Computer Vision: Part 2 (3D CV)

Dr. Nathanael L. Baisa

Lecture Content

- Introduction
- Camera Calibration
- 3D Reconstruction
- Point Clouds
- Point Clouds Data Acquisition
- Point Clouds for Robotics
- Conclusion
- References

Session Outcomes

- Gain a brief introduction to 3D computer vision.
- Acquire basic knowledge of camera calibration and 3D reconstruction.
- Understand what point cloud is and how it can be acquired.
- Get understanding of point clouds applications in robotics.

Introduction

- We see 2D images but perceive the world in 3D.

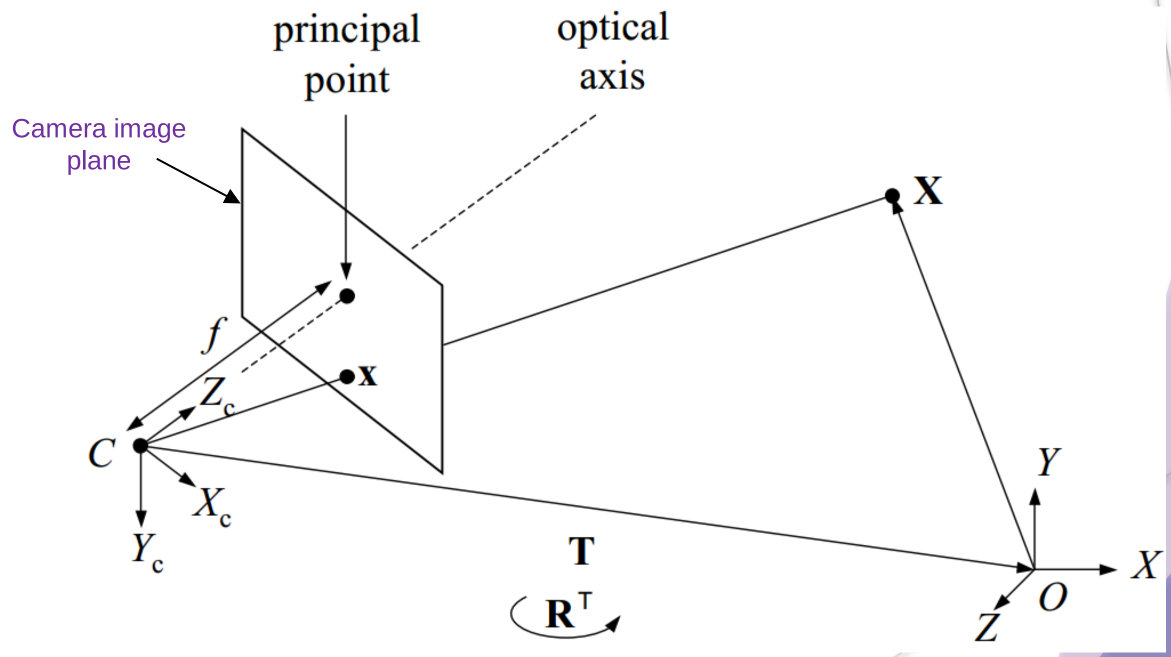
- 3D reconstruction capability is required in:
  - Intelligent robots.
  - Autonomous vehicles (self-driving cars).
  - Augmented and virtual reality.

Camera Calibration

- Camera calibration is the process of estimating the camera parameters:
  - **Intrinsic parameters:** The effective focal length, principal point (optical center) of the image plane, skew and lens distortion i.e. optics and internal geometry of the camera.
  - **Extrinsic parameters:** Camera pose (rotation and translation) with respect to the world coordinate system.

Camera Calibration

- $[u\ v\ 1]^T \sim \mathbf{P}[X\ Y\ Z\ 1]^T$
- $\mathbf{P} \sim \mathbf{K}[\mathbf{R}\ \mathbf{T}]_{3x4}$
  - **K** – Intrinsic matrix.
  - [**R T**] – Extrinsic matrix.
  - **P** – Projection Camera matrix.



- C – Camera coordinate system.
- O – World coordinate system.

- *f* is focal length.
- Pinhole projection of a 3D point **X** onto a camera image plane.

Camera Calibration

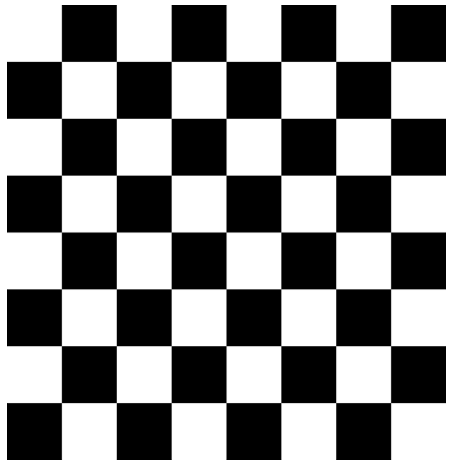
- **K** is an upper triangular intrinsic camera calibration matrix of the form:

$$\mathbf{K} = \begin{bmatrix} \alpha_u & s & u_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

- where α_u and α_v are scale factors, s is skew, and $\mathbf{u}_0 = [u_0\ v_0]^T$ is the principal point. Usually, pixels are assumed to be square in which case $\alpha_u = \alpha_v = \alpha$ and $s = 0$. Hence, α can be considered to be the focal length of the lens expressed in units of the pixel dimension.
- The principal point is where the optical axis intersects that camera's image plane.

Camera Calibration

- 3D world points (at least 6) and their corresponding 2D image points are needed e.g. using multiple images of a calibration pattern such as checkerboard.



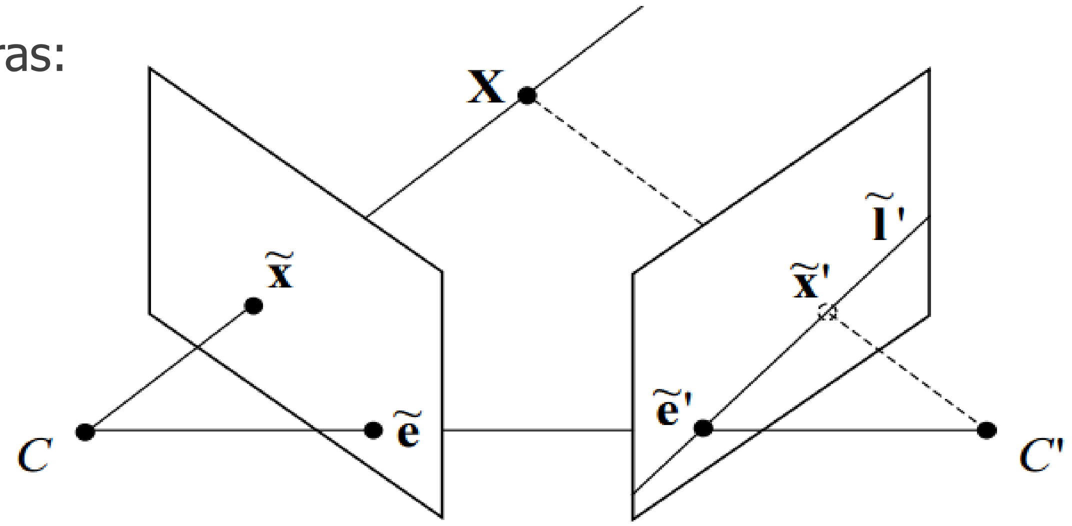
- Once the projection matrix $\mathbf{P}_{3x4}$ has been estimated, the first 3×3 sub-matrix can be decomposed (by QR decomposition i.e. $\mathbf{P}_s = \mathbf{KR}$) into an upper triangular intrinsic camera calibration matrix **K** and an orthonormal rotation matrix **R**.

3D Reconstruction

- Camera systems calibration.
- Feature extraction.
- Feature points correspondence through matching.
- Reconstruction algorithms:
  - 2 views – Stereo vision.
  - N views – Sequential or batch methods.

Two-image 2D-to-3D Reconstruction Method: Stereo Vision

- Epipolar geometry for two cameras:
  - Baseline – $\mathbf{CC'}$
  - Epipoles - $\tilde{\mathbf{e}}$ and $\tilde{\mathbf{e}}'$
  - Epipolar plane - $\mathbf{CXC'}$
  - **C** and **C′** are camera centers.



- Two cameras taking the image of the same scene.
- Epipole is the point of intersection of line through camera centers and the image planes.
- Given the projection $\tilde{\mathbf{x}}$ of a 3D point **X** in one image, its projection $\tilde{\mathbf{x}}'$ in a second image is restricted to the corresponding epipolar line $\tilde{\mathbf{l}}'$.

Two-image 2D-to-3D Reconstruction Method: Stereo Vision

- **Epipolar constraint:** Essential matrix ($\mathbf{E}_{3x3}$) relates corresponding image points (at least 8) in two views:

$$\tilde{\mathbf{x}}^{\mathrm{T}}\mathbf{E}\tilde{\boldsymbol{x}}' = \mathbf{0}, \qquad \mathbf{E} \sim [\boldsymbol{T}]_{\mathbf{x}}\boldsymbol{R}$$

- $[\boldsymbol{T}]_{\mathbf{x}}$ is the cross-product matrix, where:

$$\text{For } \mathbf{T} = [\,t_x \quad t_y \quad t_z\,]^\top,\ [\mathbf{T}]_\times = \begin{bmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{bmatrix}.$$

- This epipolar constraint can be expressed using pixel positions:

$$\tilde{\mathbf{x}} \sim \mathbf{K}^{-1}\tilde{\mathbf{u}} \;\; => \tilde{\mathbf{u}}^{\mathrm{T}}\mathbf{F}\tilde{\mathbf{u}}' = 0,$$

Two-image 2D-to-3D Reconstruction Method: Stereo Vision

- $\mathbf{F}_{3x3} \sim \mathbf{K}^{-1\mathrm{T}}\mathbf{E}\mathbf{K}'^{-1}$ is the fundamental matrix.
- Fundamental Matrix **F** maps a point in one image to a line (epiline) in the other image. This is calculated from matching points from both images.
- NOTE:
  - The fundamental matrix **F** is just like the essential matrix **E**, except that **F** operates in image pixel coordinates whereas **E** operates in physical coordinates.
  - Calibrated cameras → Essential matrix.
  - Un-calibrated cameras → Fundamental matrix.

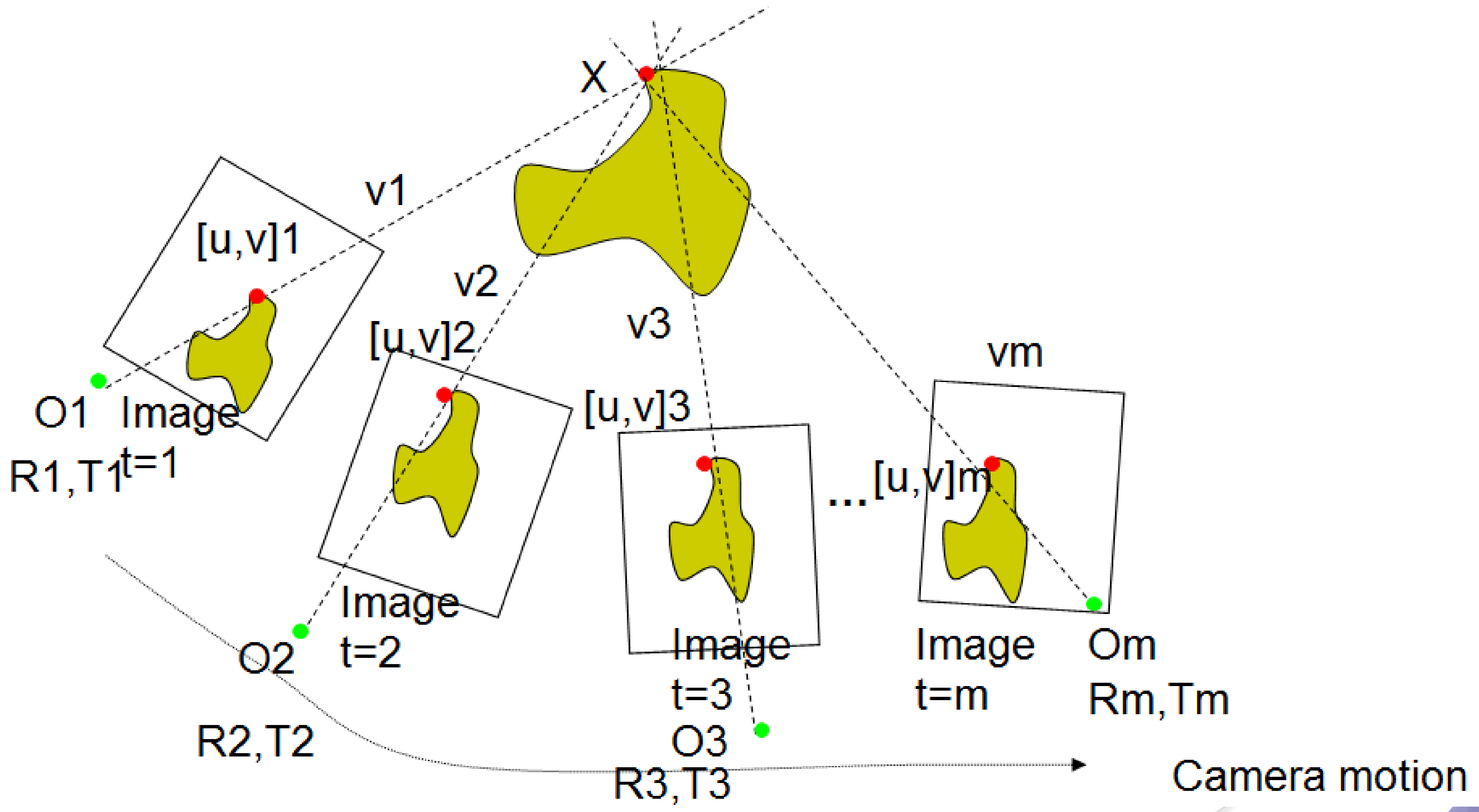
Two-image 2D-to-3D Reconstruction Method: Stereo Vision

- If the matrices $\mathbf{K}$ and $\mathbf{K'}$ are known, the recovered $\mathbf{F}$ can be transformed into $\mathbf{E}$ as

$$\mathbf{E} \sim \mathbf{K'}^{\mathrm{T}}\mathbf{F}\mathbf{K}$$

- The essential matrix $\mathbf{E}$ can be decomposed into $\mathbf{R}$ and $\mathbf{T}$ using singular value decomposition (SVD).
- The projection matrices ($\mathbf{P}$ and $\mathbf{P'}$) can be obtained from the recovered $\mathbf{R}$ and $\mathbf{T}$ and the known $\mathbf{K}$ and $\mathbf{K'}$.
- Given projection matrices, 3D points can be computed from their measured image positions in two or more views $\rightarrow$ Triangulation.

N-image 2D-to-3D Reconstruction Method



N-image 2D-to-3D Reconstruction Method: Sequential Method

- Order of images are used like in a move.
- Incorporating successive views one at a time.
- One possibility is to exploit the two-view epipolar geometry that relates each view to its predecessor.
- E.g. Known intrinsic parameters, essential matrices are estimated linearly using 8 or more points correspondences (e.g. using eight-point algorithm) and decomposed to give relative camera orientation and the direction of camera translation. And then 3D points are estimated.

N-image 2D-to-3D Reconstruction Method: Sequential Method

- From image features ($\mathbf{u}_{ij}$, $\mathbf{v}_{ij}$), structure from motion (SFM) gives an initial estimate of projection matrices $\mathbf{P}_i$ and 3D points $\mathbf{X}_j$.

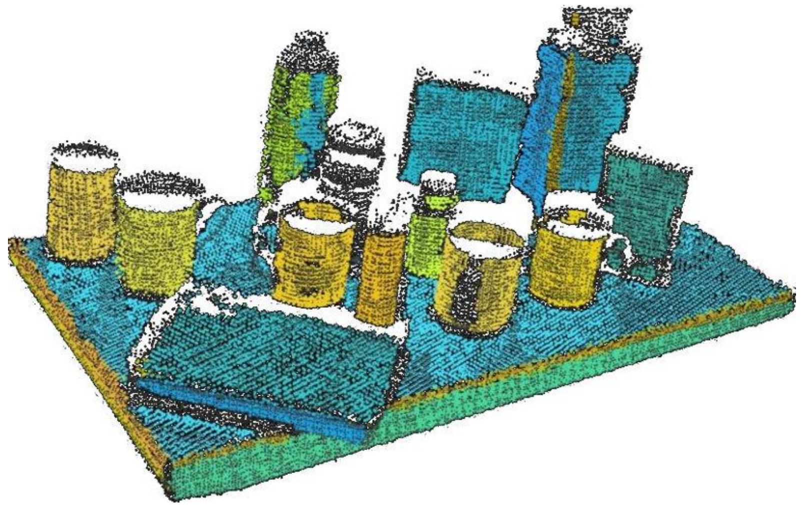
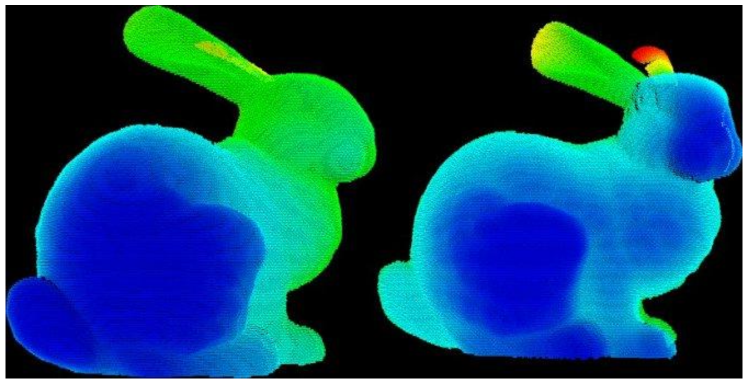
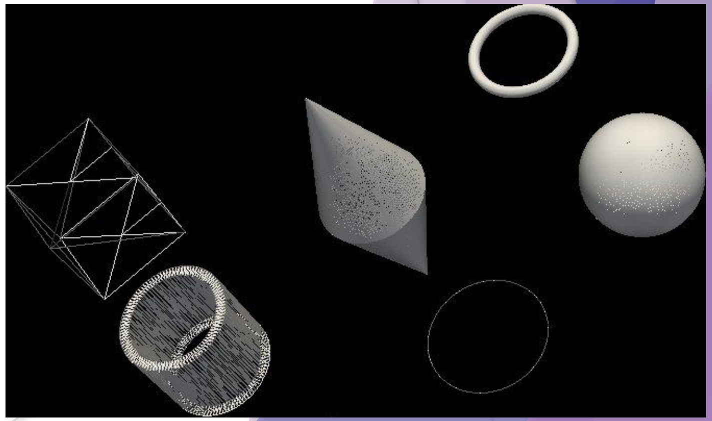
- Usually it will be necessary to refine this estimate using iterative non-linear optimisation to minimize an appropriate cost function (a weighted sum of squared re-projection errors) $\rightarrow$ bundle adjustment.

N-image 2D-to-3D Reconstruction Method: Batch Method

- Order of images can be random.
- Bundle adjustment approach:
  - Guess iteratively the solution for 3D to explain the measurements of feature points in all images.
  - A typical non-linear optimization problem.
  - Gauss-Newton for non-linear optimization method can be used.

Point Clouds

- A point cloud is a discrete set of data points in space. The points may represent a 3D shape or object. Each point position has its set of Cartesian coordinates (X, Y, Z).
- XYZ, NxNyNz (normals) and RGB data could be available.

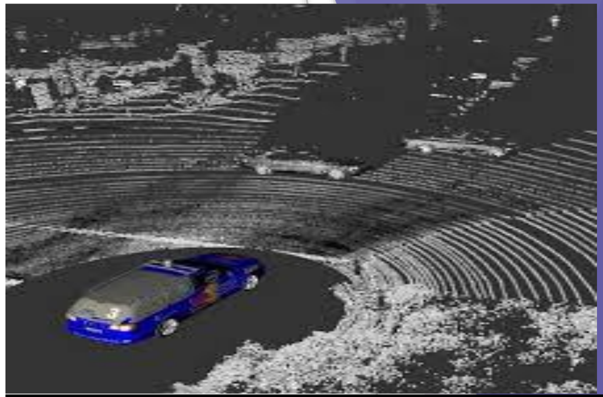




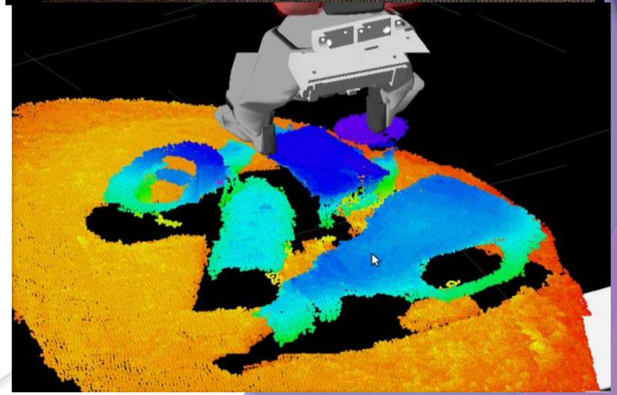
Point Clouds Data Acquisition

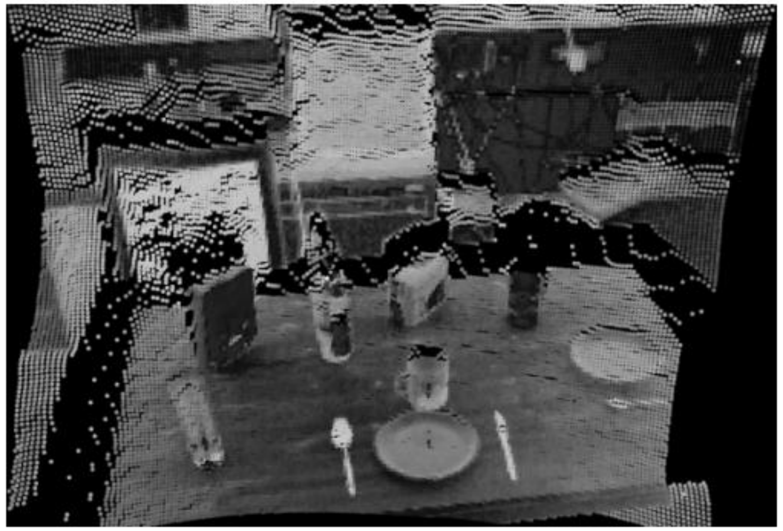
- Laser scans (high quality).
- Stereo cameras (passive & fast but dependent on texture).
- Time of flight cameras (fast but not as accurate/robust).
- Kinect-style Sensors such as Kinect, RealSense, etc.
- Computer generated.

Point Clouds in Robotics

- Navigation / Obstacle avoidance.
- Object recognition, and registration for pose estimation using iterative closest point (ICP).
- Grasping and manipulation, etc.

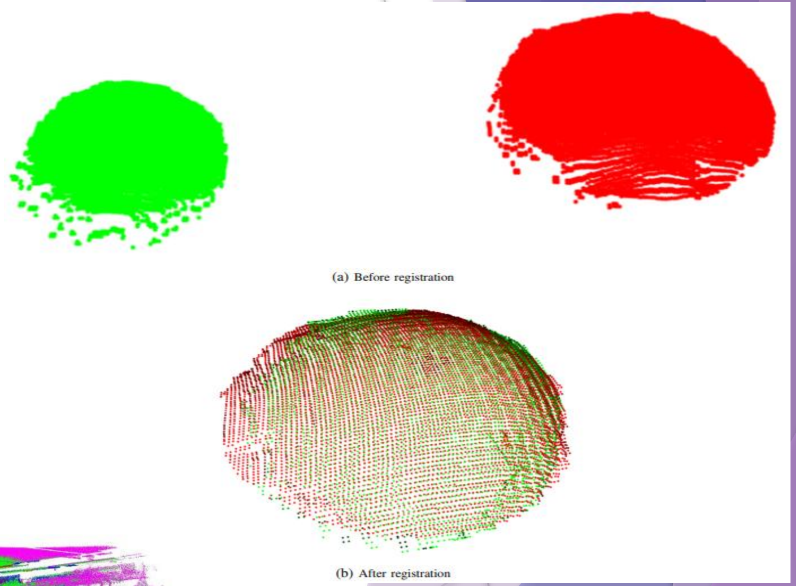


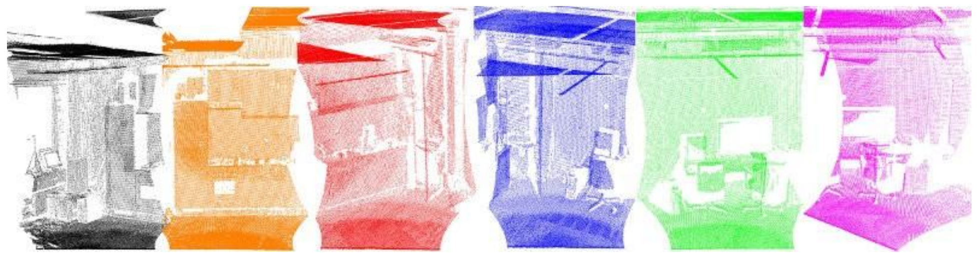


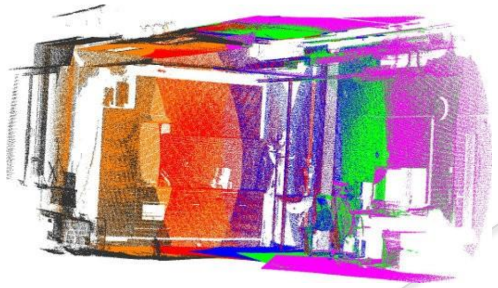


Point Clouds in Robotics

- Process **point clouds** by visiting http://www.open3d.org/ such as
  - Finding number of points in a given point cloud raw data.
  - Visualization of point cloud data.
  - Downsampling point cloud data as well as removing outliers.
  - Extracting features from a given point cloud data, for instance, using Fast Point Feature Histograms (FPFH).
  - Registering two point clouds data using Iterative Closest Point (ICP).




Point clouds


Registered point cloud

Conclusion

- Though 3D scene can be reconstructed from 2D camera images, it is also possible to obtain 3D point clouds directly using:
  - RGB-D sensors - combine RGB colour information with per-pixel depth information.
    - Kinect (structure light method – uses dots rather than strips).
  - Lidar (time of flight laser method).
  - Stereo camera using triangulation and bundle adjustment.
  - Monocular depth estimation using deep learning.
  - 3D reconstruction from monocular images using deep learning.
  - etc.

- 3D computer vision is very crucial for intelligent robotics applications.

References

- R. Szeliski, 'Computer Vision: Algorithms and Applications', Springer, 2021. [https://szeliski.org/Book/]
- R. Hartley and A. Zisserman, '*Multiple view geometry in computer vision'* Cambridge university press, 2003.
- https://mi.eng.cam.ac.uk/~cipolla/publications/contributionToEditedBook/2008-SFM-chapters.pdf
- https://docs.opencv.org/3.4/da/de9/tutorial_py_epipolar_geometry.html
- https://www.cse.psu.edu/~rtc12/CSE486/lecture15.pdf
- OpenCV: https://opencv.org/
- Open3D: http://www.open3d.org/
- https://huggingface.co/learn/computer-vision-course/en/unit0/welcome/welcome
- https://github.com/polygon-software/python-visual-odometry
- https://github.com/luigifreda/pyslam
- https://github.com/alyssaq/3Dreconstruction