (SfM)
- Multiview stereo (MVS)
- Parallax phenomenon
- Requires scaling info

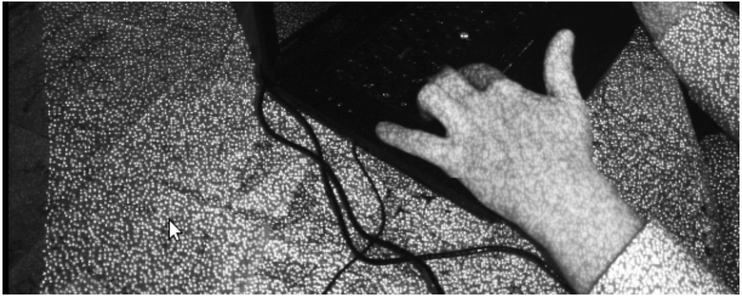




Parallax demo
(click for animation)

Top 3 reality capture techniques

Microsoft Kinect



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URL https://commons.wikimedia.org/wiki/File:Kinect2-ir-image.png

Structured light

Triangulation based on calibrated infrared light pattern

- Based on triangulation
- Aka “RGB-D”
- Intro’d via XBox Kinect
- iPhone 8 3D sensor

Top 3 reality capture pros and cons

Light detection and ranging

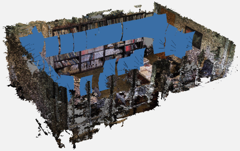
Pros: Fast; most accurate and precise*; min. post-processing; long measuring range 30m+

Cons: Expensive @ $16K+

SfM-MVS

Pros: Low entry cost; easy-to-learn; measurements w/ color; unlimited measuring range

Cons: Requires many photos; challenging indoor lighting; labor-intensive; extremely long processing times; distortions & uncertainties; unscaled*



Structured light

Pros: Easy to operate; in-expensive @ $100 to $4K

Cons: Short range 4m; averse to bright light; alignment drift

Reality capture ⇒ point clouds

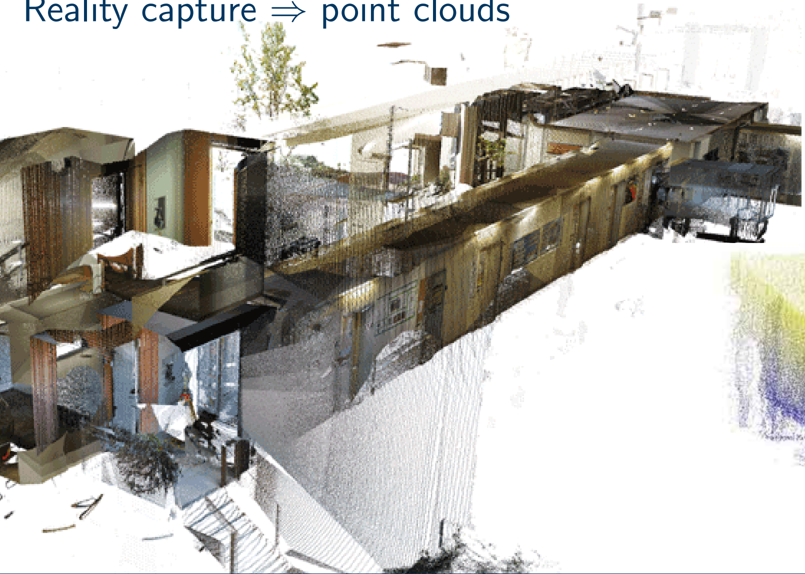
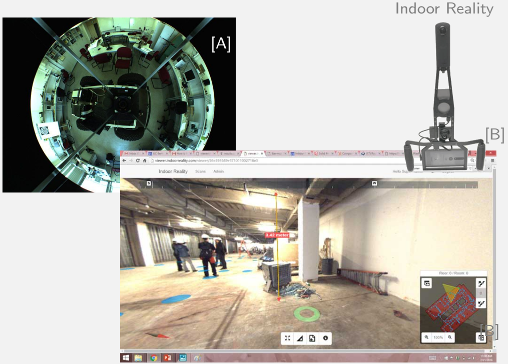


Image recognition for indoor mapping

Current state-of-the-art: panoramic images placed over LiDAR



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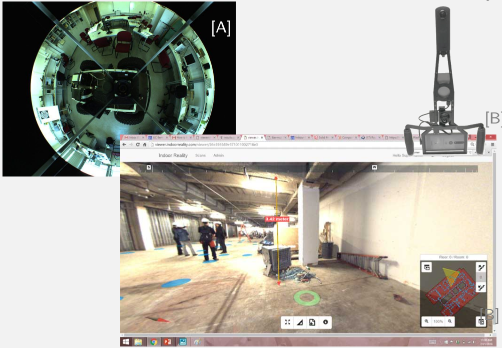

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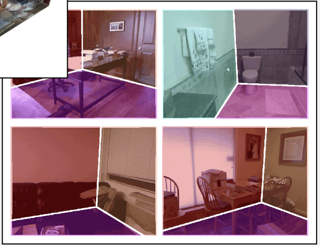
Structure from single images

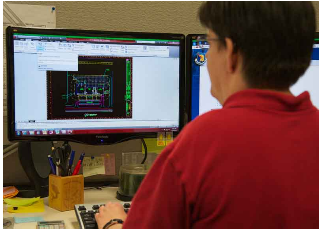
LayoutNet[10]



PlaneNet[9]

Automated indoor mapping

- Current practices
  - Manual drafting from point clouds
  - Cost and time reduce frequency of updates
  - Automation mostly for outdoor features, e.g., facades, windows, etc.
- Challenges in indoor automation
  - Geometrically complex environment in space & time
  - Clutter and obstructions $\Rightarrow$ voids in data
  - Geometry and semantics



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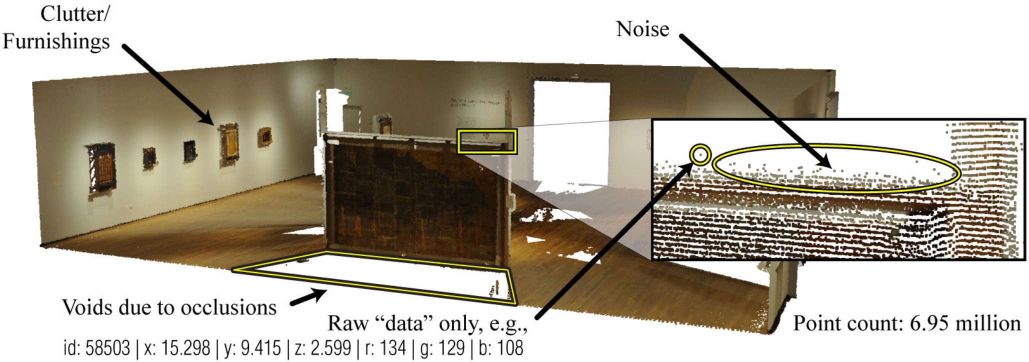
Challenges in indoor automation

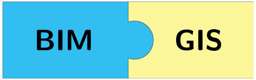


Research in automation

- Current research
  - Mostly geometric and simple semantics, e.g., floor, ceiling, wall, etc.
  - Applied statistics and machine learning
  - Context dependent ⇒ easily broken
- Emerging research
  - Apply deep learning to point clouds ⇐ requires lots of data
  - Deduce geometry and semantics, including furniture
  - DL for autonomous vehicles, e.g., VoxelNet & predecessors[11, 12, 13]
  - DL for indoors, e.g., PointNet, PointNet++[14, 15]

Research gap

- Indoor cartographic research
  - Level of detail (geometric, semantic, appearance)[16, 17]
  - Indoor mapping vs. BIM & GIS



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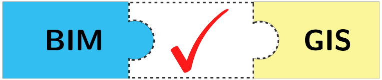

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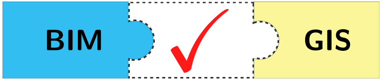

- Potential uses
  - Disaster simulation & training
  - Emergency response
  - Smart buildings & IoT
  - Hazmat planning
  - Mining of urban metals
  - Autonomous vehicles
  - Gamification
  - And many, many more!

Conclusion

- 3D indoor maps $\Rightarrow$ vital part of smart city infrastructure
- Three key processes
  - Mapping conventions: Goldilocks principle . . .
    BIM (too detailed), CityGML (too generalized), missing “just right”
  - Reality capture: many approaches, and more coming
  - Automation: just getting started with AI revolution
- Operationalizing indoor maps
  - Technology exists, trees $\Leftrightarrow$ forest
  - Missing unifying theories and conventions . . . subject of research!

Acknowledgements

This research was supported by the

National Geospatial-Intelligence Agency
Academic Research Program
Grant # HM0476-17-1-2002

All unattributed images produced by Jorge Chen, Department of Geography, University of California, Santa Barbara.

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