Sensors and Sensing
Sensor Data Processing

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Outline

1. Visual Odometry
2. Scan Matching and Registration
3. Point Cloud Processing

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Visual Odometry

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Images and Image Gradients

- Visual odometry uses camera observations and estimates the pose offset between subsequent views.
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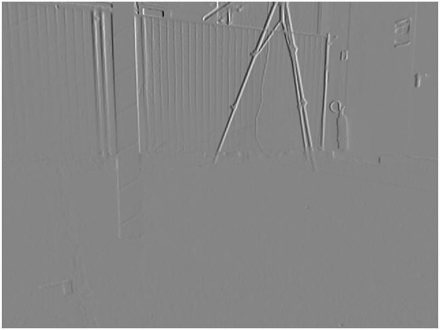

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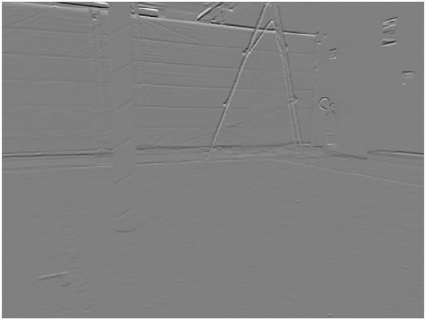


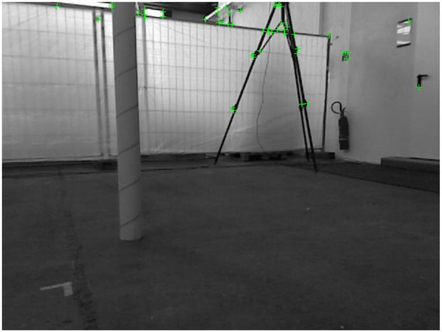
$$S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix};$$

Features

- The Sobel operators are useful for detecting edges in an image.
- Places with high gradient in several directions are an indication of a corner.
- If we can detect corners reliably in several images, we can use them as landmarks.
- Points in the image which can be reliably re-detected and compared are called features or keypoints.

Harris Corner Detector

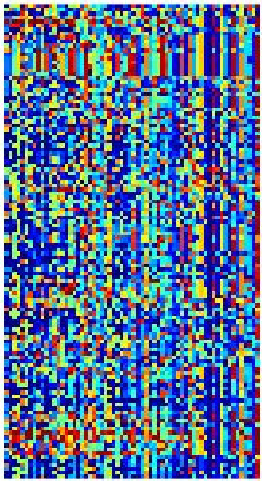
- The Harris corner detector is one of the classical approaches for choosing good features
- Based on observing the shape of derivatives while sliding a window through an image.
- Without going into details, we are interested in the smallest eigenvalue λ_{min} of the matrix:



$$M = \sum_{x,y \in W} \begin{bmatrix} G_x^2 & G_x G_y \\ G_x G_y & G_y^2 \end{bmatrix}$$

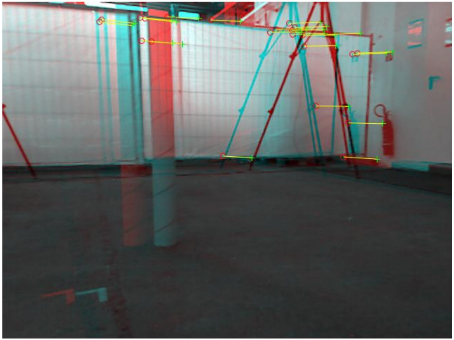
Feature Descriptors

- Once we have detected keypoints, we need to uniquely describe each point.
- Idea: represent 2D neighborhood into a 1D feature vector.
- What should go into the feature vector?
- Many descriptors possible (SIFT, SURF, ORB)



Feature matching

- Given two sets of images, we look for corresponding features.
- We can compare the Euclidean distance between descriptor vectors.
- → often with an adaptive threshold.
- Forward and reverse matches.
- We look for a consistent set of matches, often with RANSAC.



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Registration and Map Building — Overview

- Most navigation approaches require a map of the environment
- Mapping integrates multiple sensor views in a consistent model
- Registration is a sub-problem in mapping:

- Given two sets of points $\mathcal{P}_1$ and $\mathcal{P}_2$
- Find the transformation $\mathrm{T} = (\mathrm{R}, \mathrm{t})$, which brings $\mathcal{P}_2$ in alignment with $\mathcal{P}_1$

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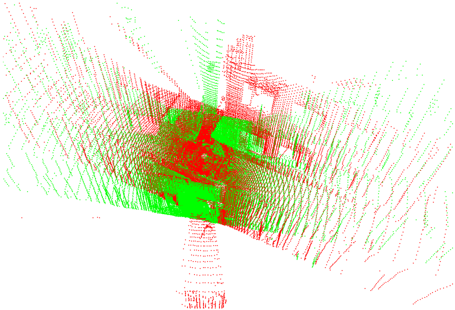

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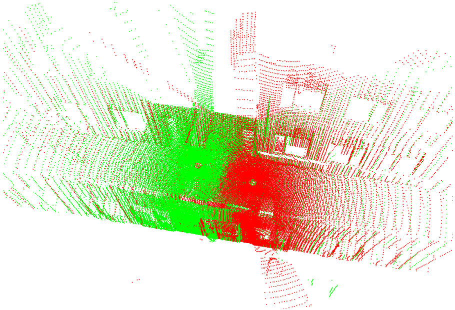

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Algorithm 1: ICP algorithm

```
while not converged do
    For each point in P1 associate closest point in P2;
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      points;
    Transform P2 by T;
    Check for convergence;
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Algorithm 2: ICP algorithm

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    Check for convergence;
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- Data association for matching points can use different metrics (poin-to-point, point-to-plane distance).
- Important to reject outliers!
- Estimating T can be done using the SVD algorithm

A Simple 1D Example — ICP algorithm

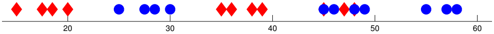

Figure: Iterative Closest Point (ICP)

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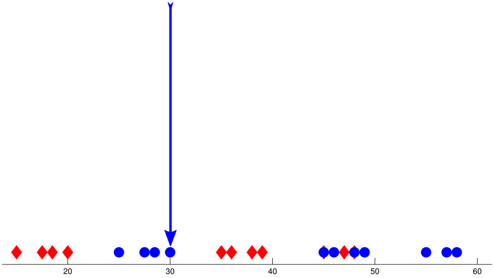

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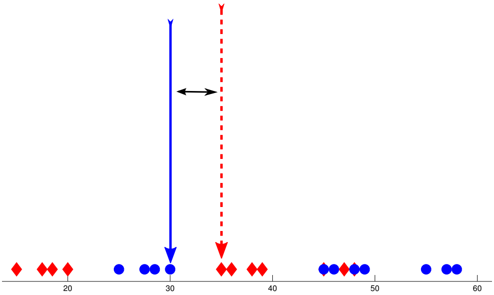

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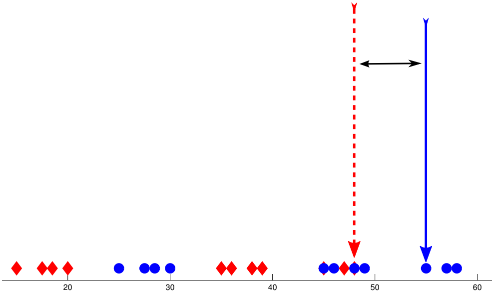

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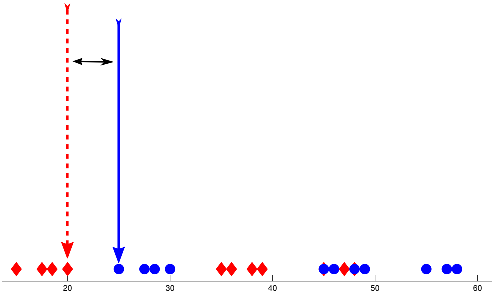

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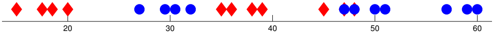

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ICP Limitations and Varriants

- Sensitive to scan overlap issues
- Local method, requires an initial guess
- Can be slow, as it iterates over all points
- Sped up varriants using efficient spatial search (e.g. Kd-Trees)

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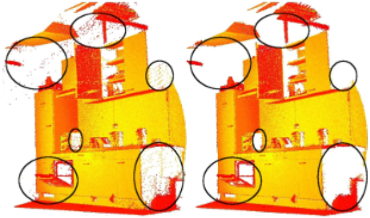
Typical Objectives

- Outlier removal
- Voxelization and spatial indexing
- Extracting high-level structures
- Building hig-level models (occupancy maps, triangle meshes)



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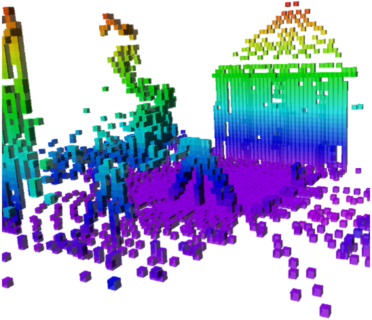

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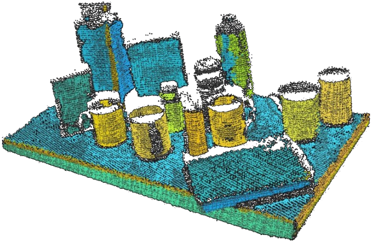

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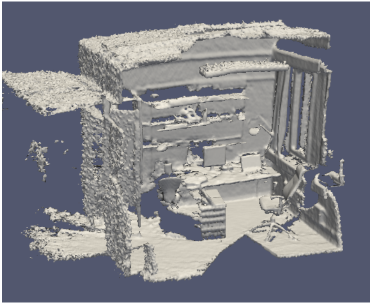

Subsampling and Volumetric Filters

- Often it is necessary to decrease the sample density of 3D points
- e. g., for faster ICP convergence
- Also, uniform density may be desireable to counter scanner position related bias.
- Common approach is to use a voxel grid and only select a single (or a set number) point from each cell.

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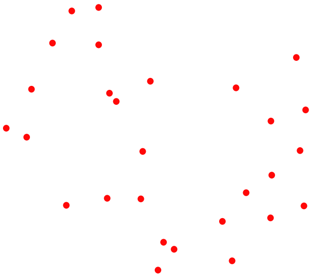

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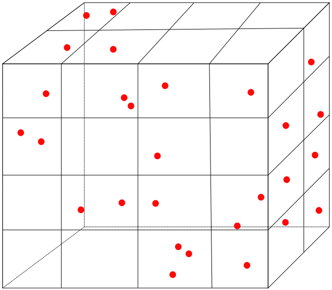

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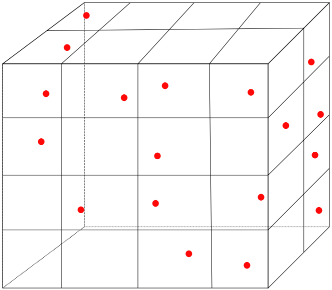


Fitting models and Data association

- Data association: How do we choose matching measurements?
- Common problem in several areas of robotics: matching landmarks for localization, points for registration, features for object detection, etc.
- Problem: noisy associations produce outliers that significantly affect solution.
- Problem: least-squares fit is sensitive to outliers.
- Solutions: use a robust norm (L1 instead of L2)
- Solutions: use a randomized algorithm for data association and iterative refinement.

Random Sample Consensus (RANSAC)

- Basic idea:
  - Select a random subset R of the data D.
  - Fit a model M to R. E.g. least squares plane fit. For matching keypoints, we estimate the transform using just the correspondences in R.
  - Check all points in D for fitness wrt M. Points that fulfill a fitness criteria are in the consensus set C.
  - Optionally, refine M with all points from C.
  - Compute a model fitness score based on the number of points in C. If fitness is better than previous models, keep M.
  - Iterate a set number of times or until convergence.

Clustering

- Clustering points together can be useful for several applications
- Clusters contain fewer points and typically fewer outliers, thus can be better suited for model fitting
- Different types of clustering can be formulated based on the distance metric used to decide if a point belongs to a cluster
- Typically, Euclidean distance metric is used
- Machine learning can be useful as a basis (k-means clustering for example), but often adhoc cluster growing approaches

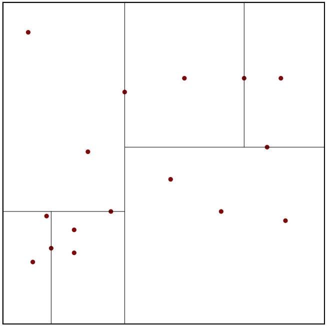
Spatial Indexing

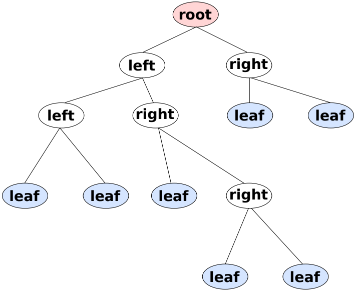
- Various data structures can be used to store point clouds.
- Typical raw data is stored as a 1D array (or 2D for a depth image parametrization).
- Depending on application, different criteria may be important:
  - Spatial complexity (memory storage).
  - Complexity of inserting a new point.
  - Complexity of retrieving a point / nearest neighbour.
- Raw data typically has $O(N)$ search and storage complexity, with $O(1)$ insertion complexity.
- Voxel grids are another often used data structure: storage complexity $O(M^3)$, average time search complexity is $O(\frac{N}{M^3})$, insertion at $O(1)$.

kd Trees and oc Trees

- Maintaining a voxel grid is often prohibitatively expensive (storage) for higher grid resolutions.
- Expected search times depend on the grid resolution as large cells can result in high number of points per cell.
- Tree structures are often used to obtain lower memory requirements at logarithmic search rates

kd Trees and oc Trees





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- Subdivide at the median point along each dimension.
- Storage: $O(N)$, Search: $O(\log N)/O(N)$, Insert: $O(\log N)/O(N)$

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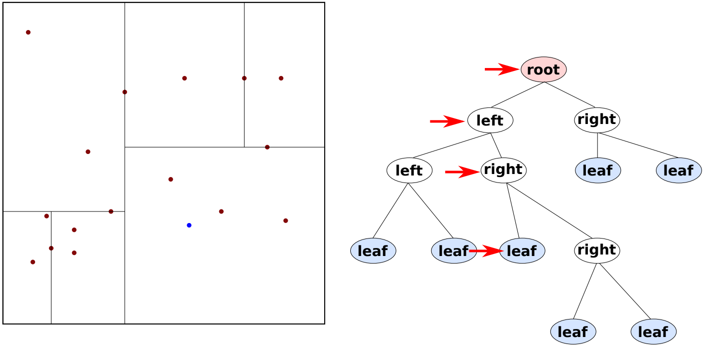

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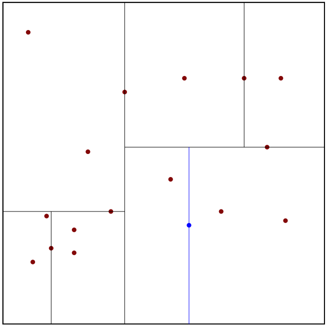

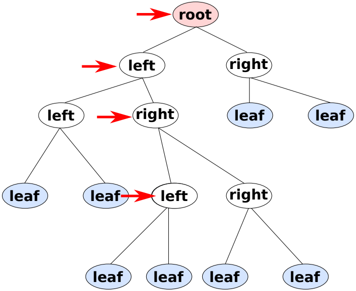

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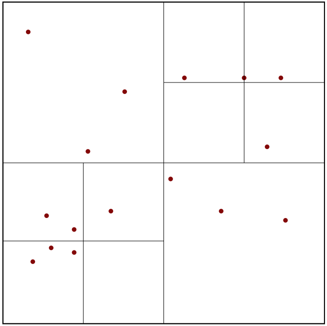

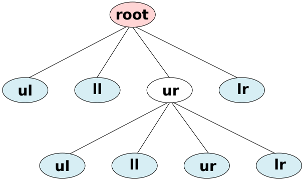

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- Similar complexity, worse tree balance.

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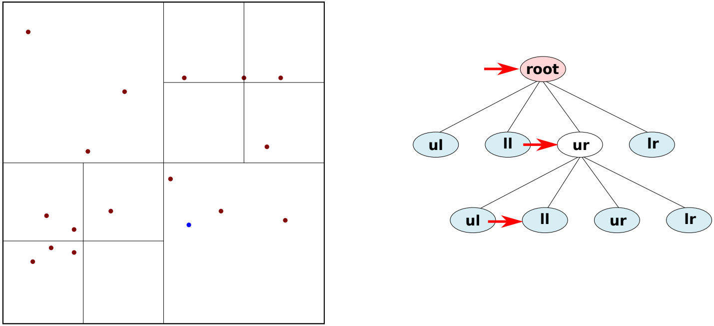

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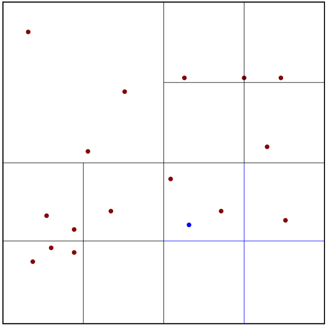

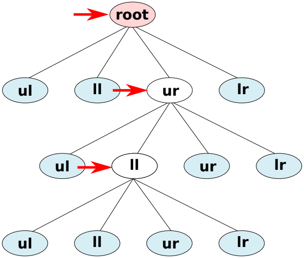

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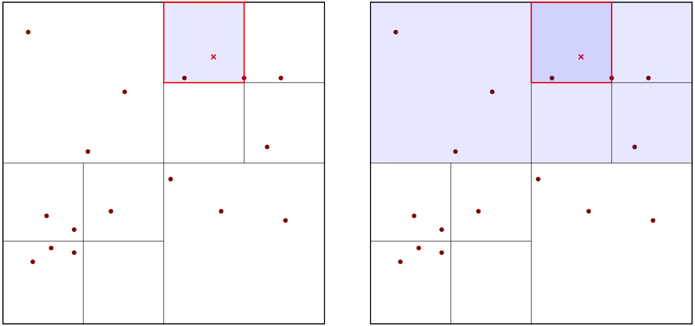

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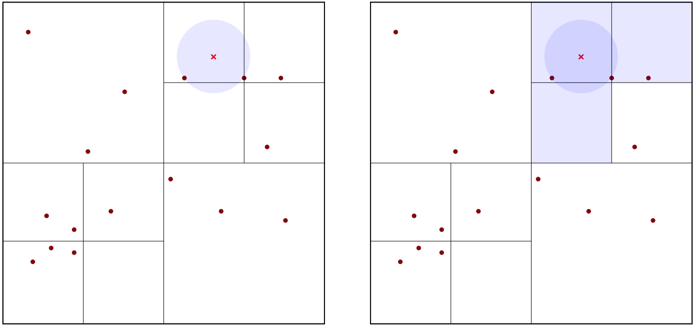

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