KinectFusion

Lecturer: Zhi-Hao Lin

Date	Торіс	Papers	Lecturer 1	Lecturer 2	Archeologist 1	Archeologist 2	Private Investigator	Industrial Practitioner	Critic	Graduate Student	Hacker 1	Hacker 2	Hacker 3	Discussion
Sept 12	MVS	KinectFusion	Z	hi-Hao	She	enlong	Shenlong	Albert Zhai	Zhi-Hao	Albert Zhai	ICP (Zhi-Hao)	2D Depth Fusion (Shenlong)	-	
Sept 17	SLAM	DROID-SLAM	rmoan2		ying22	xialinh2	jw116	jrc9	zhiyul6	yuezeng4	ksa5	wenqij5		
Sept 19	Learning-based SFM	<u>Camera as Rays</u>	dyyao2		ads10	haoyuyh3	yuqunwu2	jiahuad2	amitabh3	haoz19	amballa2	ozgurk2		
Sept 26	Mesh & Tedrahedron	<u>DMTet</u>	zixuan32	ying22	jw116	wch7	hongchix	runpeid2	hanlinm2	jiaweiz9	haozhe3	weijiel4		
Oct 8	Neural Volumes	DeepSDF	xialinh2	ads10	junzhew3	zixuan32	ziyang8	mkg7	rmoan2	vlasz2	junkun3	jackiel4		
Oct 10	Deep Learning on 3D	<u>fVDB</u>	haoyuyh3		ksa5	wenqij5	dyyao2	hongyig3	haozhen3	haozhe3	tcheng12	shaowei3		
Oct 17	Differentiable Rendering	<u>NVDiffRast</u>	wch7	junzhew3	amballa2	ozgurk2	guangy2	meih3	nisar2	junkun3	cconway4	yufengl2		
Oct 22	Neural Radiance	Gaussian Splats	nisar2	ziyang8	haozhe3	weijiel4	yuezeng4	xialinh2	ying22	tcheng12	jrc9	zhiyul6		
Oct 24	Neural Surface	<u>NeuS</u>	wenqij5	haozhen3	junkun3	jackiel4	haoz19	haoyuyh3	ads10	cconway4	jiahuad2	amitabh3	yuqunwu2	
Oct 29	Neural Inverse rendering	Rendering synthetic object	ozgurk2	guangy2	tcheng12	shaowei3	jiaweiz9	wch7	jw116	jrc9	runpeid2	hanlinm2	hongchix	
Oct 31	Monocular Geometry	Recovering surface layout	weijiel4	yuezeng4	cconway4	yufengl2	vlasz2	zixuan32	junzhew3	jiahuad2	mkg7	rmoan2	ziyang8	
Nov 5	Few-View Geometry	Mast3R	jackiel4	haoz19	jrc9	zhiyul6	ksa5	wenqij5		runpeid2	hongyig3	haozhen3	dyyao2	
Nov 7	3D Editing	Enhancing Photorealism E	shaowei3	jiaweiz9	jiahuad2	amitabh3	amballa2	ozgurk2	yuqunwu2	mkg7	meih3	nisar2	guangy2	
Nov 19	3D Simulation	PhysGaussian	yufengl2	vlasz2	runpeid2	hanlinm2	haozhe3	weijiel4	hongchix	hongyig3	xialinh2	ying22	yuezeng4	
Nov 21	3D Generation	<u>Get3D</u>	zhiyul6		mkg7	rmoan2	junkun3	jackiel4	ziyang8	meih3	haoyuyh3	ads10	haoz19	
Dec 3	Parametric Articulated Shapes	<u>SMPL</u>	amitabh3	yuqunwu2	hongyig3	haozhen3	tcheng12	shaowei3	dyyao2	ksa5	wch7	jw116	jiaweiz9	
Dec 5	Dynamic 3D Understanding	Dynamic Fusion	hanlinm2	hongchix	meih3	nisar2	cconway4	yufengl2	guangy2	amballa2	zixuan32	junzhew3	vlasz2	
	Time			12		12	6	6	6	6		12		10

KinectFusion: Real-Time Dense Surface Mapping and Tracking*

Richard A. Newcombe Imperial College London

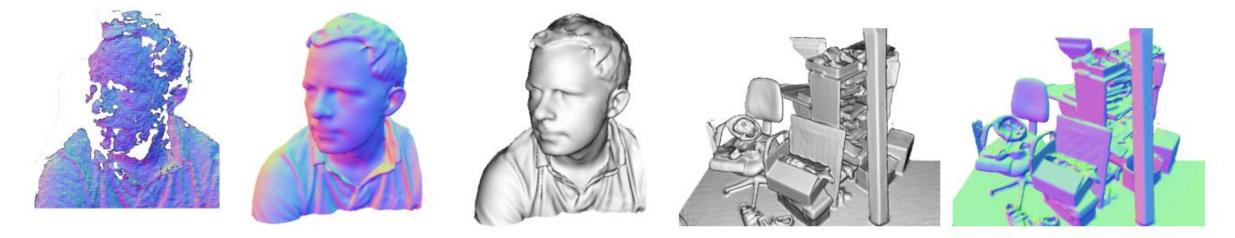
Andrew J. Davison Imperial College London Shahram Izadi Microsoft Research

Pushmeet Kohli

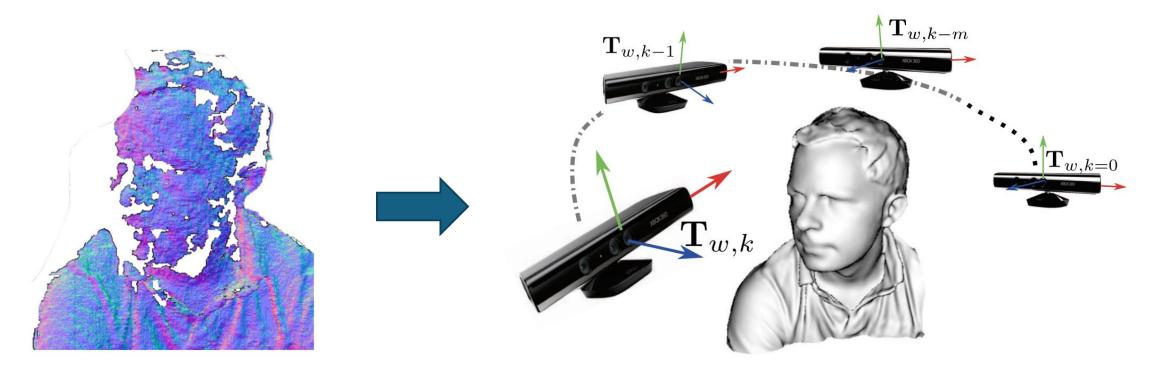
Microsoft Research

Otmar Hilliges Microsoft Research

Jamie Shotton Microsoft Research David Molyneaux Microsoft Research Lancaster University Steve Hodges Microsoft Research David Kim Microsoft Research Newcastle University Andrew Fitzgibbon Microsoft Research



KinectFusion: Background



Depth Sensor Sequences

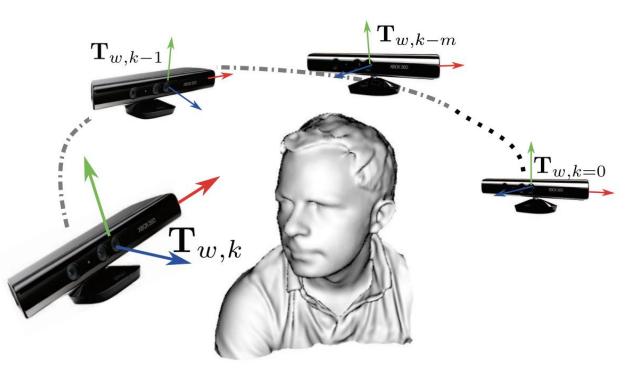
Complete Shape and Camera Poses

Image credit: Newcor

KinectFusion: Background

Tracking: Estimate camera pose T

Mapping: 3D reconstruction



Complete Shape and Camera Poses

Image credit: Newcor

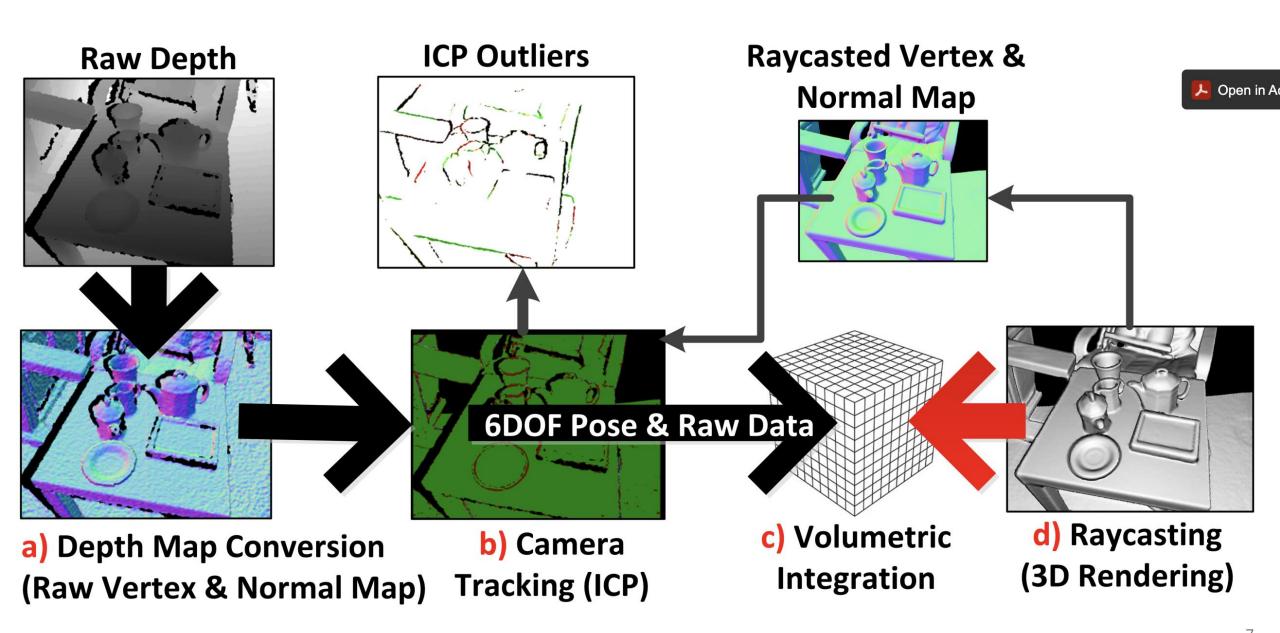


Image credit: Newcombe

KinectFusion: ICP-based Camera Tracking

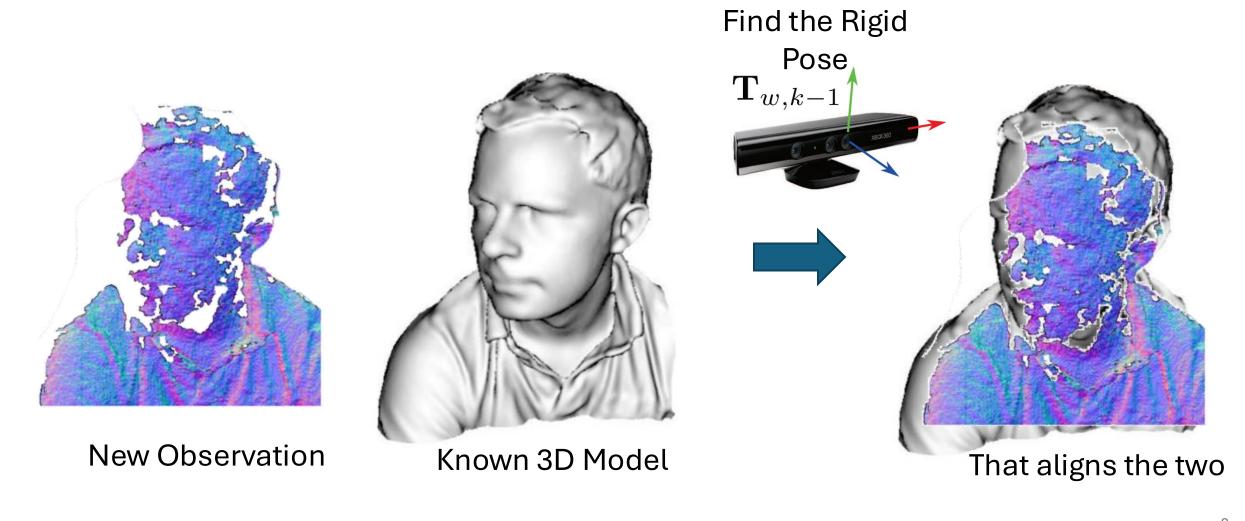
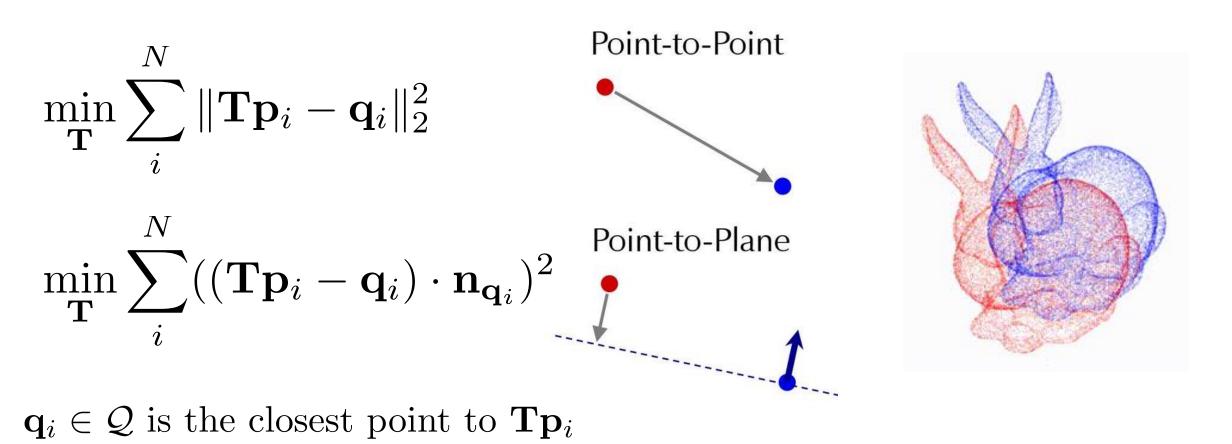


Image credit: Newcor

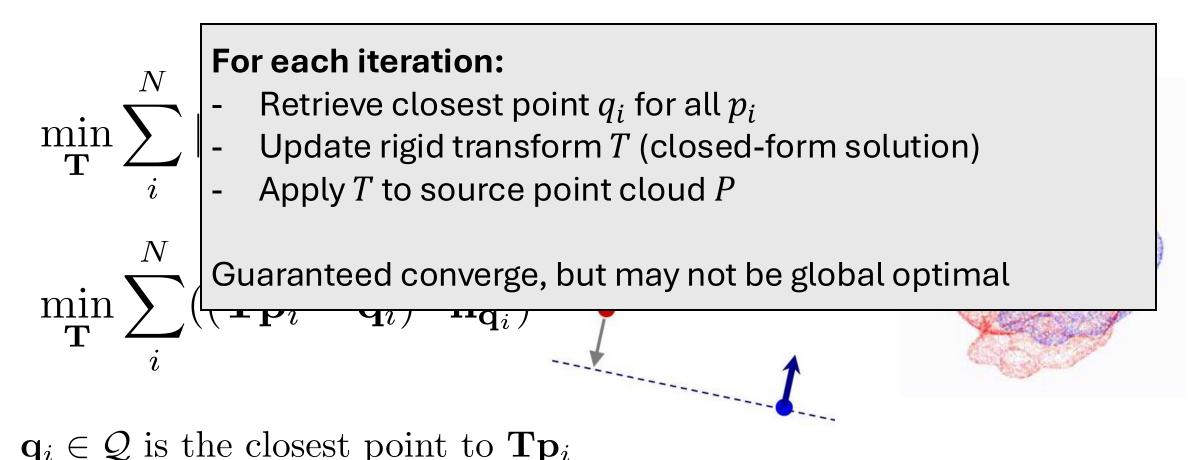
KinectFusion: ICP-based Camera Tracking

Finding the rigid transform that minimize the average distance between the two set of point cloud.



KinectFusion: ICP-based Camera Tracking

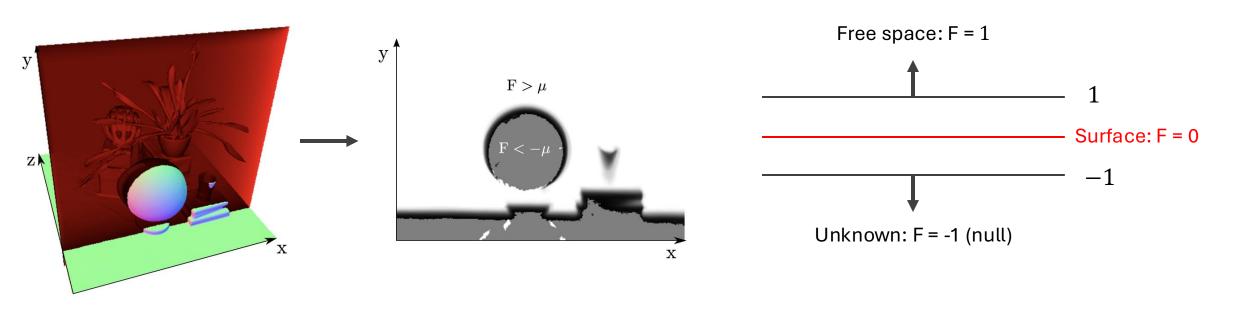
Finding the rigid transform that minimize the average distance between the two set of point cloud.



KinectFusion: TSDF

Truncated Sign Distance Function





3D scene

2D slice

KinectFusion: TSDF

-0.9	-0.3	0.0	0.2	1	1	1	1	1
-1	-0.9	-0.2	q .0	0.2	1	1	1	1
-1	-0.9	-0.3	0.)	0.1	0.9	1	1	1
-1	-0.8	-0.3	0.0	0.2	0.8	1	1	1
-1	-0.9	-0.4	-0.1	Q.1	0.8	0.9	1	1
-1	-0.7	-0.3	0,0	0.3	0.6	1	1	1
-1	-0.7	-0.4	00		0	-	1	1
-0.9	-0.7	-0.2	90	0.2	0.8	0.9	1	1
-0.1	0.0	0.0	0.1	0.3	1	1	1	1
0.5	0.3	0.2	0.4	0.8	1	1	1	1

2D TSDF

Measured depth

$$\delta(p) = D(\pi(p)) - ||p - c||_2$$
Threshold

$$F(p) = \begin{cases} \frac{\delta(p)}{\mu}, & \text{if } |\delta(p)| \le \mu \end{cases}$$

 $(sign(\delta(p)), if |\delta(p)| > \mu$

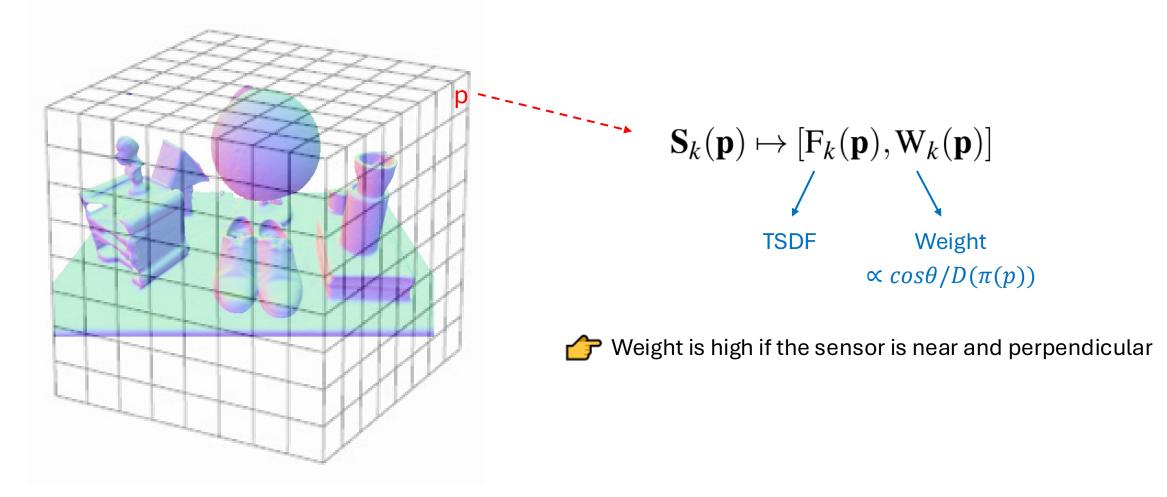
TSDF

Image credit: https://itnext.io/understanding-real-time-3d-reconstruction-and-kinectfusion-33d61d1cd402

Microsoft Kinect

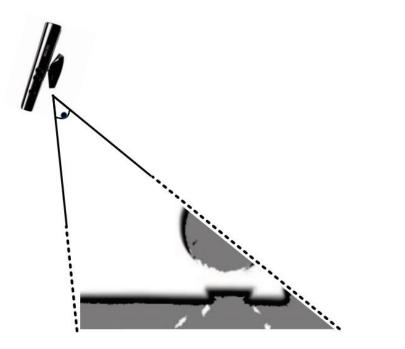
KinectFusion: TSDF

Store values in each voxel grid

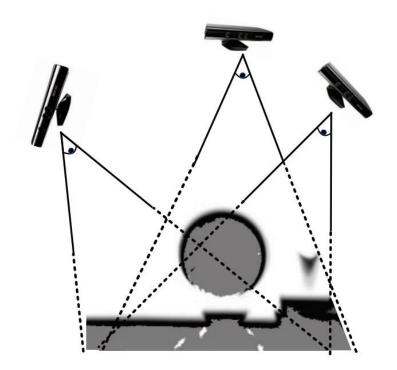


KinectFusion: Volume Integration

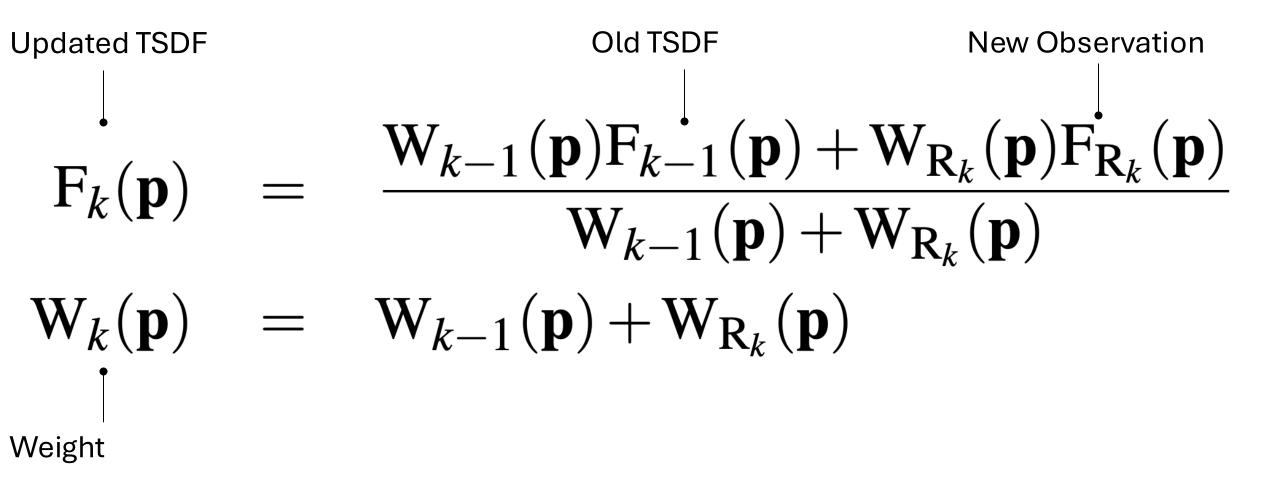
Each sensor provides a partial (noisy) observation of the signed distance function



Volume integration recursively update the map by integrating new observation.



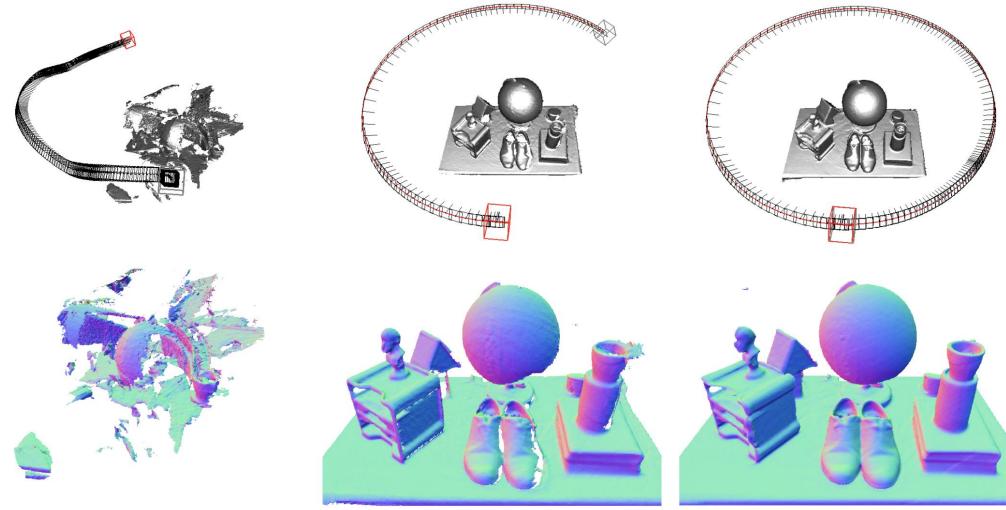
KinectFusion: Volume Integration



Running weighted average

KinectFusion: Volume Integration

Frame-to-model alignment is more stable and accurate than frame-to-frame



(a) Frame to frame tracking

(b) Partial loop

(c) Full loop

KinectFusion: Results



The Past and the Future of KinectFusion

Archeologist: Shenlong Wang

Past and Future

- What was the status of VSLAM at the time of KinectFusion?
- What opportunities at that time enabled KinectFusion?
- What was the academic impact of KinectFusion afterwards?
- What was the industrial impact of KinectFusion?

Real-time camera tracking and mapping (e.g. PTAM):

- Real-time and robustness in camera tracking is possible
- Maps are represented as a set of sparse feature points
- No real-time dense reconstruction

Why dense map is appealing?

Parallel Tracking and Mapping for Small AR Workspaces

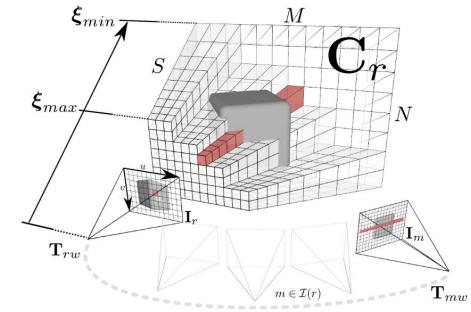
Extra video results made for ISMAR 2007 conference

Georg Klein and David Murray Active Vision Laboratory University of Oxford

Klein and Murray, Parallel Tracking and Mapping for Small AR Workspaces ISMAR 2007 20

Dense Tracking and Mapping (DTAM)!

Maps --> dense cost volume at keyframes.



DTAM: Dense Tracking and Mapping in Real-Time

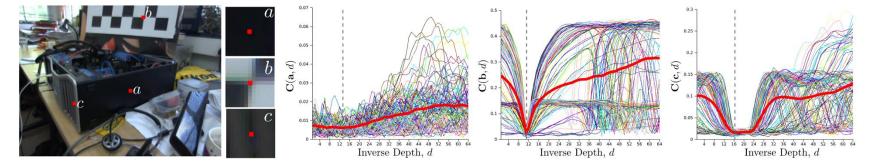
Richard A. Newcombe, Steven J. Lovegrove and Andrew J. Davison Department of Computing, Imperial College London, UK [rnewcomb, sl203, ajd]@doc.ic.ac.uk

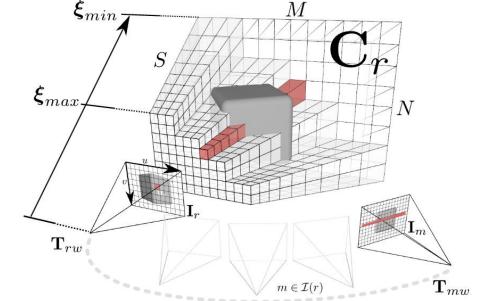
Dense Tracking and Mapping (DTAM)!

- Maps --> dense cost volume at keyframes.
- Cost: sum of photometric error error:

$$\mathbf{C}_{r}(\mathbf{u},d) = \frac{1}{|\mathcal{I}(r)|} \sum_{m \in \mathcal{I}(r)} \|\rho_{r}\left(\mathbf{I}_{m},\mathbf{u},d\right)\|_{1} \qquad \rho_{r}\left(\mathbf{I}_{m},\mathbf{u},d\right) = \mathbf{I}_{r}\left(\mathbf{u}\right) - \mathbf{I}_{m}\left(\pi\left(\mathrm{KT}_{mr}\pi^{-1}\left(\mathbf{u},d\right)\right)\right).$$

Intuition: 1. warping image using true depth value yield smaller photometric error (brightness consistency) 2. averaging overall multiple images makes the cost to be robust.





DTAM: Dense Tracking and Mapping in Real-Time

- Real-time Sparse SLAM method doesn't provide dense reconstruction of the scene.
- Dense SLAM starts emerging and provides dense 3D maps, do not provide truly real-time dense recon, and are limited under certain illumination.
- Desiderata: real-time, dense, robust

Klein and Murray, Parallel Tracking and Mapping for Small AR Workspaces ISMAR 2007

Opportunities in 2011

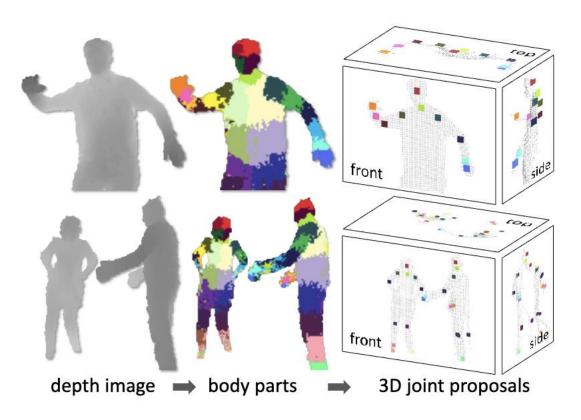
• Sensor: Kinect is out!

Real-Time Human Pose Recognition in Parts from Single Depth Images

Jamie ShottonAndrew FitzgibbonMat CookToby SharpMark FinocchioR1chard MooreAlex KipmanAndrew BlakeMicrosoft Research Cambridge & Xbox Incubation







25 Shotton et al. *Real-time human pose recognition in parts from single depth images*, CVPR 2011 Best Paper.

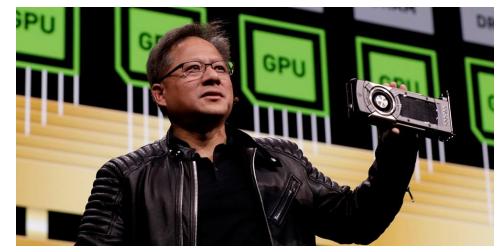
Opportunities in 2011

- GPGPUs and CUDA library
- TSDF fusion and normal

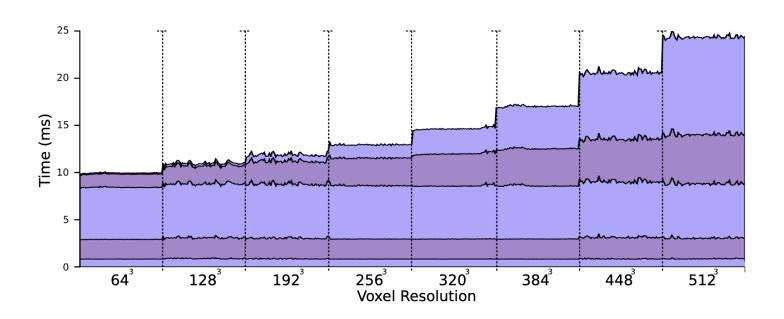
estimation are highly parallel

computation

• GPU helps a ton







Real-Time Human Pose Recognition in Parts from Single Depth Images

CVPR 2011

Jamie Shotton, Andrew Fitzgibbon, Mat Cook, Toby Sharp, Mark Finocchio, Richard Moore, Alex Kipman, Andrew Blake

Microsoft[®] Research

Xbox Incubation

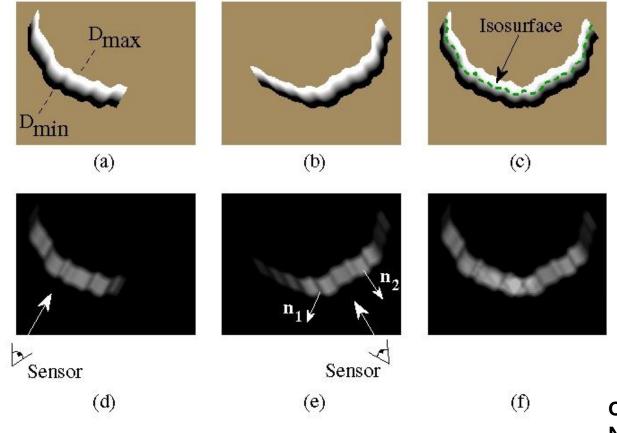
Opportunity: Volume Integration

- Signed distance function to represent 3D geometry
- Value distance of a point to its closet surface
- Positive outside surface, Negative inside surface, Zero -- Isosurface

4	4	3	3	3	3	3	3	3	3	4	4
4	3	2	2	2	2	2	2	2	2	3	4
3	2	1	1	1	1	1	1	1	1	2	3
3	2	1	-1	-1	-1	-1	-1	-1	1	2	3
3	2	1	-1	-2	-2	-2	-2	-1	1	2	3
3	2	1	-1	-2	-3	-3	-2	-1	1	2	3
3	2	1	-1	-2	-2	-2	-2	-1	1	2	3
3	2	1	-1	-1	-1	-1	-1	-1	1	2	3
3	2	1	1	1	1	1	1	1	1	2	3
4	3	2	2	2	2	2	2	2	2	3	4
4	4	3	3	3	3	3	3	3	3	4	4

Opportunity: Volume Integration

• Good news: partial SDF from multiple scans can be integrated



$$D_{i+1}(\mathbf{x}) = \frac{W_i(\mathbf{x})D_i(\mathbf{x}) + w_{i+1}(\mathbf{x})d_{i+1}(\mathbf{x})}{W_i(\mathbf{x}) + w_{i+1}(\mathbf{x})}$$
$$W_{i+1}(\mathbf{x}) = W_i(\mathbf{x}) + w_{i+1}(\mathbf{x})$$

Curless and Levoy, A Volumetric Method for Building Complex₉ Models from Range Images, SIGGRAPH 96



Scale up to very large scenes and faster

• Key idea: use hashing to store only occupied voxels

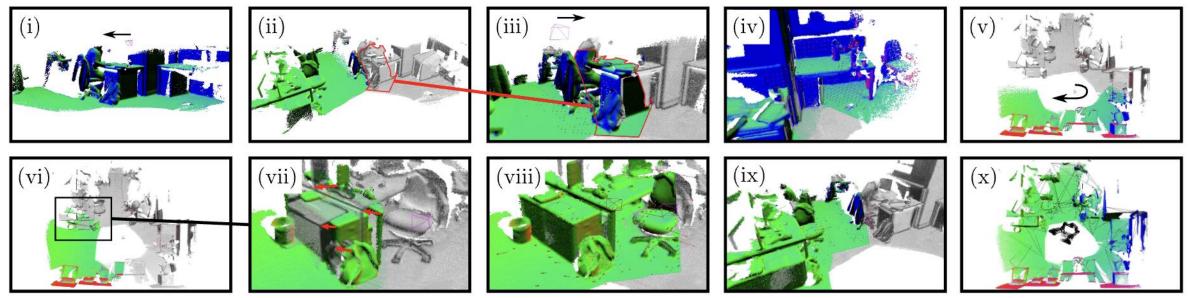
Real-time 3D Reconstruction at Scale using Voxel Hashing

Matthias Nießner^{1,3}Michael Zollhöfer¹Shahram Izadi²Marc Stamminger¹¹University of Erlangen-Nuremberg²Microsoft Research Cambridge³Stanford University



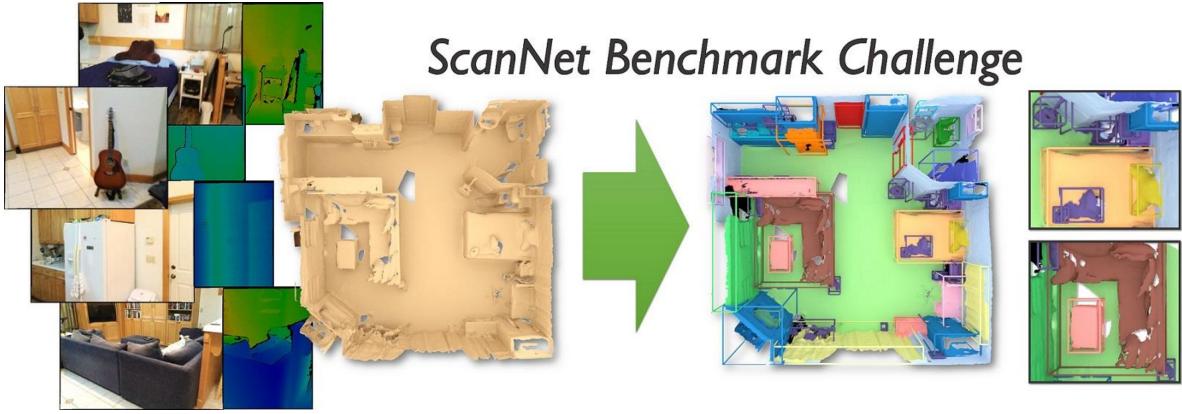
Solving drifting and global consistency

• Key idea: represent the 3D with explicit geometry primitives so we can directly "deform" locally to align globally



Whelan et al. ElasticFusion: Real-Time Dense SLAM and Light Source Estimation, IJRR 16

• Data engine for many tasks: e.g. 3D scene understanding



Dai et al. ScanNet: Richly-annotated 3D Reconstructions of Indoor Scenes, CVPR 2017

• Extended to dynamic scenes



Live Input Depth Map



Live Model Output



Correction RGB Image (unused)



Canonical Model Reconstruction

Warped Model

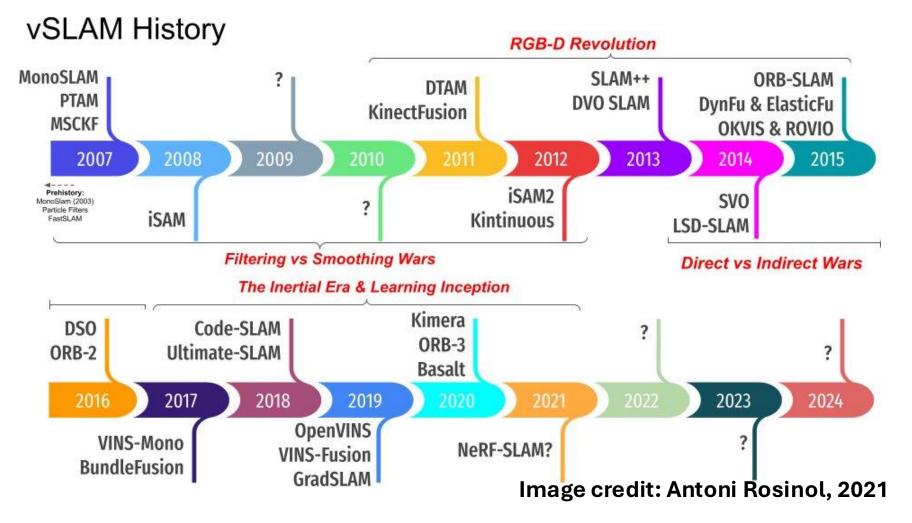
Newcombe, et al. DynamicFusion: Reconstruction and Tracking of Non-rigid Scenes in Real-Time, CVPR 2015

• Real-time 3D reconstruction product in iPhone



ARKit for 3D Reconstruction

VSLAM \rightarrow what happened next?





Andrew Davison:

MonoSLAM, KinectFusion, DTAM, SLAM++, ElasticFusion, SemanticFusion, CodeSLAM, iMap, Gaussian splatting slam

Good survey: Cadena, Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age, TRO, 2016

Private Investigator: Richard Newcombe

Shenlong Wang

- PhD: Imperial College at London
- Advisor: Andrew J. Davison



Surreal Vision Ltd Oct 2014 - Sep 2015 · 1 yr



Researcher University of Washington Dec 2012 - Sep 2015 · 2 yrs 10 mos



Research student

Imperial College London Apr 2008 - Nov 2012 · 4 yrs 8 mos

Working in the cognitive robotics and robot vision groups.



Research intern Microsoft Research, Cambridge Sep 2010 - Dec 2010 · 4 mos VP, Research Science Meta · Full-time Aug 2022 - Present · 2 yrs 2 mos United States

FB Facebook 4 yrs 9 mos

- **Director of Research Science** 2018 - Sep 2022 · 4 yrs 9 mos
- Director of Research Science Jan 2018 - Aug 2022 · 4 yrs 8 mos

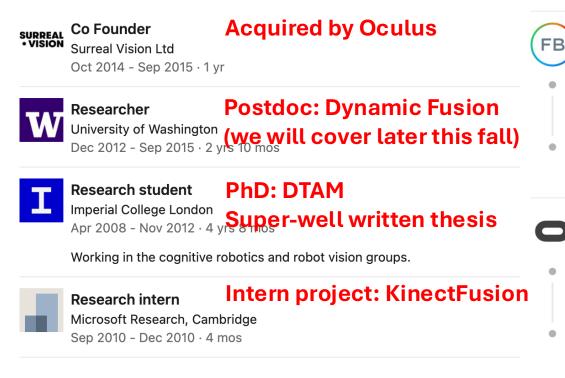
Oculus VR 4 yrs 8 mos

Director, Research Science Jan 2017 - Aug 2019 · 2 yrs 8 mos

Manager, Research Science 2015 - 2017 · 2 yrs United States



- PhD: Imperial College at London
- Advisor: Andrew J. Davison



VP, Research Science Meta · Full-time Replica, Ego4D Aug 2022 - Present · 2 yrs 2 mos United States



DeepSDF (we will cover later this fall)

- **Director of Research Science** 2018 - Sep 2022 · 4 yrs 9 mos
- **Director of Research Science** Jan 2018 - Aug 2022 · 4 yrs 8 mos
- Oculus VR 4 yrs 8 mos

Acquired by Facebook

- **Director, Research Science** Jan 2017 - Aug 2019 · 2 yrs 8 mos
 - Manager, Research Science 2015 - 2017 · 2 yrs United States



Lesson: #1: Write an excellent PhD thesis that people can learn from it

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	3.1 3.2 3.3 3.4 3.5 Cor 4.1 4.2	Geometry	61 62 68 70 78 81 82 84

Excellent literature review for V-SLAM

Well-written tutorial on Dense SLAM

3D Vision and Optimization 101

Primal dual for depth denoising

Lesson: #2: the joy of live demos that work

- Live demo: easier for people to run, reproduce and appreciate
- Real-time: easier for people to turn into actual products
- System-level optimization: a great testament to your coding skills



Richard Newcombe

VP, Research Science at Reality Labs Research Verified email at cs.washington.edu - <u>Homepage</u> Artificial Intelligence Augmented Reality Computer Vision SLAM Robotics 🛃 FOLLOW

41

TITLE	CITED BY	YEAR
KinectFusion: Real-Time Dense Surface Mapping and Tracking RA Newcombe, S Izadi, O Hilliges, D Molyneaux, D Kim, AJ Davison, Mixed and Augmented Reality (ISMAR), 2011 10th IEEE International Symposium	5301	2011
Deepsdf: Learning continuous signed distance functions for shape representation JJ Park, P Florence, J Straub, R Newcombe, S Lovegrove Proceedings of the IEEE/CVF conference on computer vision and pattern	3575	2019
Kinectfusion: real-time 3d reconstruction and interaction using a moving depth camera S Izadi, D Kim, O Hilliges, D Molyneaux, R Newcombe, P Kohli, J Shotton, Proceedings of the 24th annual ACM symposium on User interface software and	3051	2011
DTAM: Dense tracking and mapping in real-time RA Newcombe, SJ Lovegrove, AJ Davison 2011 international conference on computer vision, 2320-2327	2627	2011
Slam++: Simultaneous localisation and mapping at the level of objects RF Salas-Moreno, RA Newcombe, H Strasdat, PHJ Kelly, AJ Davison Proceedings of the IEEE conference on computer vision and pattern	1125	2013
Dynamicfusion: Reconstruction and tracking of non-rigid scenes in real-time RA Newcombe, D Fox, SM Seitz Proceedings of the IEEE conference on computer vision and pattern	1100	2015

KinectBot

KinectFusion Product Idea

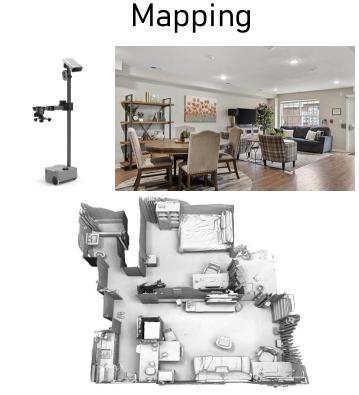
Albert Zhai

KinectBot: your helpful household robot

- A mobile robot with a Kinect camera and a simple arm
- Keeps track of objects around the home and performs general manipulation tasks
 - "KinectBot, bring me my keys!"
- 3D mapping powered by KinectFusion



KinectBot: how it works



- KinectBot will tour the house every few hours
- Each time, build a 3D map using KinectFusion

KinectBot: how it works



- KinectBot will tour the house every few hours
- Each time, build a 3D map using KinectFusion

Identifying Objects





- Use KinectFusion's dynamic object segmentation abilities to find objects that move
- Gradually build up a database of all objects and their last locations

KinectBot: how it works

Mapping



- KinectBot will tour the house every few hours
- Each time, build a 3D map using KinectFusion

Identifying Objects

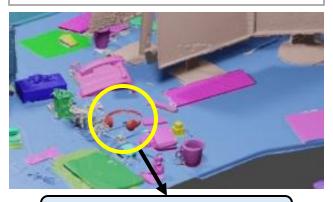




- Use KinectFusion's dynamic object segmentation abilities to find objects that move
- Gradually build up a database of all objects and their last locations

Task Execution

"Bring me my headphones"



Planning Models

- Use off-the-shelf models and object database to perform task
 - VLM for retrieval and text understanding
 - Grasping model
 - Motion planner

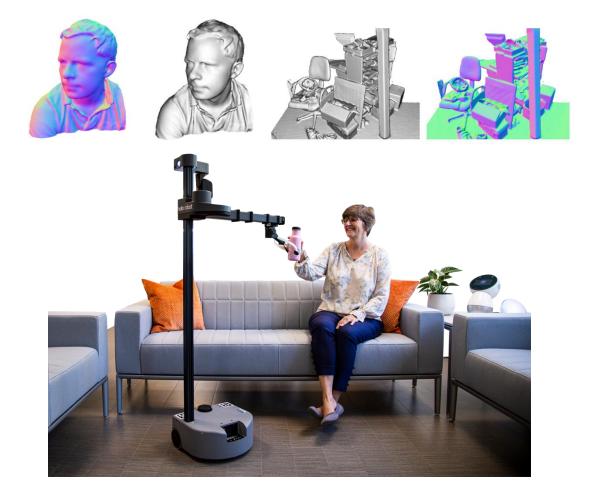
KinectBot: highlights and limitations

Highlights

- Real-time capability of KinectFusion allows for dynamic mapping and segmentation even when people are moving around
- Kinect system is relatively cheap

Limitations

- Relies on objects being moved to be detected
- Tours may take a while; does not update in between tours



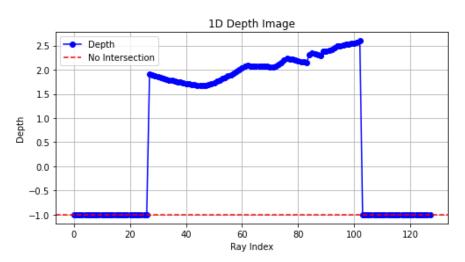
Hacker: 2D KinectFusion

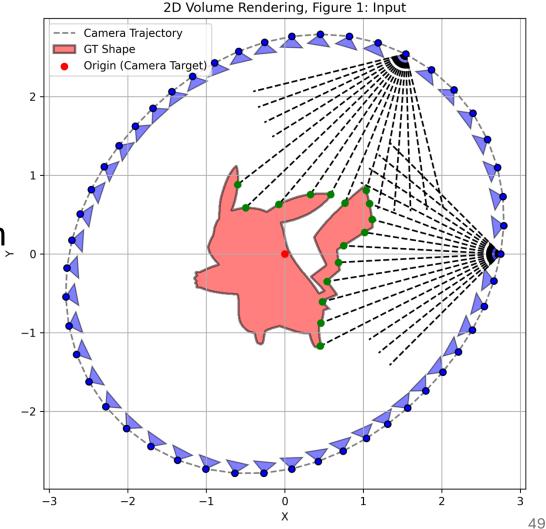
Shenlong Wang

Code will be available on our shared Github repo (Zhi-Hao will share later today) 48

Kinect Fusion in a 2D World

- Assuming we live in a 2D world, everyone perceives the 2D world through a 1D perspective imaging.
- One day, 2D computer scientists invented a '1.5D' camera, where each pixel captures the depth of the ray.



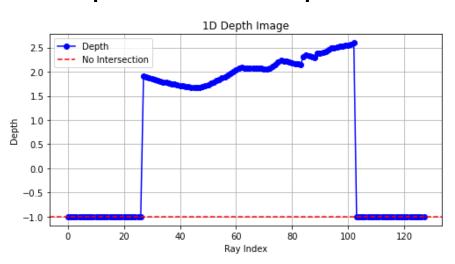


Kinect Fusion in a 2D World

- Assuming we live in a 2D world, everyone perceives the 2D world through a 1D perspective imaging.
 - Camera Trajectory GT Shape Origin (Camera Targe One day, They want to use this invention to reconstruct the invented shape of their giant idol – the holy rodent of electricity. pixel cap

-3

-2

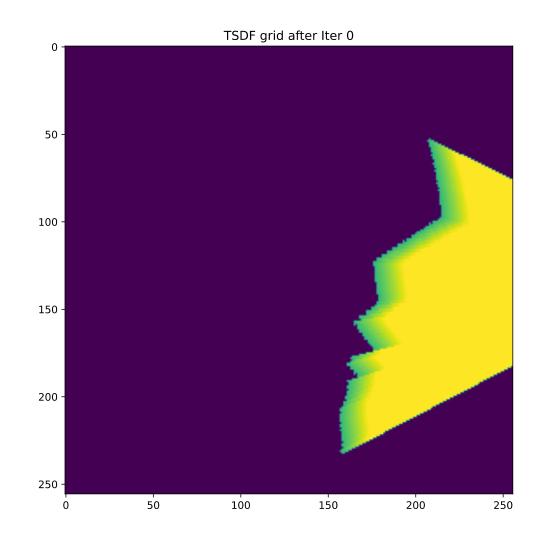


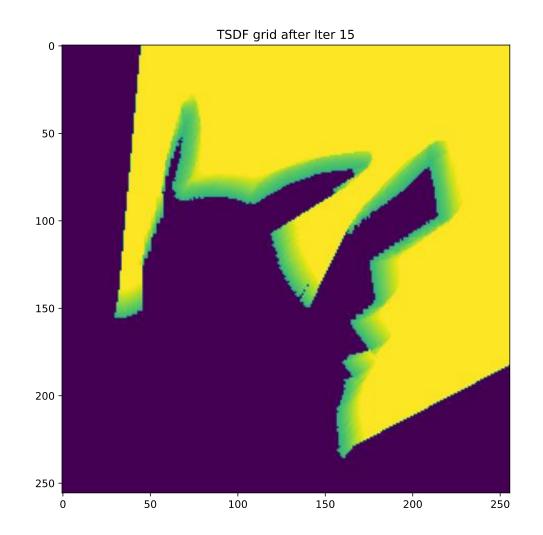


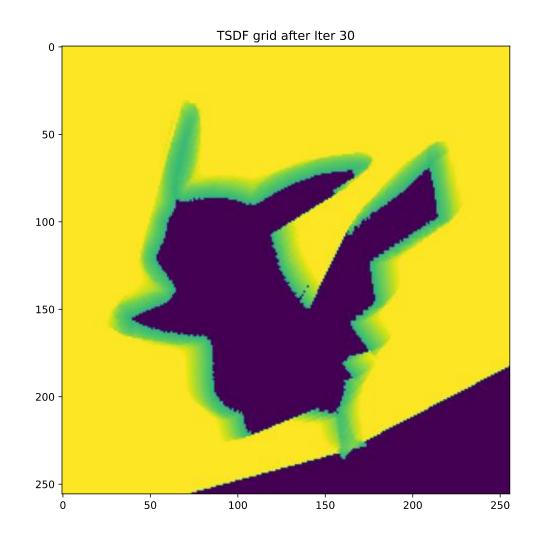
2

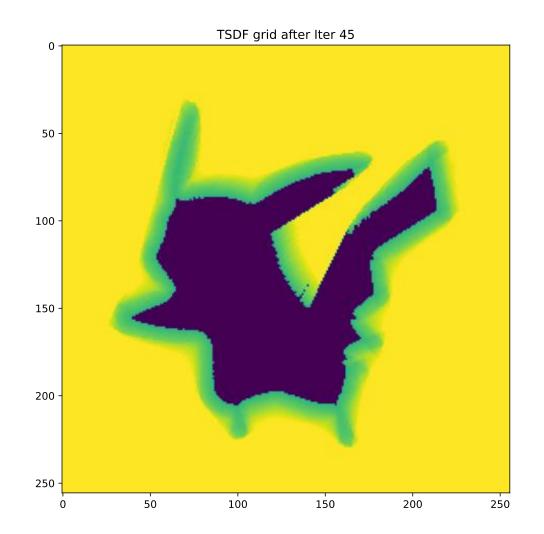
2D Volume Rendering, Figure 1: Input

 $^{-1}$

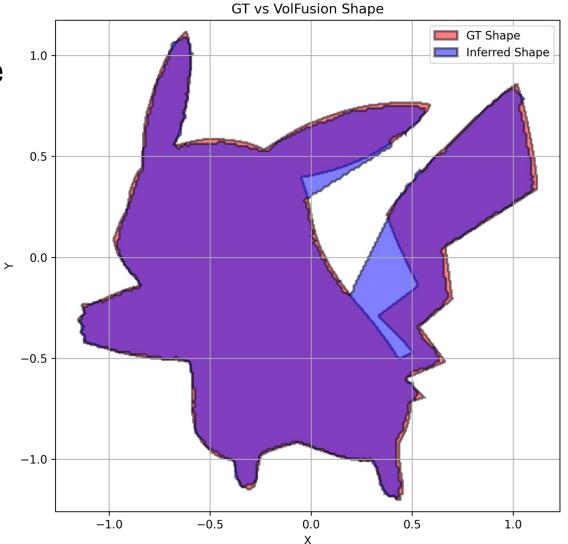








- Depth sensor has no noise but why it's not perfect?
- Any idea to improve that?



Where I could improve

I kept updating all free space & use a simple weight.

def update_tsdf(tsdf_grid, weight_map, sdf, visibility_mask, trunc_threshold=0.1)

Update the TSDF grid and the weight map based on the new SDF values.

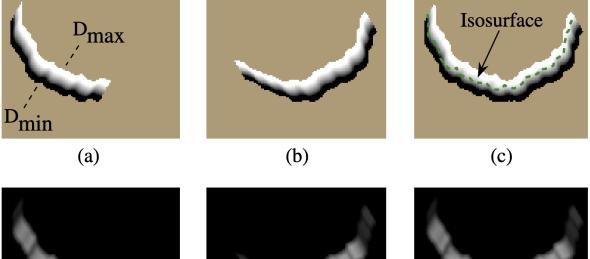
Parameters:

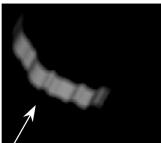
- tsdf_grid: The current TSDF grid.
- weight map: The current weight map.
- sdf: The signed distance function values for the visible points.
- visibility_mask: Mask of visible points in the grid.
- trunc threshold: The truncation threshold for the SDF.

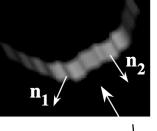
Returns:

- Updated TSDF grid and weight map. mask = visibility_mask & (sdf > -trunc_threshold)

tsdf grid[mask] += sdf[mask] weight map[mask] += 1return tsdf_grid, weight_map









Sensor

Sensor

Points with normal facing sensor should get higher weight, why?

Lessons learned

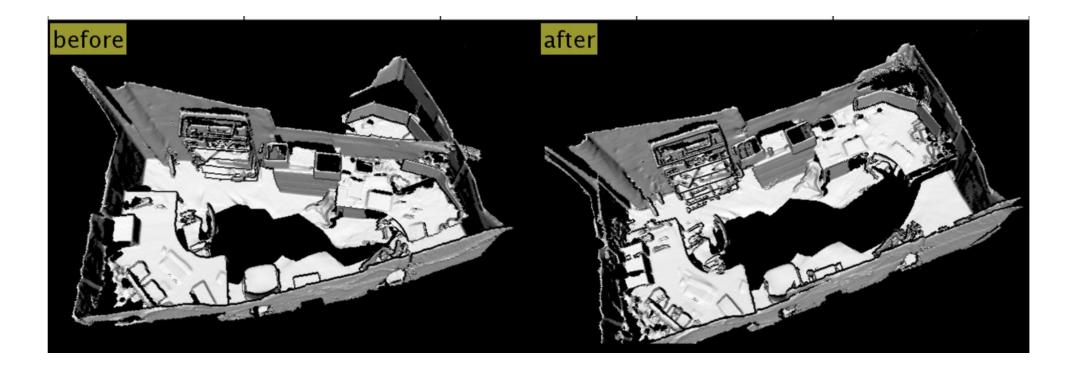
- Depth sensor has no noise but why it's not perfect?
- Any idea to improve that?

Critic

Zhi-Hao Lin as Reviewer #2

Camera drifts with incremental ICP!

- Only works well for small camera motion
- Camera drifts for large planar structure, resulting deformation
- Loop closure requires user manual input that's not cool!



Camera drifts with incremental ICP!

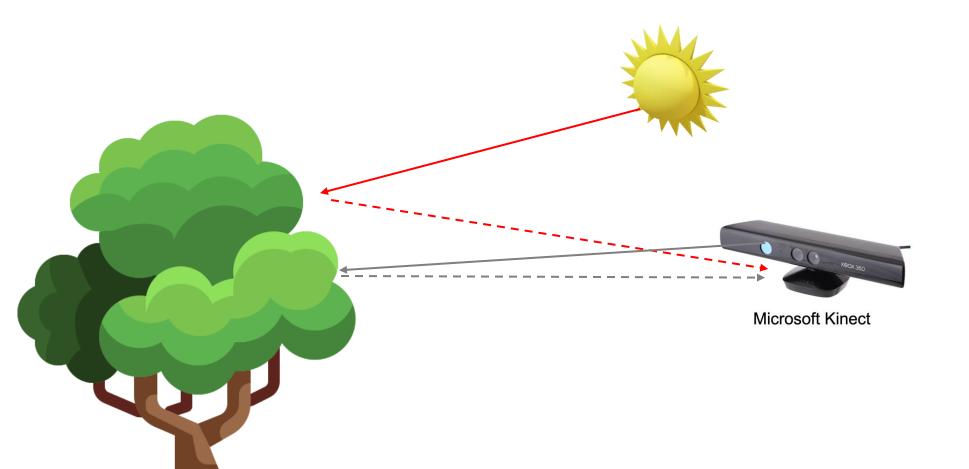
- Only works well for small camera motion
- Camera drifts for large planar structure, resulting deformation
- Loop closure requires user manual input that's not cool!
- Does RGB information help?





Only works for indoor!

• Structured light camera (Kinect) doesn't work well in outdoor scenes



We want lidar!

MICROSOFT / TECH

Microsoft kills Kinect again



Image: Microsoft

/ Microsoft will no longer make the Azure Kinect Developer Kit.

PRESS RELEASE March 18, 2020

Apple unveils new iPad Pro with breakthrough LiDAR Scanner and brings trackpad support to iPadOS

6 🗙 🛛 🔗

By Jay Peters, a news editor who writes about technology, video games, and virtual worlds. He's submitted several accepted emoji proposals to the Unicode Consortium.

Aug 21, 2023, 2:00 PM CDT



New Magic Keyboard Designed for iPad Pro Features a Floating Design, Backlit Keyboard and Trackpad, Delivering the Best Typing Experience Ever on iPad

We want lidar!

- Structured light camera (Kinect) doesn't work well in outdoor scenes
- Does the algorithm still work by replacing Kinect with LiDAR?

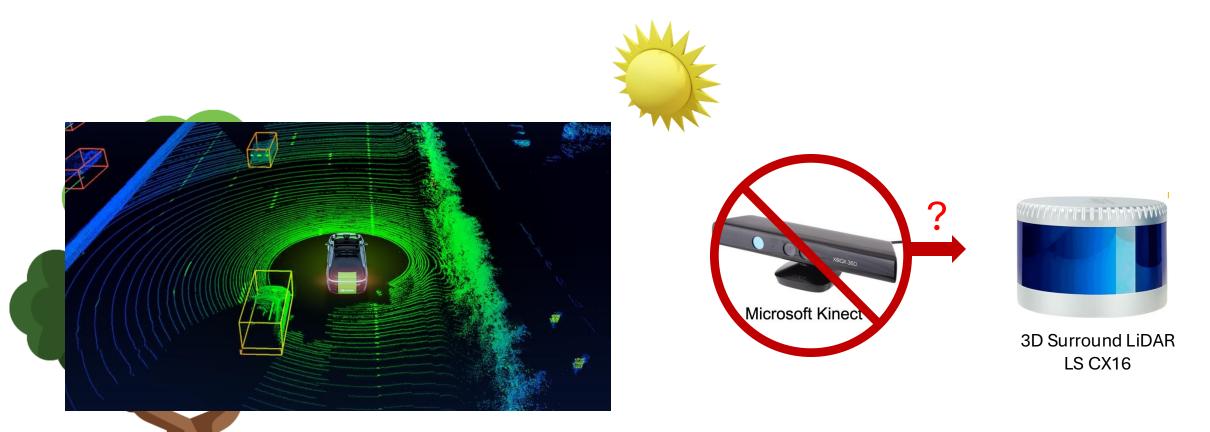
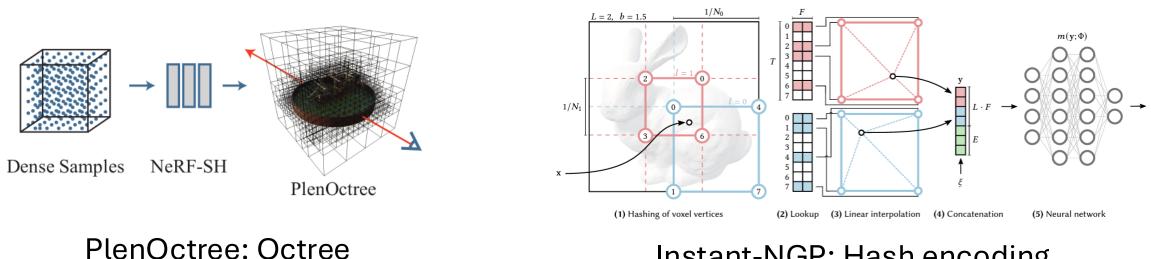


Image credits: https://blogs.nvidia.com/blog/lidar-sensor-nvidia-drive/

Out of memory error!!

- Dense voxel grid is memory-consuming and not scalable
- improve with hierarchical, sparse data structures

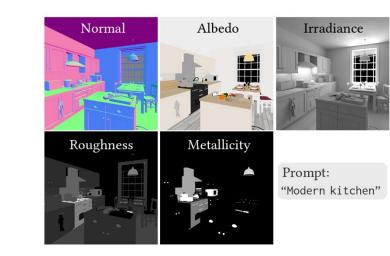


Instant-NGP: Hash encoding

We want more than a surface mesh!

- KinectFusion reconstructs geometry, but some information is missing:
- Transparency
- Material (e.g., roughness, metallic)
- Lighting
- Non-rigid object, motion





RGB↔X: Image decomposition and synthesis using material- and lighting-aware diffusion models

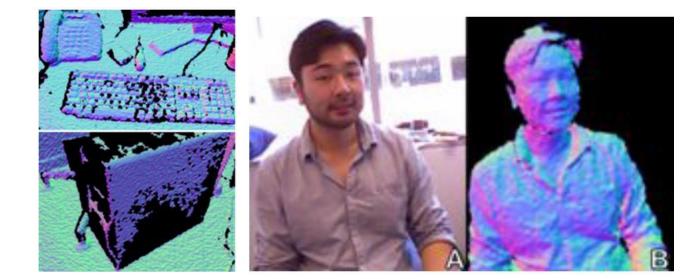
Graduate Student

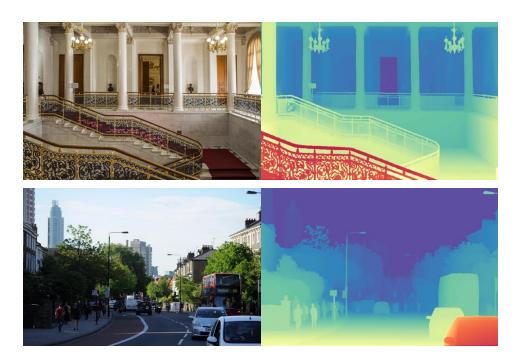
Albert Zhai

Idea 1: KinectFusion with Learned Depth Prior

Motivation

- Kinect has limited range and has holes in each frame
- Can we leverage learned depth to fill in the gaps and extend the range?



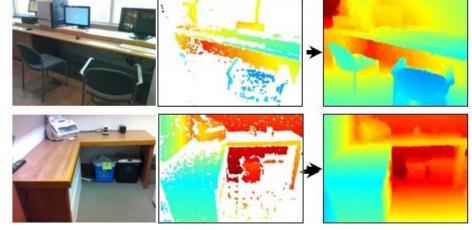


Idea 1: KinectFusion with Learned Depth Prior

Approach

- Kinect depth can be used to improve learned depth
 - Existing baselines
 - Fit a simple warping per-region from learned to Kinect
 - Fine-tune depth network in the test scene
- Can also consider uncertainty from the fused TSDF





Input: RGB-D from sensor

Complete Depth



Image credits: DeepCompletion, SuperPrimitives, RCVD

Idea 2: Active Mapping with KinectFusion

- Using KinectFusion, how should we move to build a complete map of a scene as fast as possible?
- Train an agent to do so via reinforcement learning (in sim)
- Design questions: input representation, action space, reward function

