RBE/CS 549 course project

WPI

# Iterative Closest Point Algorithm for Point Cloud Registration

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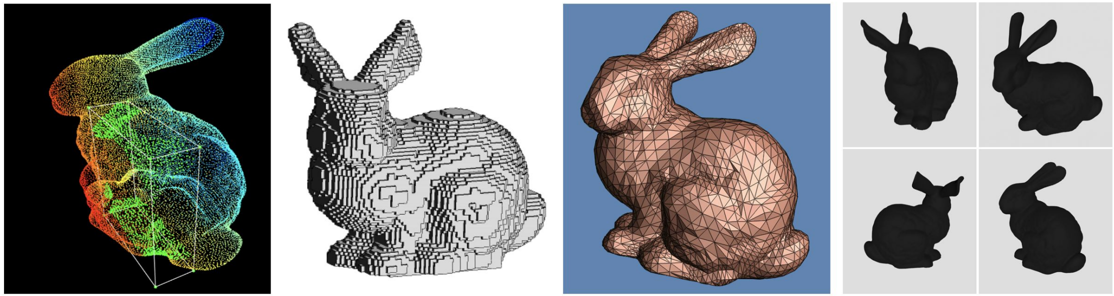
# Introduction

- 3D data representation
- Point clouds, Voxel clouds, meshes, etc.

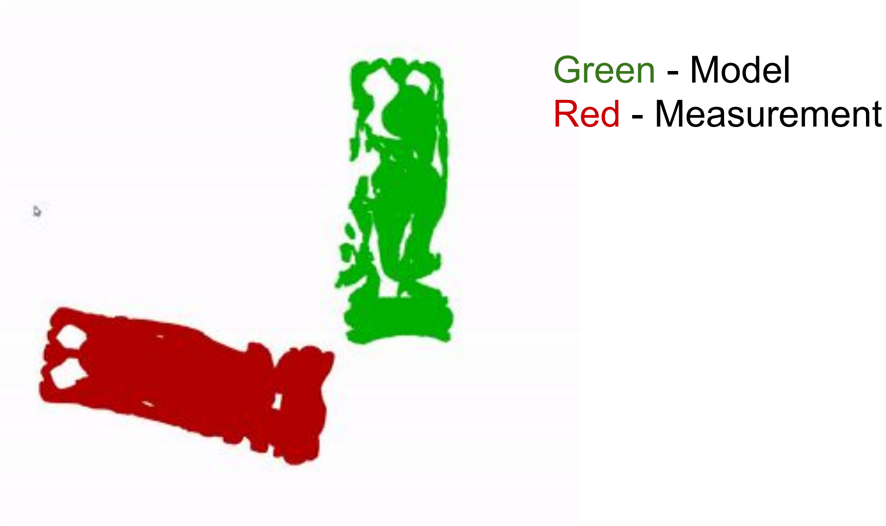


(a) (b) (c) (d)

Fig.1 *(a) point cloud (source: Caltech), (b) voxel grid (source: IIT Kharagpur), (c) triangle mesh (source: UW), (d) multi-view representation (source: Stanford)*

# What is registration of a point cloud ?

- The problem of consistently aligning a given 3D point cloud with a reference model




*Registration of model(green) with the data(red)*

# Problem statement

End  Goal : Register 2 Point Clouds using ICP

Successful registration involves:

1. Accurate Correspondence
2. Accurate Rotation and Translation

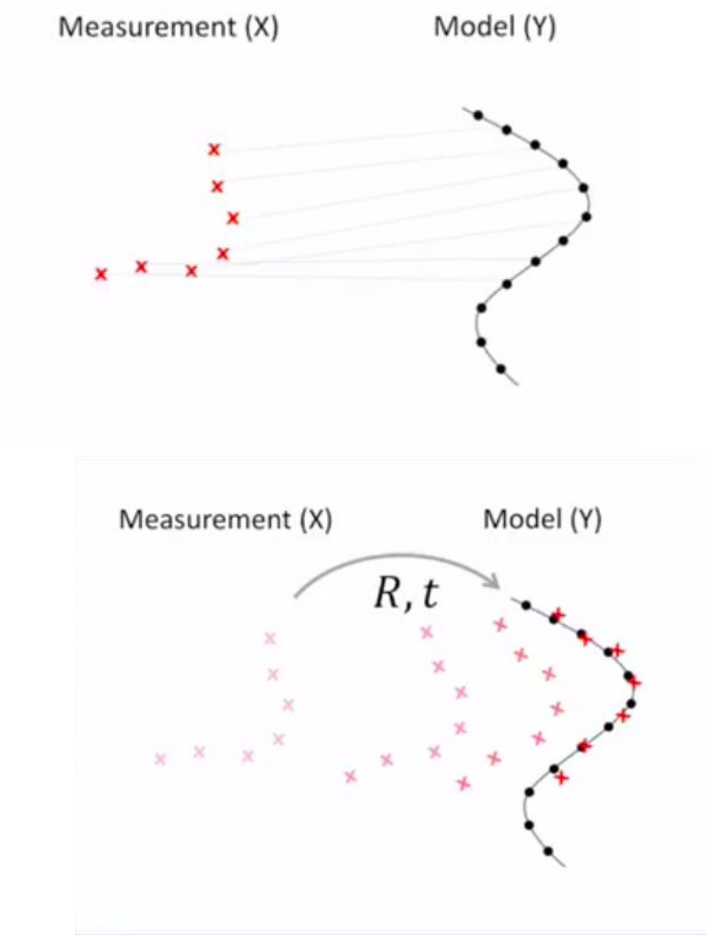
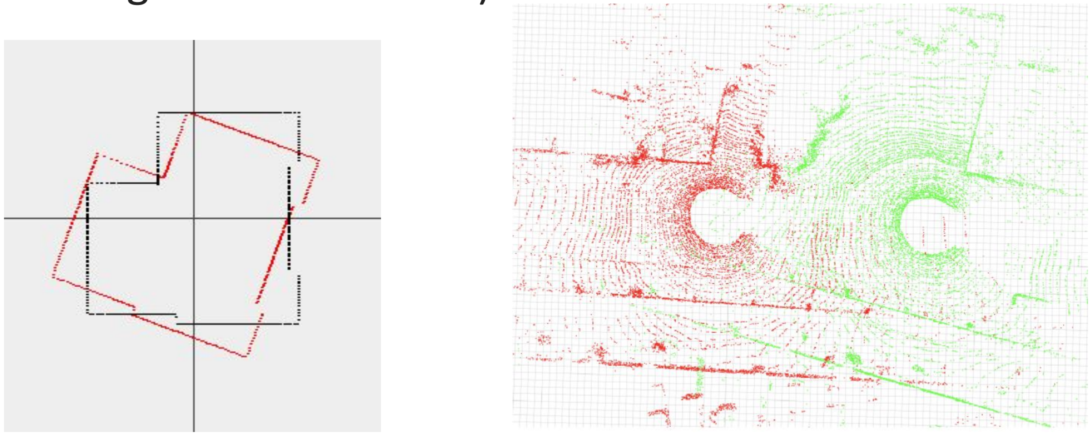



Fig.2 *Steps for Registration (source: UPenn)*

# What is ICP?

- **I**terative **C**losest **P**oint Algorithm
- ICP is one of the widely used algorithms in aligning 2D/3D data (simply said it is a widely used registration method)



(a) (b)

Fig.2 *(a) 2D unaligned scan data (source: [5]), (b) unaligned 3D scan data (source: [6])*

# What is ICP?

- The algorithm iteratively revises the transformation (combination of translation and rotation) needed to minimize an error metric.
- Usually the error metric is a distance from the source to the reference point cloud, such as the sum of squared differences between the coordinates of the matched pairs.

$$Error = min \sum_{j=1}^{m} \| c_j - T(b_j) \|^2$$

# Algorithm

**Algorithm 1:** ICP

**Input:**

$A = \{a_i \in \mathbb{R}^3, i = 1, 2, ..., n\}$

$B = \{b_j \in \mathbb{R}^3, j = 1, 2, ..., m\}$

initial transformation: $T_0 \in SE(3)$

**Output:** $T \in SE(3) thatalignsAandB$

Initialize: $T \leftarrow T_0$

**while** *not converged* **do**

  **Correspondence:**

  $c_j = FindClosestPoint(T(b_j)), c_j \in A$

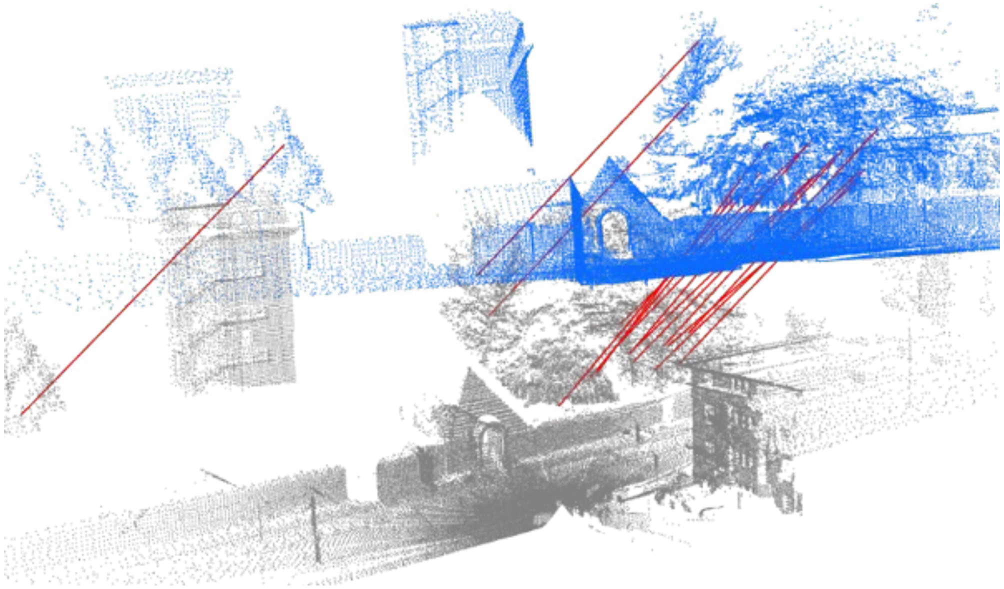
  **Minimization:**

  $T = argmin \sum_{j=1}^{m} \| c_j - T(b_j) \|^2$

**end**

*P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 14, no. 2, pp. 239-256, Feb. 1992, doi: 10.1109/34.121791.*

# Finding Correspondences



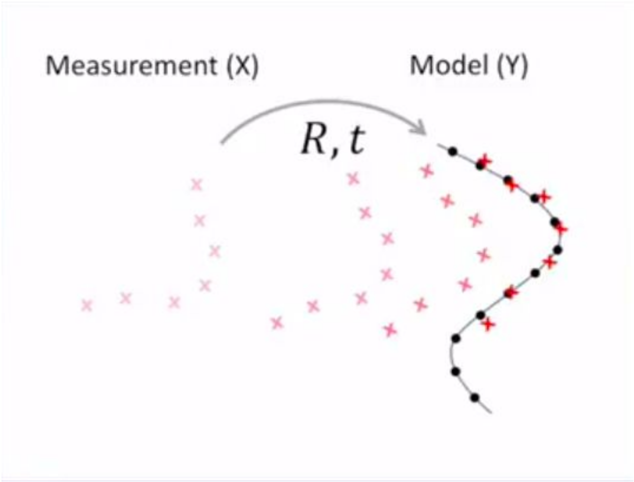
Using KD Tree find the nearest point.

# Finding Appropriate Rotations and Translations

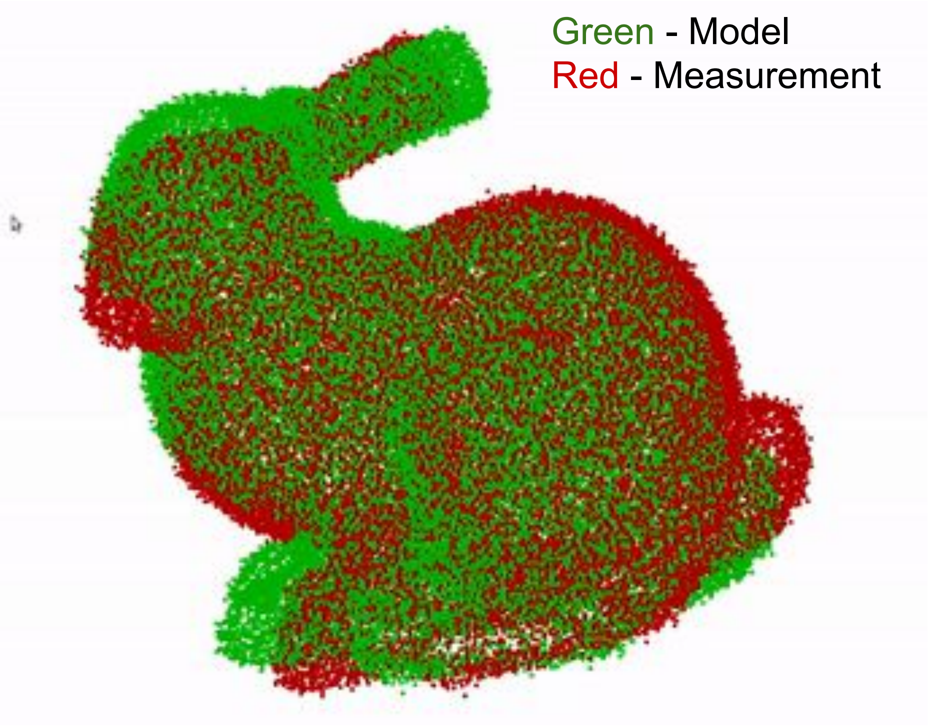
- Rotation is found using SVD to minimize the error

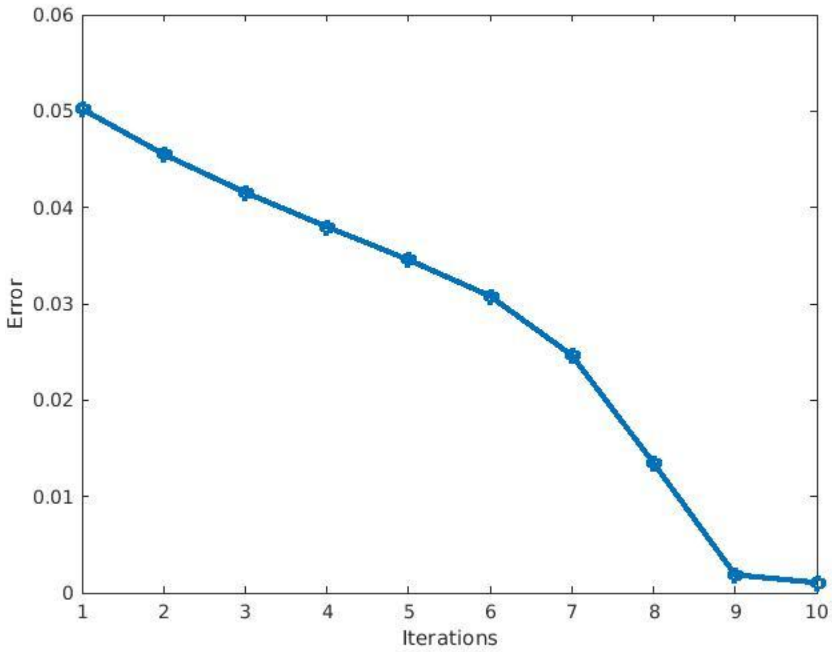
$$Error = min \sum_{j=1}^{m} \| c_j - T(b_j) \|^2$$

- t = y - Rx

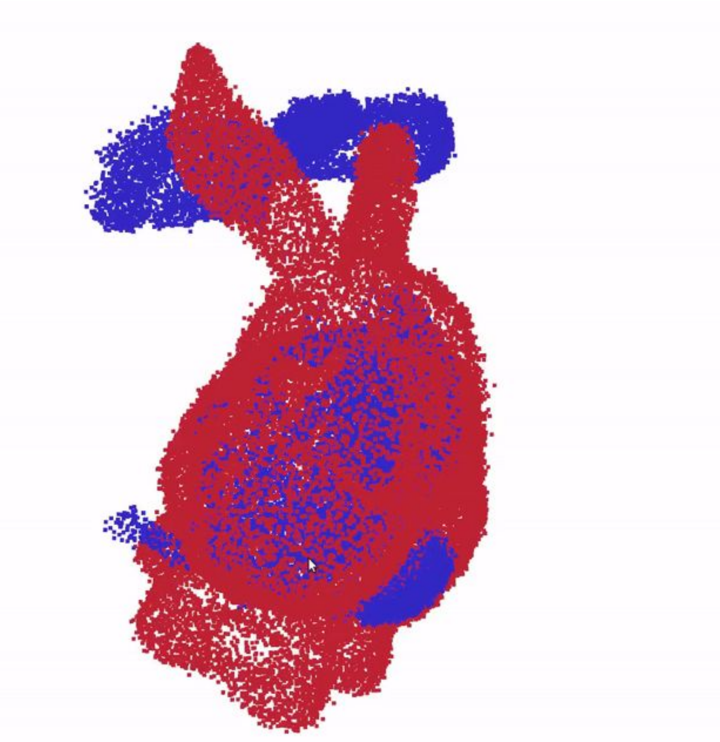


# Result


Green - Model
Red - Measurement


0.06
0.05
0.04
0.03
0.02
0.01
0
Error
1
2
3
4
5
6
7
8
9
10
Iterations

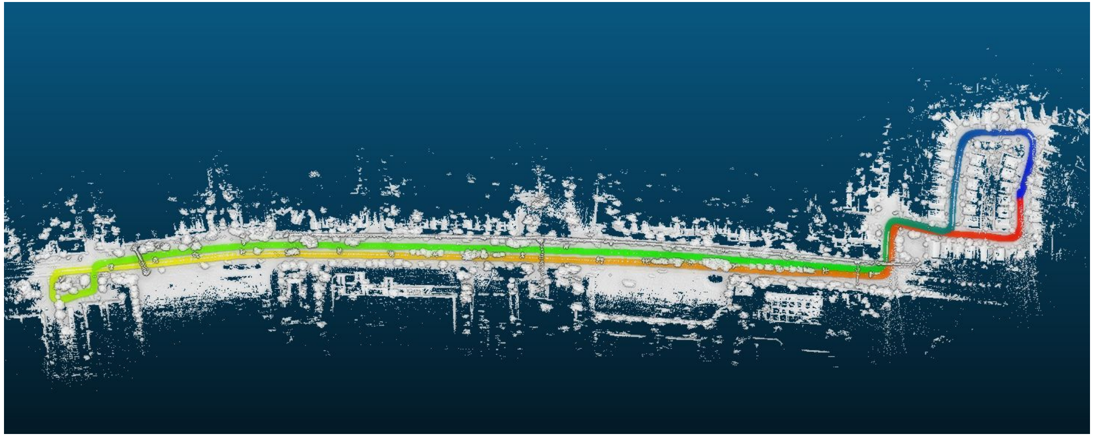
# Failure to register partial point cloud



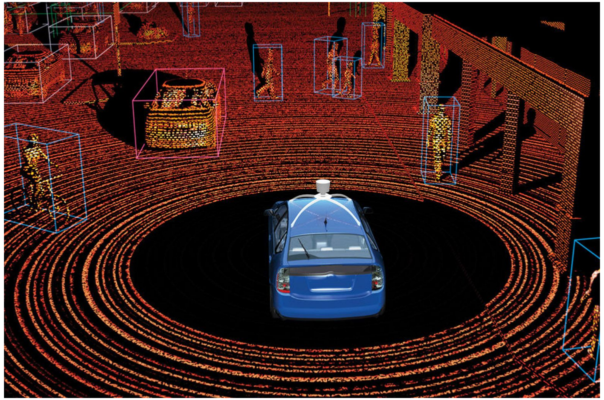
*Partial point cloud registration using ICP*

# Why do we care about “ Registration” ?

- Autonomous Vehicle Localization
- Visual Odometry for UAVs and Unmanned Ground Vehicles
- 3D Terrain Mapping



3D Terrain Mapping. Source: Unmanned Systems Lab, TAMU



Visualization of a LiDAR point cloud. Source: Graham Murdock for Popular Science

# Advantages and Disadvantages of ICP

**Advantages**:

- Relatively easy to understand
- Does not require local feature extraction
- Algorithm can be generalized to n-dimensional space

**Disadvantages:**

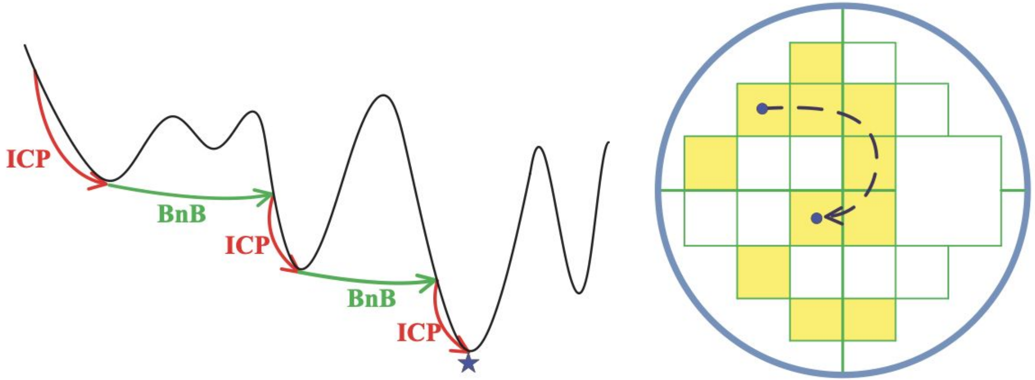
- Converges to local minima
- Convergence time depends on initializations of Rotation and Translation
- Is sensitive to outliers
- High “time complexity” in finding point associations
- Cannot handle partial point cloud registration

# Overcoming the Drawbacks of ICP

- Speed up closest point selection using KD-trees and Dynamic Caching
- Avoid Local minima by removing outliers, using information besides just geometry (colour, curvature), etc
- Carefully initializing R and T to decrease convergence time.
- **G**lobal **O**ptimal **ICP**

# GoICP (Extended work)

- Overcomes the local minima problem by computing the **G**lobal **O**ptima.
- Recursive usage of BnB search and vanilla ICP to search the entire SE(3) space.

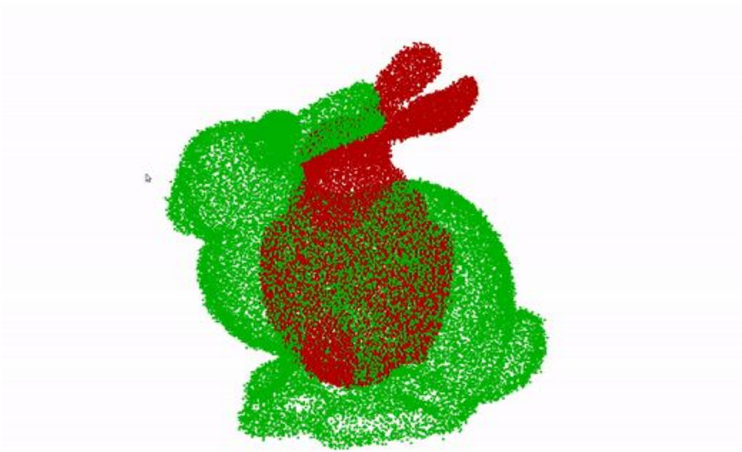




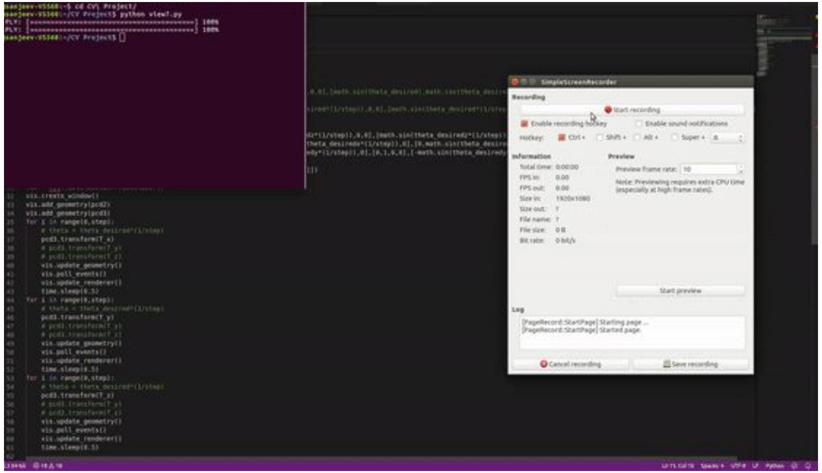
J. Yang, H. Li, Y. Jia, *Go-ICP: Solving 3D Registration Efficiently and Globally Optimally*, International Conference on Computer Vision (ICCV), 2013

# Comparison of GoICP and standard ICP

Partial point cloud registration using Standard ICP



Partial point cloud registration using GoICP



# References


1. https://thegradient.pub/beyond-the-pixel-plane-sensing-and-learning-in-3d/
2. http://pointclouds.org/documentation/tutorials/registration_api.php
3. https://en.wikipedia.org/wiki/Iterative_closest_point
4. P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 239-256, Feb. 1992, doi: 10.1109/34.121791.
5. https://web.iiit.ac.in/~abhimanyu_p/index.html?
6. Segal, A., Haehnel, D. and Thrun, S., 2009, June. Generalized-icp. In *Robotics: science and systems* (Vol. 2, No. 4, p. 435).

# Finding R, t

Let us summarize the steps to computing the optimal translation $\mathbf{t}$ and rotation $R$ that minimize

$$\sum_{i=1}^{n} w_i \left\|(R\mathbf{p}_i + \mathbf{t}) - \mathbf{q}_i\right\|^2 .$$

1. Compute the weighted centroids of both point sets:

$$\bar{\mathbf{p}} = \frac{\sum_{i=1}^{n} w_i \mathbf{p}_i}{\sum_{i=1}^{n} w_i}, \quad \bar{\mathbf{q}} = \frac{\sum_{i=1}^{n} w_i \mathbf{q}_i}{\sum_{i=1}^{n} w_i}.$$

2. Compute the centered vectors

$$\mathbf{x}_i := \mathbf{p}_i - \bar{\mathbf{p}}, \quad \mathbf{y}_i := \mathbf{q}_i - \bar{\mathbf{q}}, \qquad i = 1, 2, \ldots, n.$$

3. Compute the $d \times d$ covariance matrix

$$S = XWY^{\mathsf{T}},$$

   where $X$ and $Y$ are the $d \times n$ matrices that have $\mathbf{x}_i$ and $\mathbf{y}_i$ as their columns, respectively, and $W = \operatorname{diag}(w_1, w_2, \ldots, w_n)$.

4. Compute the singular value decomposition $S = U\Sigma V^{\mathsf{T}}$. The rotation we are looking for is then

$$R = V \begin{pmatrix} 1 & & & & \\ & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & \det(VU^{\mathsf{T}}) \end{pmatrix} U^{\mathsf{T}}.$$

5. Compute the optimal translation as

$$\mathbf{t} = \bar{\mathbf{q}} - R\bar{\mathbf{p}}.$$