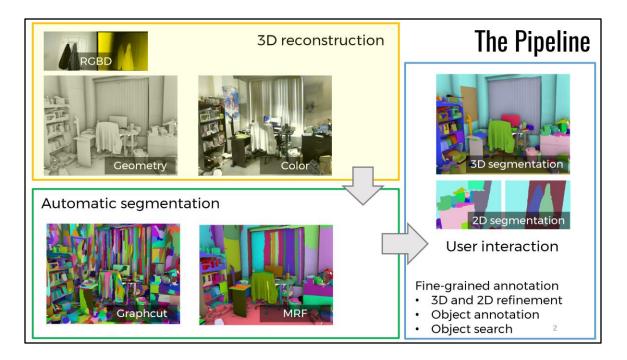


Hi everyone, thank you for coming this presentation!



So here we will start by exploring the state-of-the-art techniques in 3D reconstruction. Here, we focus on scanning devices for consumers at the cost of a few hundred dollars.

3D reconstruction is an important step in the entire pipeline because we know that, building a dataset is always costly, therefore, we would like to start with high-quality reconstruction.

Motivation

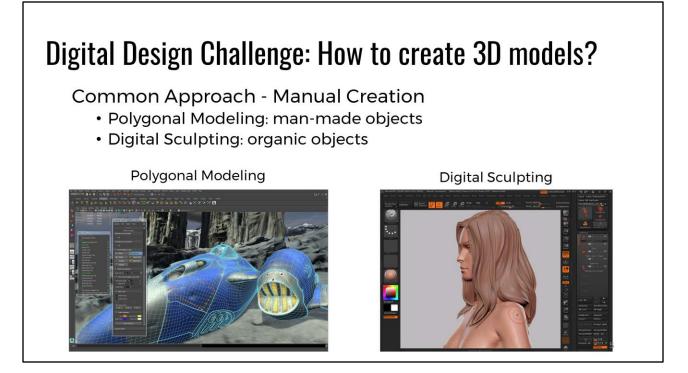
- Deep learning requires availability of massive 3D data.
- How to acquire 3D scenes efficiently?

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Before I go into details.

Let's first take a quick look of a brief pipeline of the Digital Design and Manufacturing process.

Usually, we have some design ideas, and then we make use of digital design tool, such as 3D modeling software to create the 3D objects. With the 3D objects then we can manufacture them.



The first problem is how to create the 3D objects? A common approach is by manual creation by modeling artist. For example, polygonal modeling for man-made objects, digital sculpting for organic objects.

Manual Creation - Limitations

- Need modeling expertise
- Labor intensive & tedious
- Huge money & time investment
- Non-scalable

Experienced Artist: 7 days

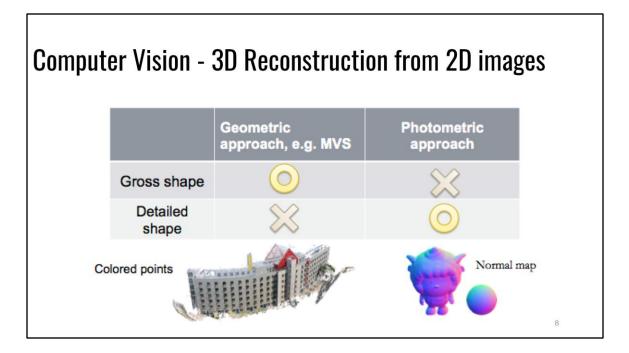


But there are lot of limitations in doing this. First, you need to have the expertise. However, even if you are an expert, it will still take you time for the modeling task. For example, it takes 7 days for an experienced artist to model this complex character. Which means it cost money and time.

Manual Creation - Limitations Modeling time for an entire city?

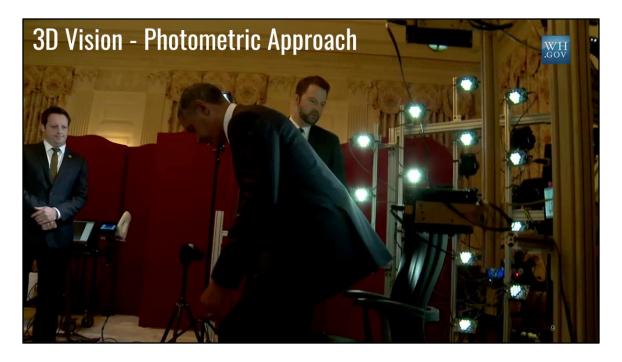


Further more, it is not really scalable, what if I ask you to model the whole city?



So an alternative is to explore photogrammetry. From recorded photographs, we try to obtain the 3D information of the scene such as surface coordinates, surface orientation, size, etc.

In computer vision, this is often referred to as 3D reconstruction, and overall we can categorize common techniques into two categories:

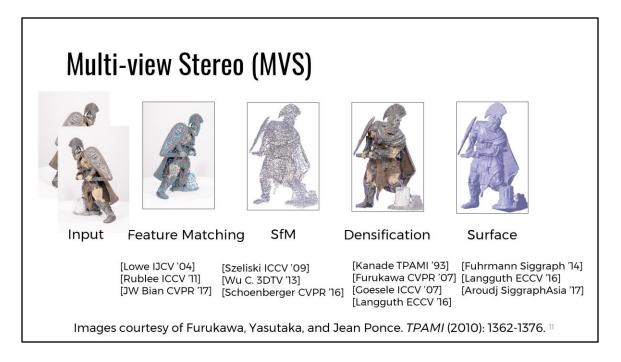


The key idea is to illuminate the target from different lighting directions. Notice the change of lighting on the President's face from 0:15.



Large-scale Multi-view Stereo, Seitz et al., University of Washington, 2013

Another approach is multi-view stereo, which requires taking photos from different angles. This is the preferred method for outdoor scene reconstruction, since it can cover a large area and produce a rough geometry of the scene compared to the photometric approach. So we will focus more on this approach in later section.



A typical multi-view stereo reconstruction pipeline. Different applications may use different implementations of each of the main blocks, but the overall approach is:

- Collect images
- Find sparse correspondences between image pairs (feature matching)
- Compute camera parameters for each image (SfM)
- Reconstruct the 3D geometry of the scene from the set of images and corresponding camera parameters (Densification + Surface)
- Optionally reconstruct the materials of the scene.

In the recent years, more research has been put to improve each stage in this pipeline.

I also want to highlight that the Structure-from-Motion problem is very similar to the visual SLAM problem in robotics. However, visual SLAM is often performed in realtime with a camera, while the Structure-from-Motion problem is more general, which requires no fixed camera information and focusing more on quality of reconstruction.

Outdoor Reconstruction

National Heritage Board

- Reconstructing tangible heritages
- Develop surface from point clouds algorithms
- VR viewer app



Outdoor Reconstruction

Drones to collect images

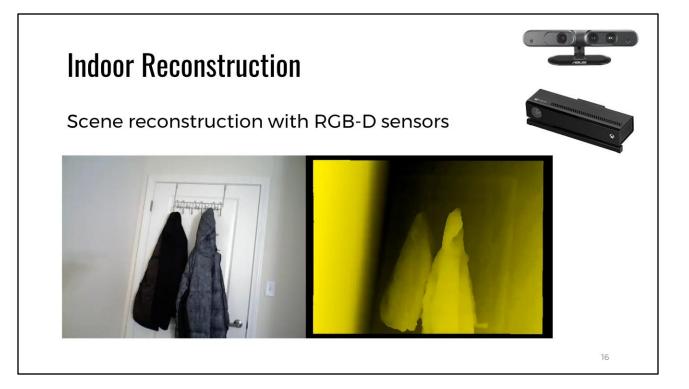




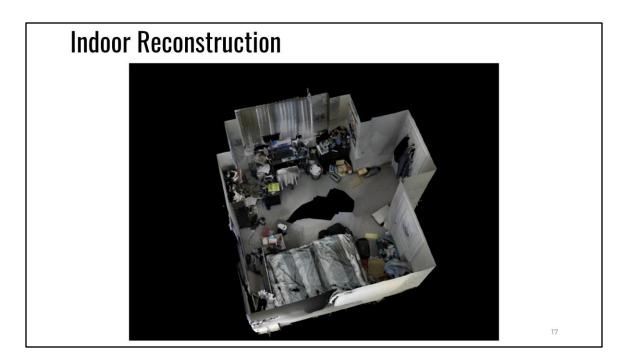
Here is one of the reconstruction where data is captured by ourselves. In this example, we use only a DSLR camera and capture eye-level images by letting the operator walk about the building.



Here is a reconstruction with data captured by a drone.

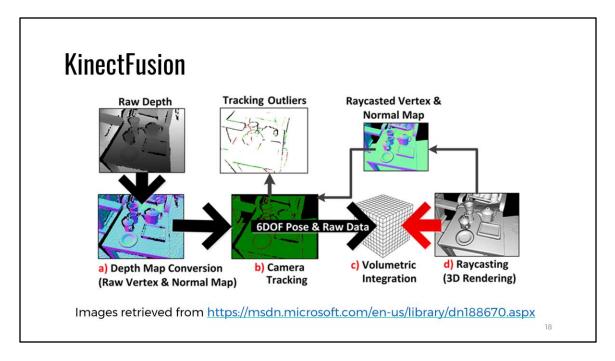


Our input is a color and depth video of a scene captured by a consumer-grade RGBD camera. To record a video, we connect the camera to a laptop and move the camera slowly in the scene. This example shows a color and depth video captured by an Asus Xtion depth camera.



We then reconstruct the scene from the input video. We represent the scene as a triangular mesh.

The texture of the mesh is computed by taking the median value of all color pixels that correspond to each vertex.



After the release of MS Kinect

There have been many prior works about RGBD reconstruction. One of the most well-known work is probably KinectFusion. It takes as input a sequence of depth images (recorded from a depth sensor such as Kinect, Asus Xtion, or Structure Sensor, etc.) and perform real-time camera tracking and depth frame alignment to produce very high-quality meshes.

To facilitate both tracking and alignment, they use a volume to represent the world.

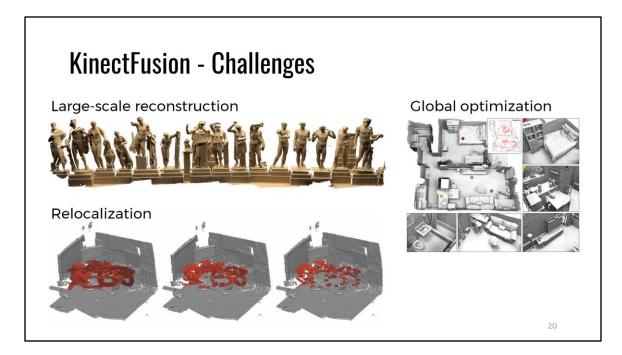
Each time a new depth frame arrives, we assume that its camera pose varies very little compared to the current pose, so we can perform an ICP to align this depth frame to the current volume (see step b).

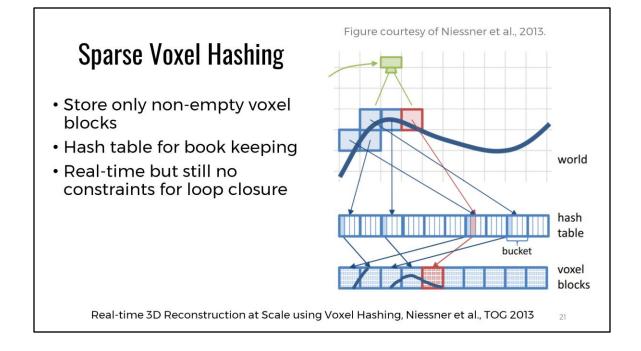
After alignment, the depth frame is accumulated into the volume (step c), refining the current mesh (imagine that each depth frame is noisy, and when more depth frames are accumulated, the surface gets nicer and nicer).

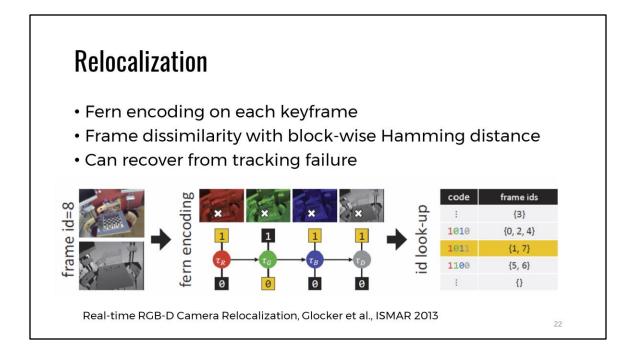
Finally, we can render the volume to screen (step d).

KinectFusion is a powerful tool to capture indoor scenes and it outputs very high surface quality with just a consumer depth sensor.

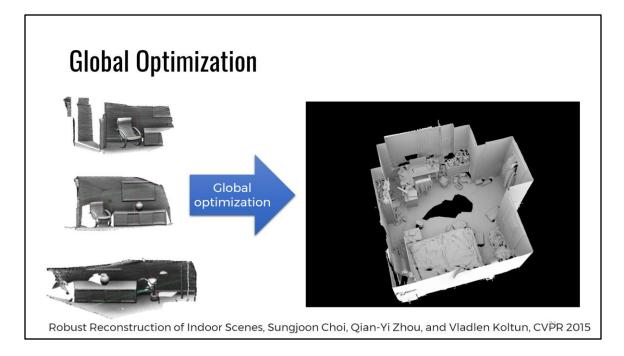
One notable drawback of KinectFusion is that the camera tracking is very simple, and thus might fail for situations like a part of the scene is not well aligned when revisited (loop closure), or it lacks a global agreement when aligning all depth frames. Several works attempt to address this issue.





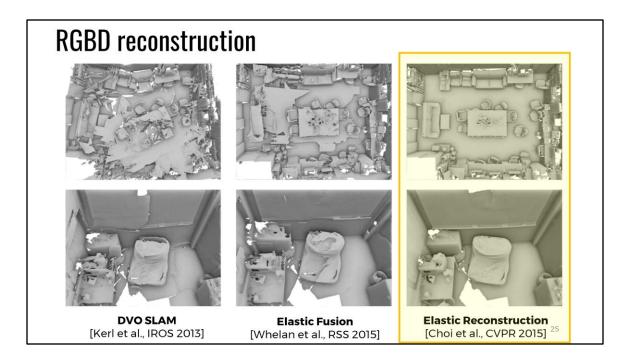


Relocalization	
Our method is based on compact encoding with randomized ferns	Real-time RGB-D Camera Relocalization, Clocker et al., ISMAR 2013



We leverage the technique proposed by Choi et al. in CVPR 2015 for global registration.

We run 3D reconstruction to align small geometry fragments (sub-scene) from KinectFusion. This global registration produces complete scene meshes.



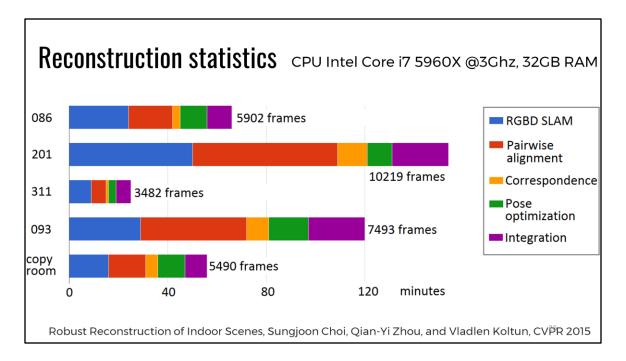
There have been many prior works about RGBD reconstruction. We focus on those that have implementation publicly available.

We tested DVO SLAM by Kerl et al, Elastic Fusion by Whelan et al, and Elastic Reconstruction by Choi et al with our scenes.

While these methods work comparably for simple scenes, for complex scenes DVO SLAM and Elastic Fusion performs poorly.

The pairwise alignment and global optimization in Elastic Reconstruction makes it robust to a wider range of scenes, and therefore, it is our method of choice for reconstruction.

The disadvantage of this approach is that non-rigid registration tends to take much longer time, and the implementation is not stable enough for use. To reconstruct our dataset, we use rigid registration in Elastic Reconstruction code. This provides highquality geometry alignment.



The performance of the reconstruction is shown in this plot.

Our scenes are reconstructed on a PC with an Intel Core i7 5960X with 16 cores at 3 GHz, and 32 GB of RAM.

Each scene takes more than an hour to finish on average, usually longer. We launch a few reconstructions at the same time to leverage parallelization.

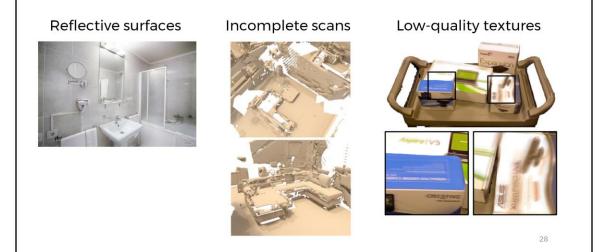
While this approach is not the fastest, the high-quality geometry output is what we require to obtain high-quality segmentation.

Real-time Reconstruction with BundleFusion

- Sparse-to-dense matching
- Local-to-global optimization
- On-the-fly model update

BundleFusion: Real-time Globally Consistent 3D Reconstruction using On-the-fly Surface Reintegration, Dai et al TOG 2017 The following sequences show **real-time** 3D reconstructions captured live using a commodity RGB-D camera

3D Reconstruction - Limitations



	Point Cloud	Triangle Mesh	Volume	Images
Storage	Efficient	Efficient	Sparse representation	Efficient
Learning	On-going research	Few previous works	Octree, KD-tree	Multiple 2D views
Rendering	Splatting	Rasterization, ray tracing	Ray marching	View interpolation

A very important design choice is scene representation. Unlike images that can be easily represented as a uniform grid, 3D scene has multiple options for representation. We provide a simple table of comparisons based on three requirements: storage, learning, and rendering.

Our color notation: good (green), applicable (yellow), more efforts required (red).

Volume needs more storage space in general since they capture the free space. This storage issue causes some limitations in learning, e.g., it is difficult to perform learning with high-resolution volumes. Sparse representation could solve the storage problem, but learning with neural network becomes no longer straightforward.

Among the representations, in the last and this year we have seen a few works about point cloud learning, which has shown some promises for robot applications as it balances between storage and learning and rendering. Another advantage is that point cloud data can be easily obtained from multiple sources such as RGB-D sensor, LiDAR, or multiple view geometry.

Another popular representation in computer graphics is triangle or quad mesh.

Unfortunately, for learning this kind of representation is more challenging. There has been some previous works about object classification or segmentation with meshes, however, there has been few works that can perform learning with general 3D scene mesh representation. This could be a great research avenue in the near future.

Finally, rendering/visualization is not a big problem, but for high-quality rendering, triangle mesh has the most advantages as it can utilize existing rendering engines built for games or film production. Other representation, one might have to resort to custom built renderers.