Loop Closure Detection Using the NDT

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Outline

- Background introduction
- Technical Approach Explanation
- Results Presentation
- Future Expectation

ÖREBRO UNIVERSITY

Doctoral Dissertation

The Three-Dimensional Normal-Distributions Transform
— an Efficient Representation for Registration,
Surface Analysis, and Loop Detection

MARTIN MAGNUSSON
Technology

**Appearance-Based Loop Detection from 3D Laser Data
Using the Normal Distributions Transform**

Martin Magnusson, Henrik Andreasson, Andreas Nüchter, and Achim J. Lilienthal

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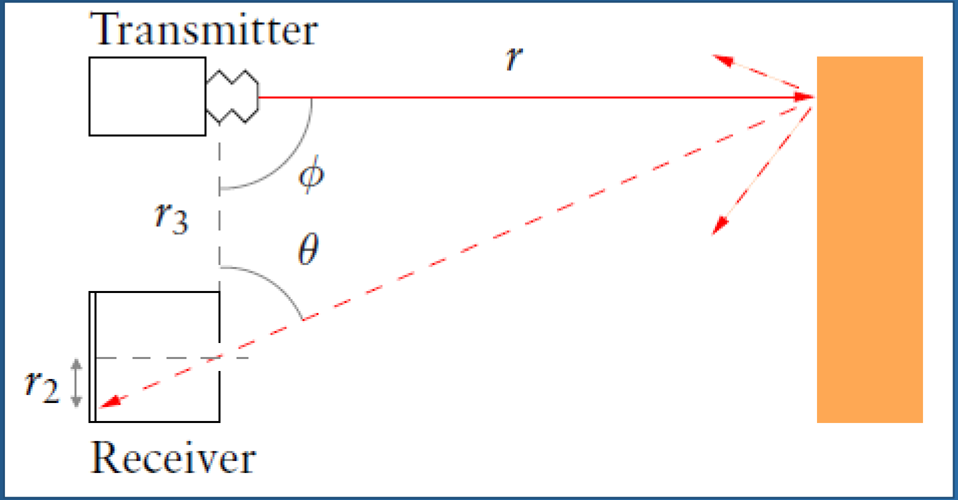
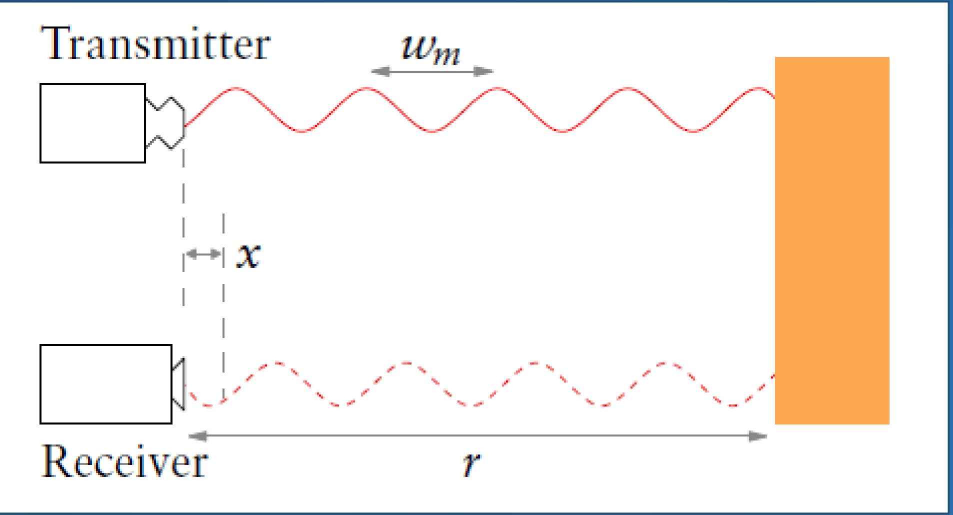
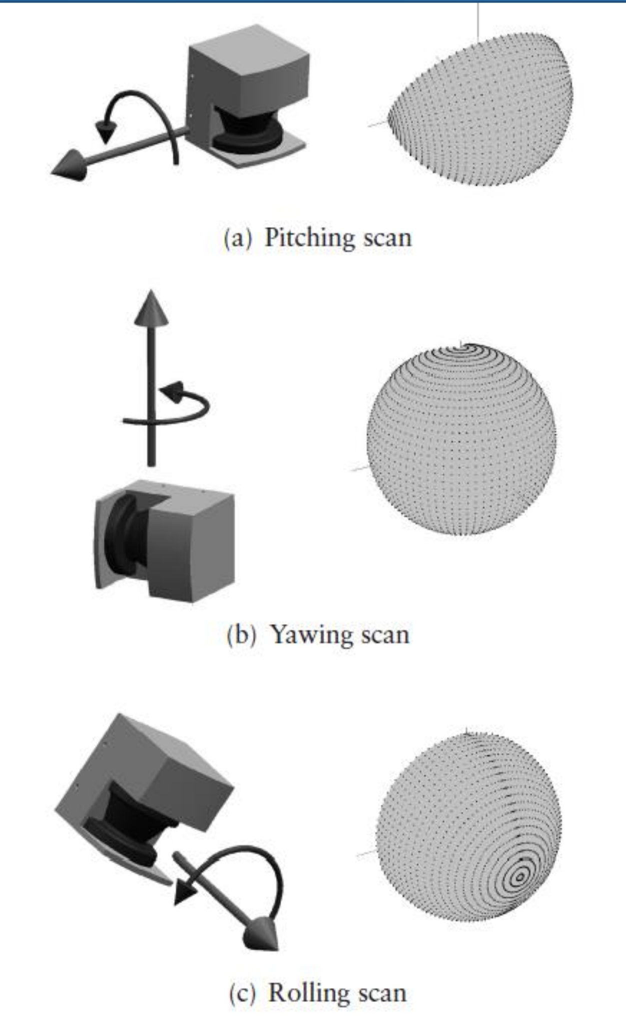
Background

Range Sensing: Lidar



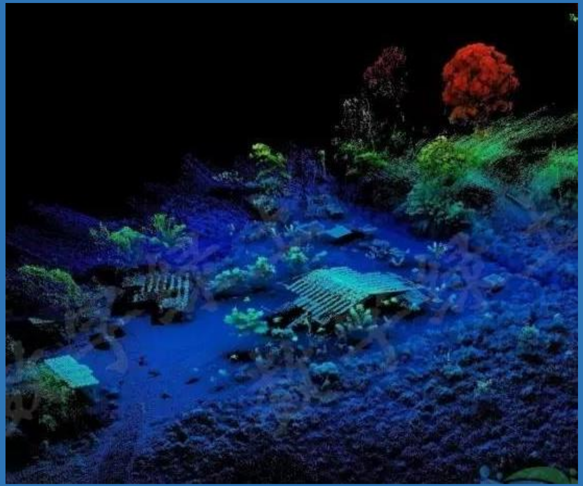




(a) Pitching scan

(b) Yawing scan

(c) Rolling scan



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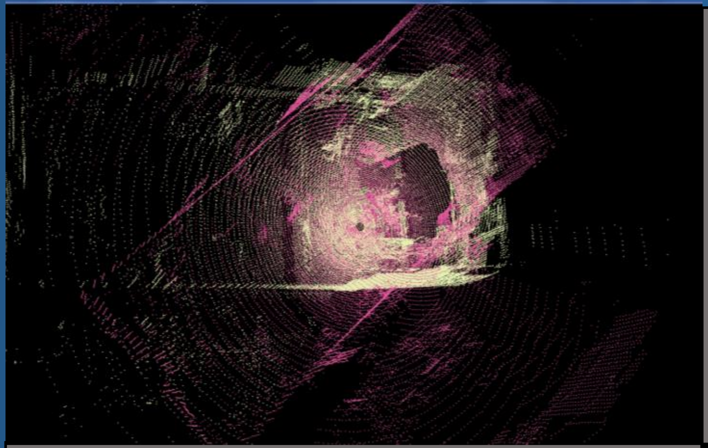
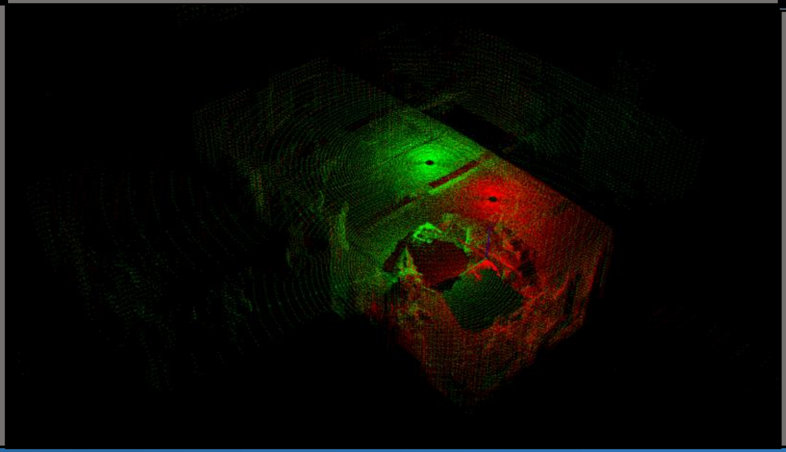
SLAM



Registration

3D Scan
Point Cloud



Loop Detection
& Relaxation

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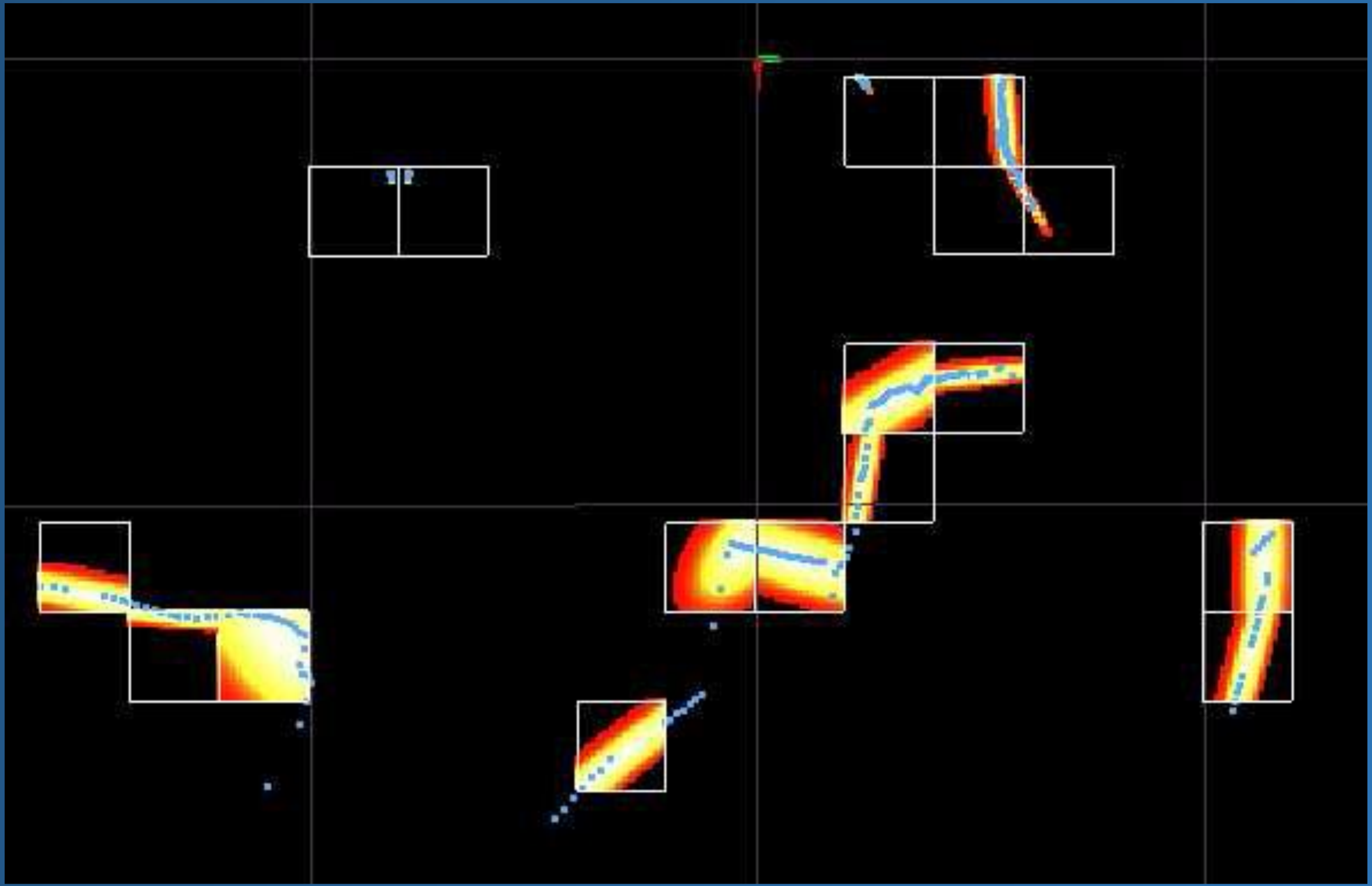
NDT for registration



Mean Vector

$$\vec{\mu} = \frac{1}{m}\sum_{k=1}^{m}\vec{y}_k,$$

$$\Sigma = \frac{1}{m-1}\sum_{k=1}^{m}(\vec{y}_k - \vec{\mu})(\vec{y}_k - \vec{\mu})^{\mathrm{T}},$$

Covariance Matrix

Probability Density Functions

$$p(\vec{x}) = \frac{1}{(2\pi)^{D/2}\sqrt{|\Sigma|}}\exp\left(-\frac{(\vec{x}-\vec{\mu})^{\mathrm{T}}\Sigma^{-1}(\vec{x}-\vec{\mu})}{2}\right)$$

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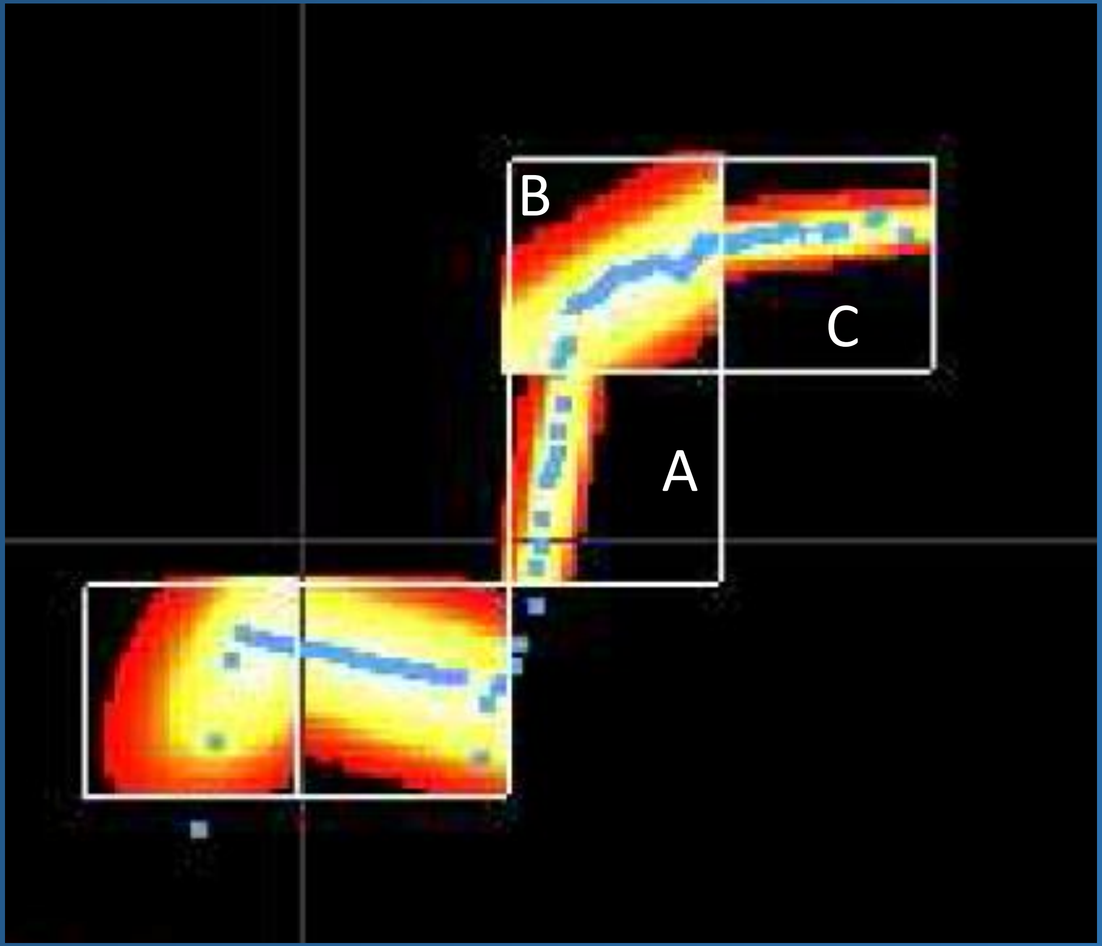
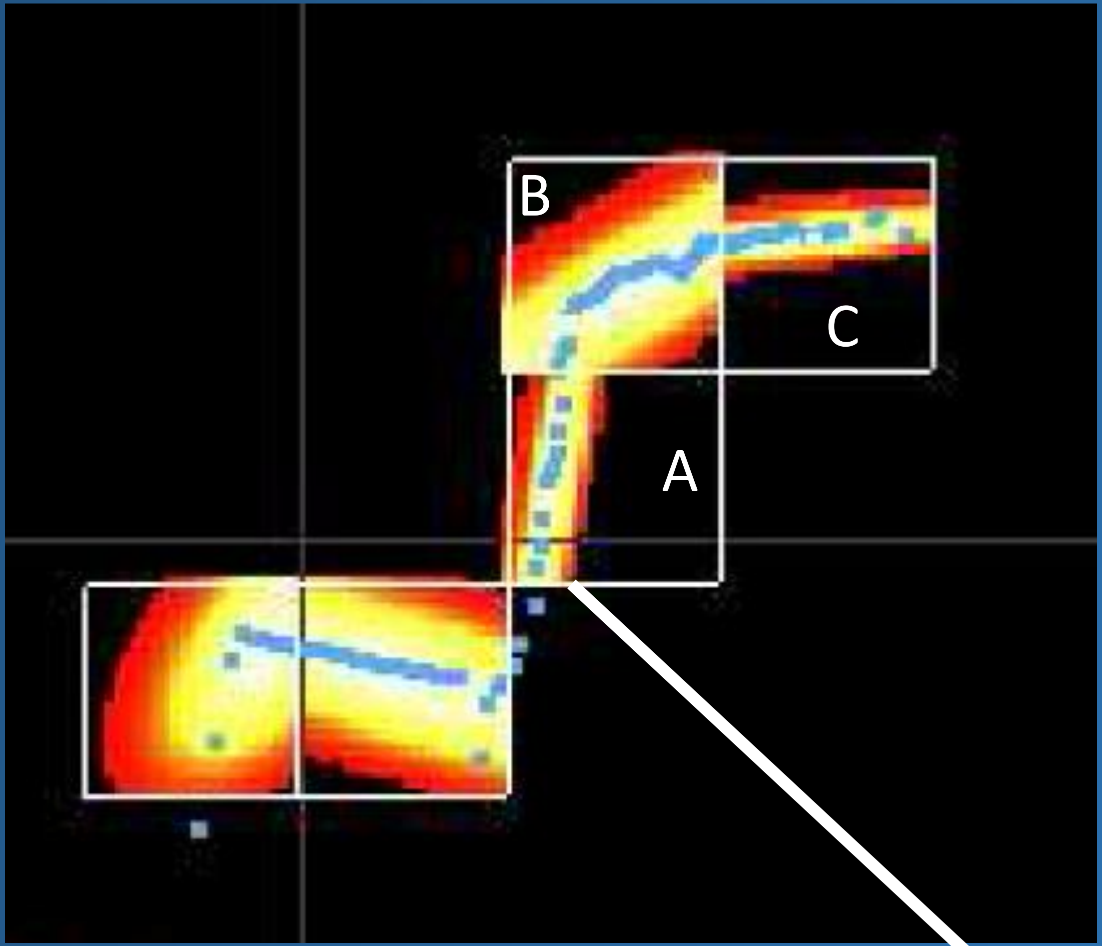
NDT for registration



$$\Sigma = \frac{1}{m-1}\sum_{k=1}^{m}(\vec{y}_k - \vec{\mu})(\vec{y}_k - \vec{\mu})^{\mathrm{T}},$$

$$\begin{bmatrix} cov(X_1,X_1) & cov(X_1,X_2) & \cdots & cov(X_1,X_n) \\ cov(X_2,X_1) & cov(X_2,X_2) & \cdots & cov(X_2,X_n) \\ & & \ddots & \\ cov(X_n,X_1) & cov(X_n,X_2) & \cdots & cov(X_n,X_n) \end{bmatrix}_{n\times n}$$

NDT for registration

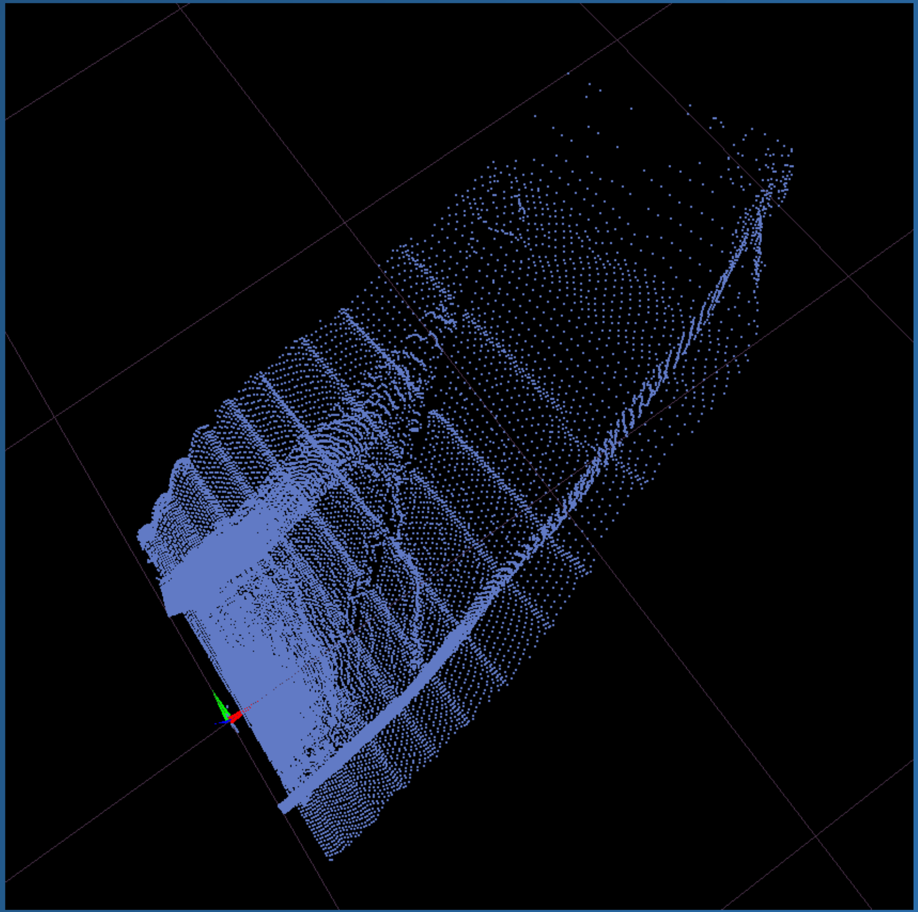


$$\Sigma = \frac{1}{m-1} \sum_{k=1}^{m} (\vec{y}_k - \vec{\mu})(\vec{y}_k - \vec{\mu})^{\mathrm{T}},$$

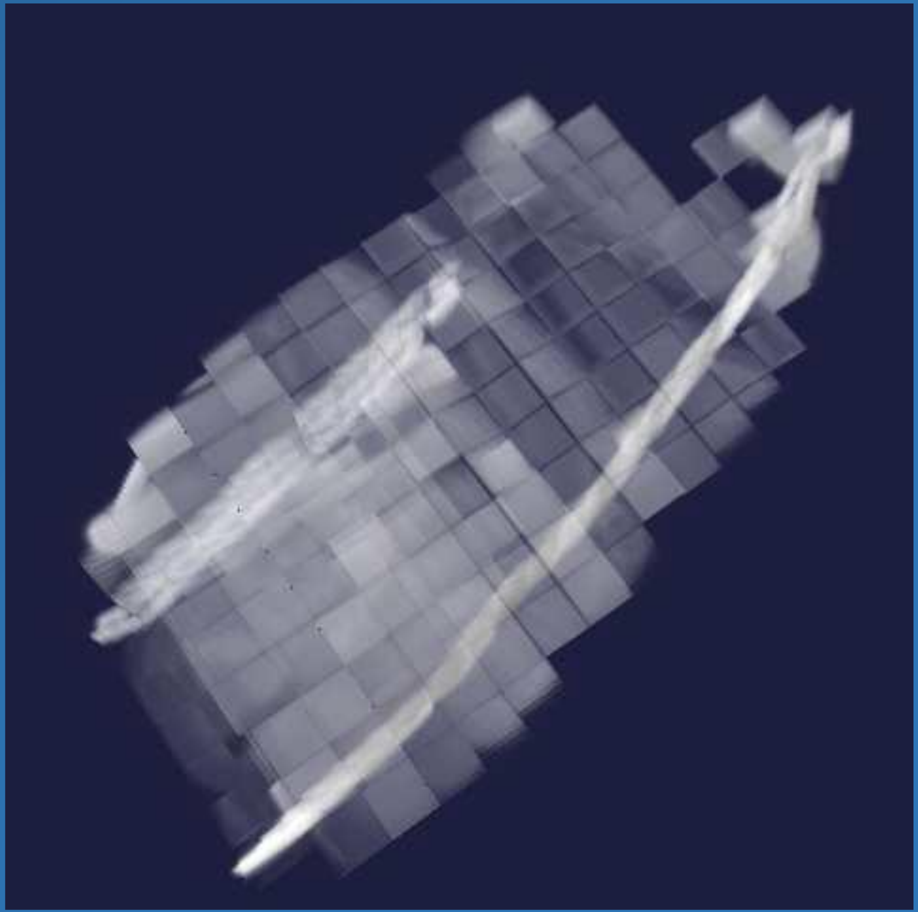
$$\begin{bmatrix} cov(X_1, X_1) & cov(X_1, X_2) & \cdots & cov(X_1, X_n) \\ cov(X_2, X_1) & cov(X_2, X_2) & \cdots & cov(X_2, X_n) \\ & & \ddots & \\ cov(X_n, X_1) & cov(X_n, X_2) & \cdots & cov(X_n, X_n) \end{bmatrix}_{n \times n}$$

Approximation of the local surface → Orientation & Smoothness

3D NDT



Original point cloud



NDT representation

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high compression ratio

3D NDT

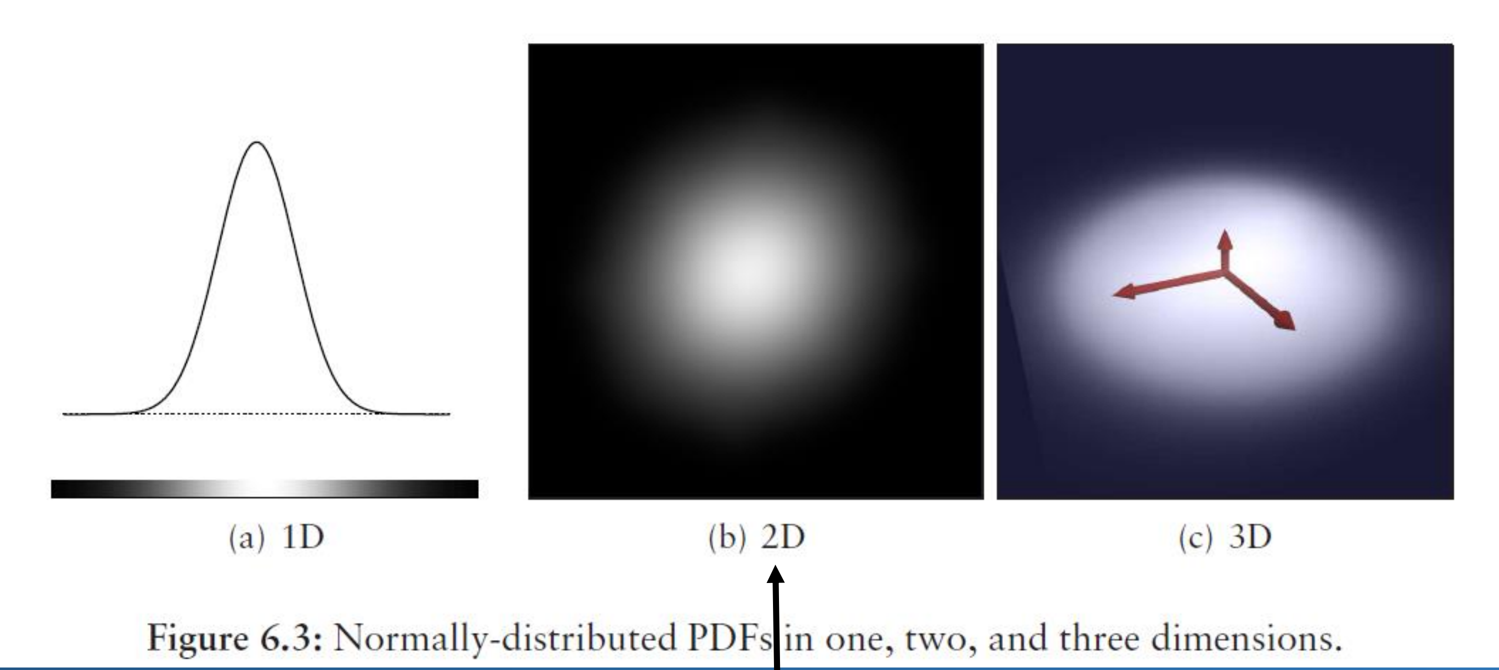
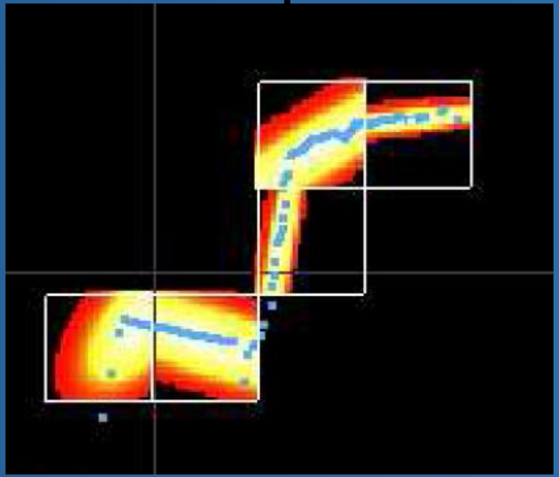


Figure 6.3: Normally-distributed PDFs in one, two, and three dimensions.



Eigenvectors & Eigenvalues of the covariance matrix

Orientation & Smoothness

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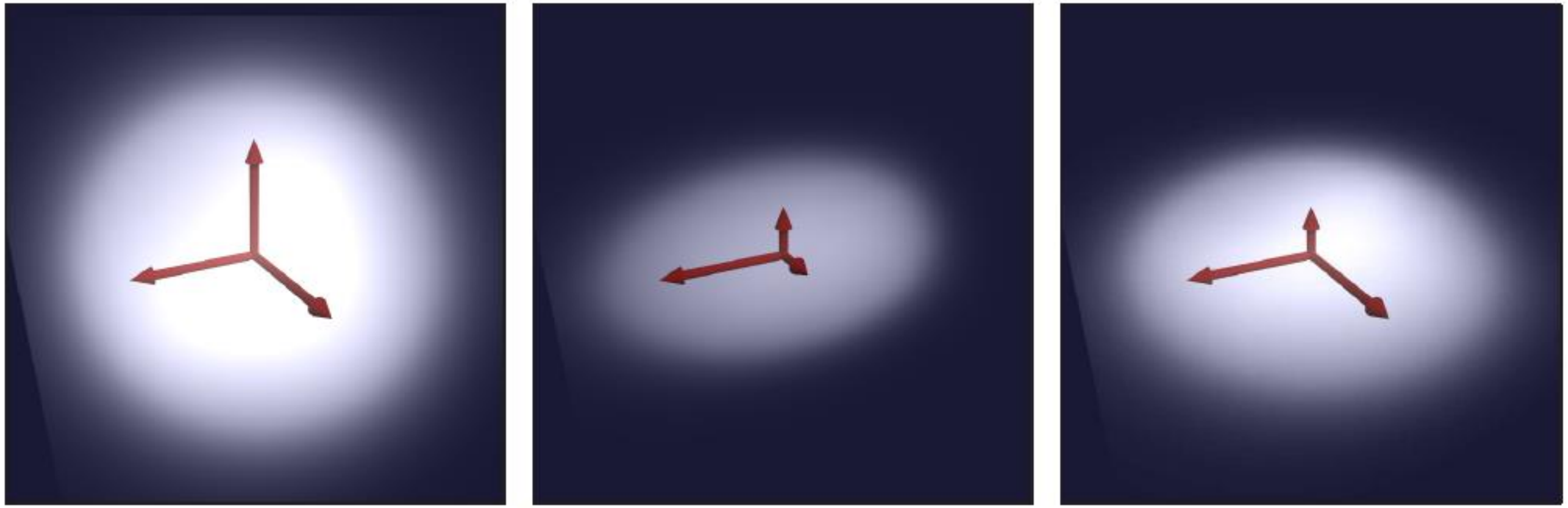
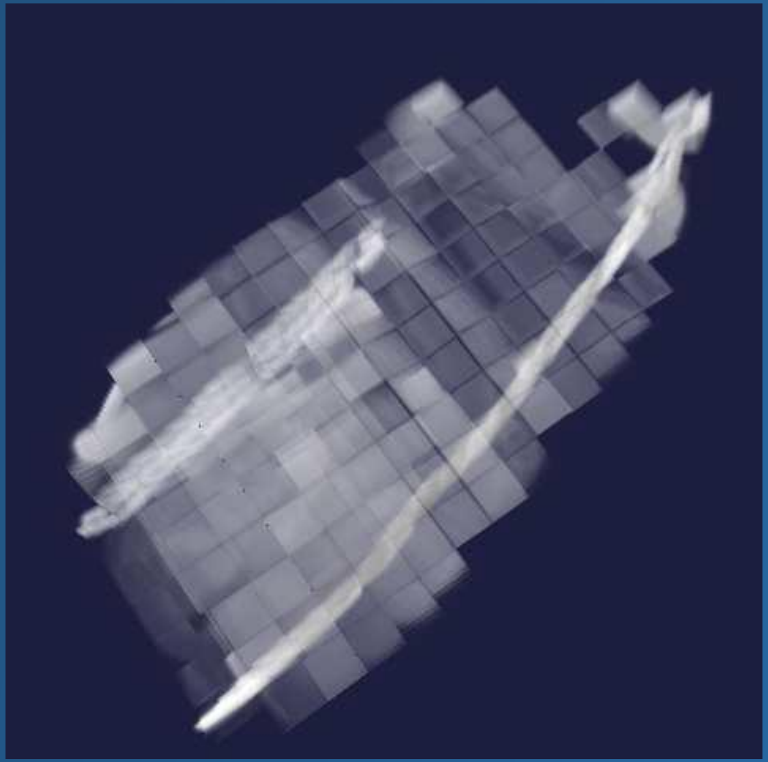
3D NDT



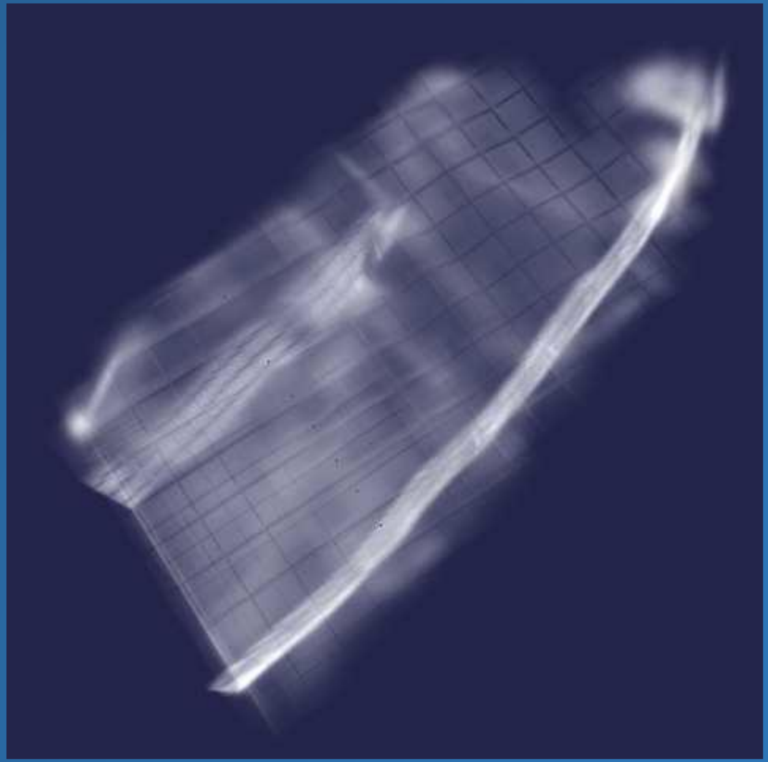
(a) Spherical: All eigenvalues approximately equal. (b) Linear: One eigenvalue much larger than the other two. (c) Planar: One eigenvalue much smaller than the others.

pointcloudlibrary

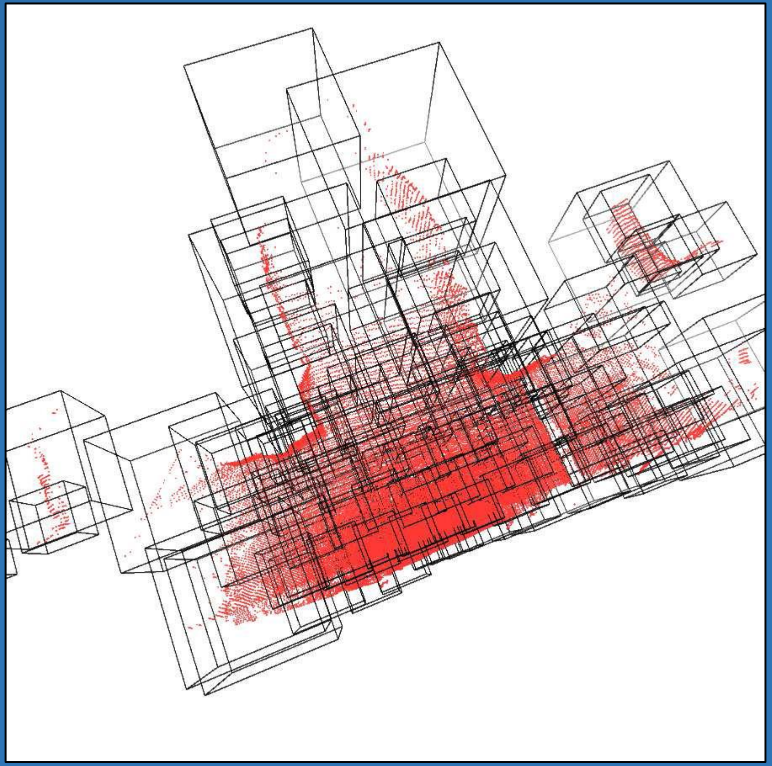
Optimization



Original NDT



Trilinear Interpolation



Octree discretization

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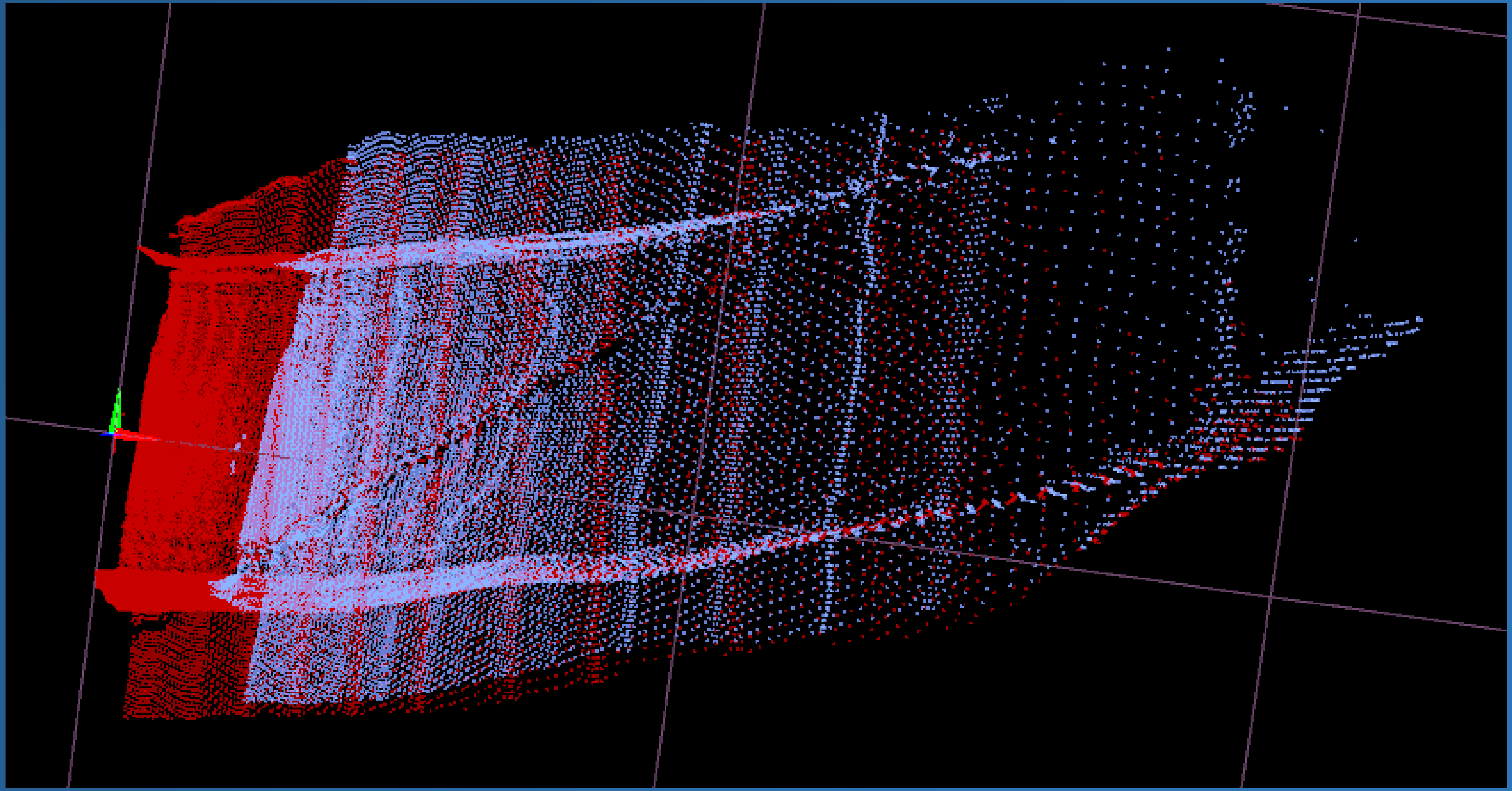
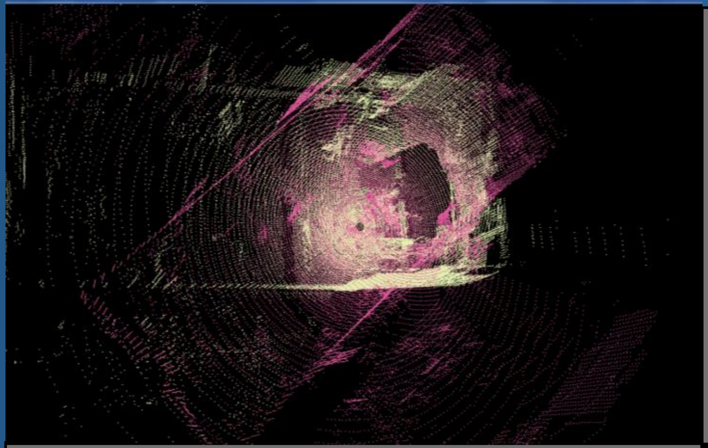
Registration results

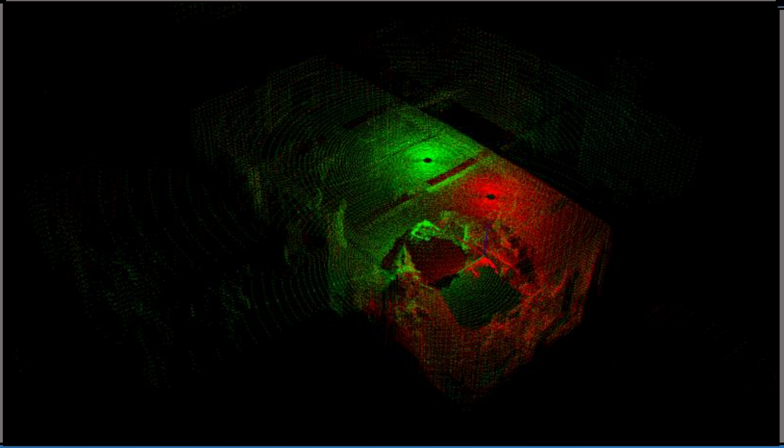


SLAM



Registration

3D Scan
Point Cloud



Loop Detection
& Relaxation

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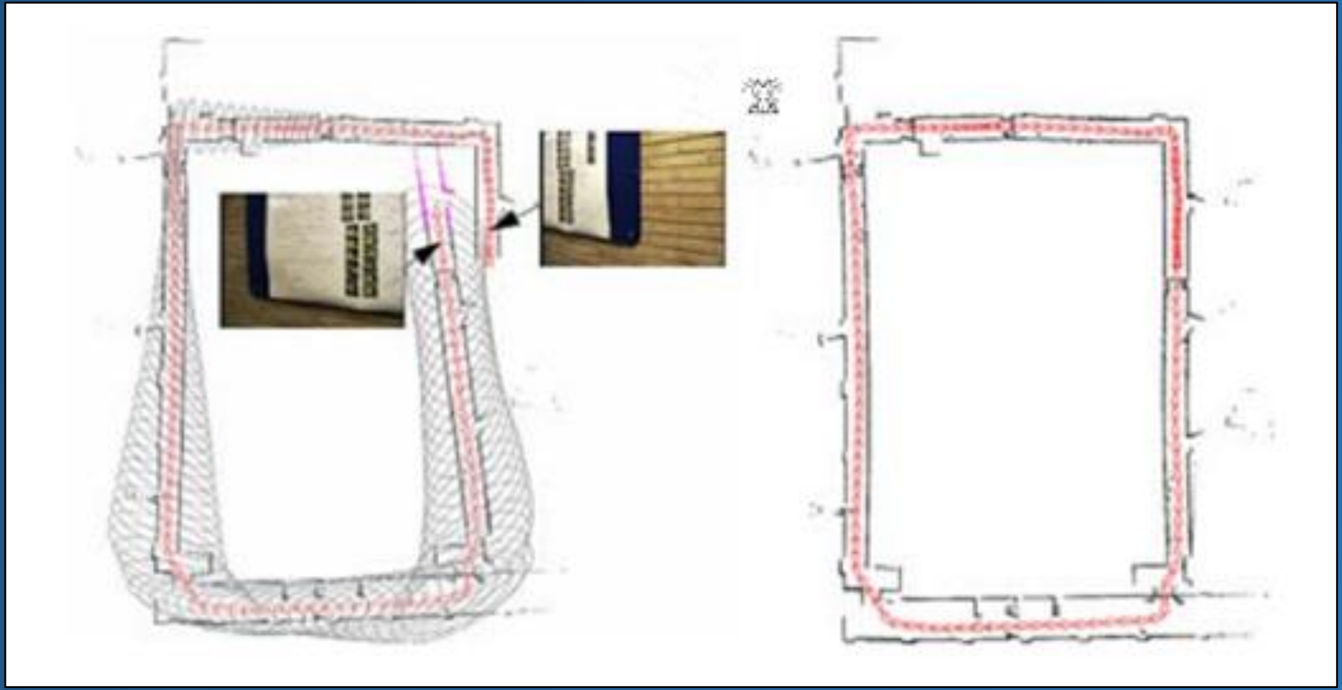
Loop Closure



2 steps: Detection & Relaxation

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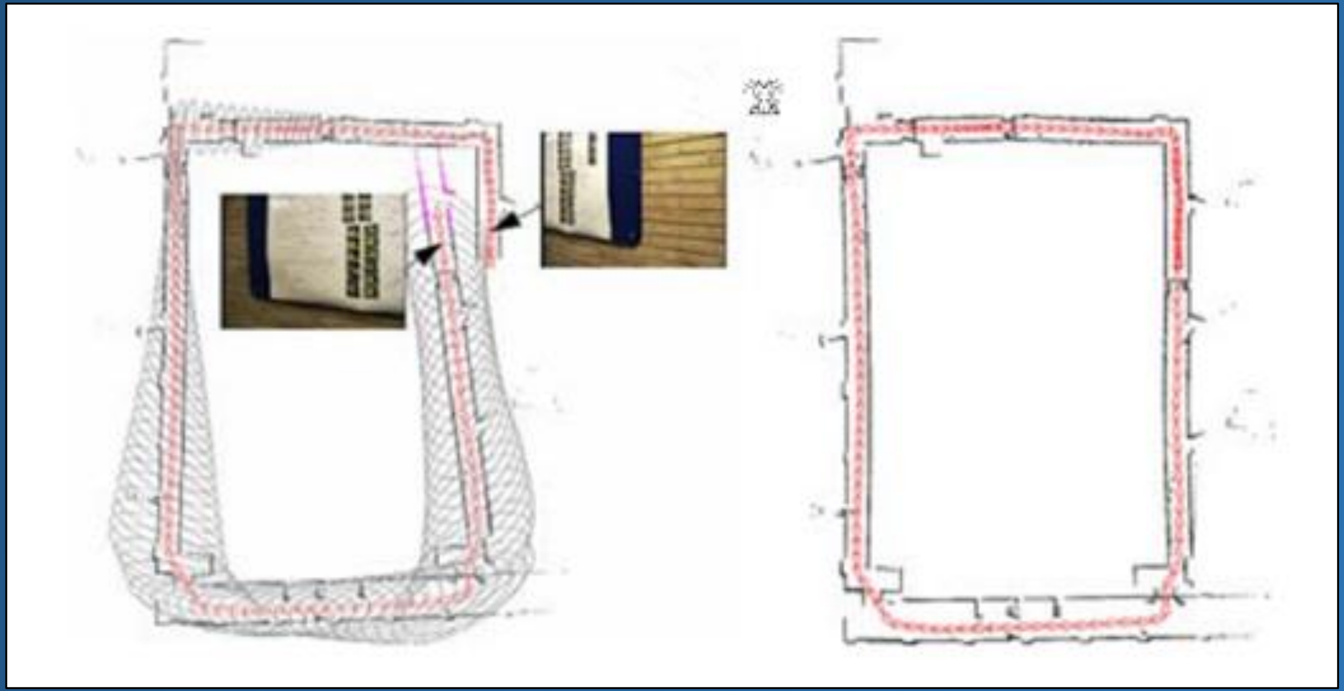
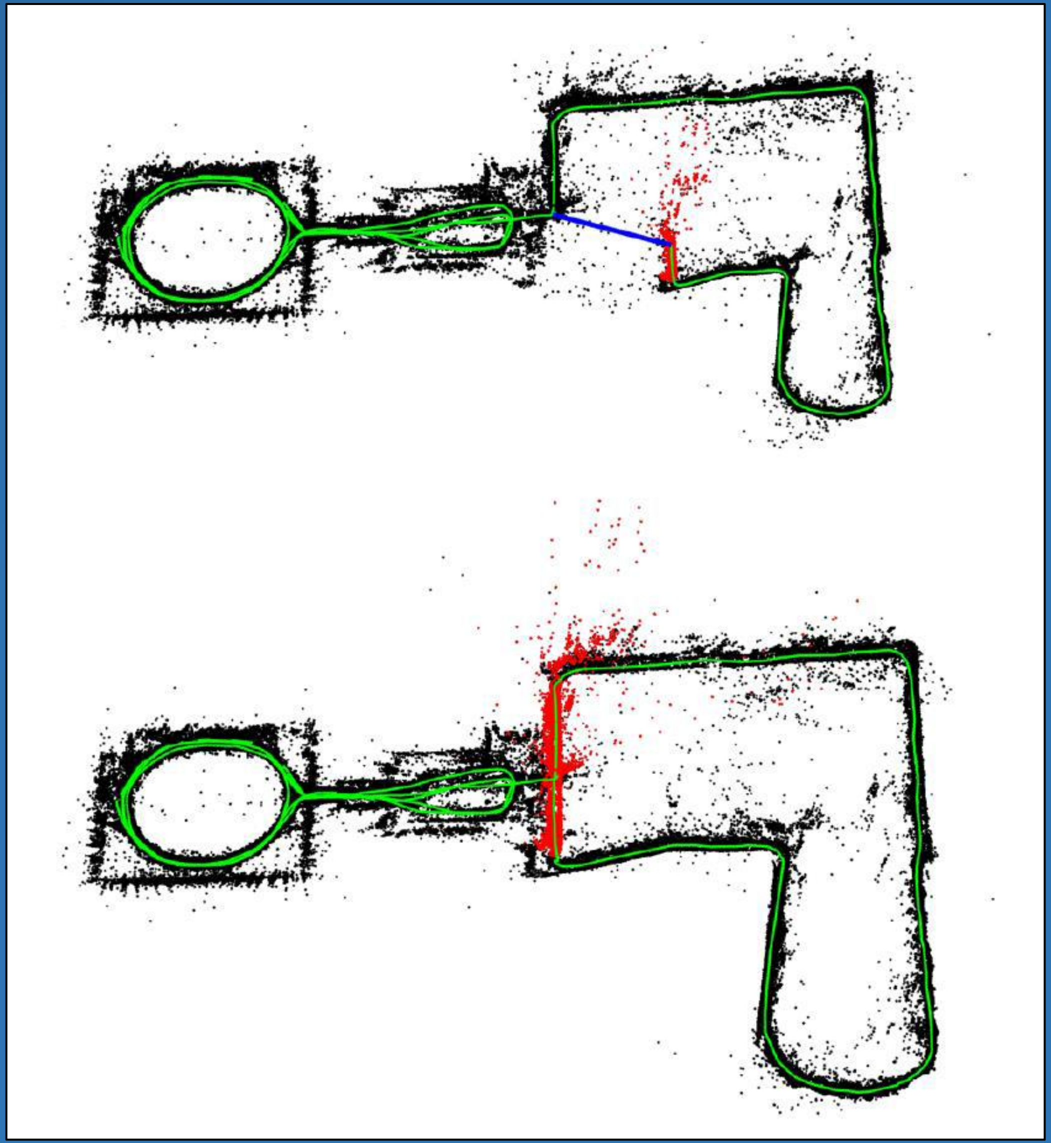
Loop Closure





2 steps: Detection & Relaxation

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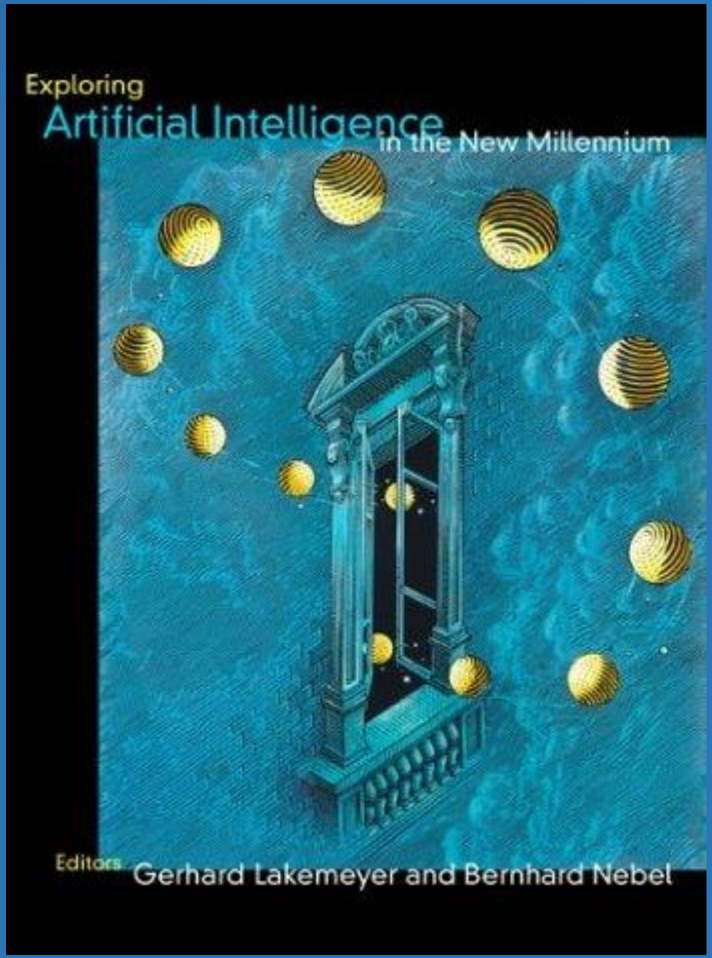
Technical Approach

"Have I seen this before?"

"Establishing the correspondence between past and present positions when closing a loop is one of the most challenging problems in robotic mapping."

Sebastian Thrun, 2002



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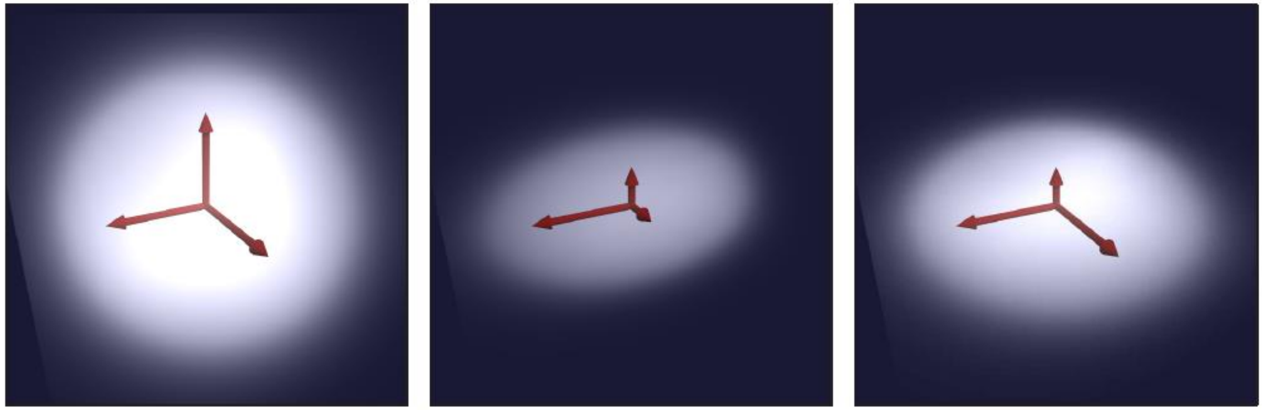
Appearance descriptor

The covariance matrices describe the shapes of the distributions.

the eigenvalues $\lambda_1 \leq \lambda_2 \leq \lambda_3$ and corresponding eigenvectors $\vec{e}_1, \vec{e}_2, \vec{e}_3$ of the covariance matrix

spherical	linear	planar
nonlinear and nonplanar	$\lambda_2/\lambda_3 \leq t_e$.	$\lambda_1/\lambda_2 \leq t_e$.



(a) Spherical: All eigenvalues approximately equal. (b) Linear: One eigenvalue much larger than the other two. (c) Planar: One eigenvalue much smaller than the others.

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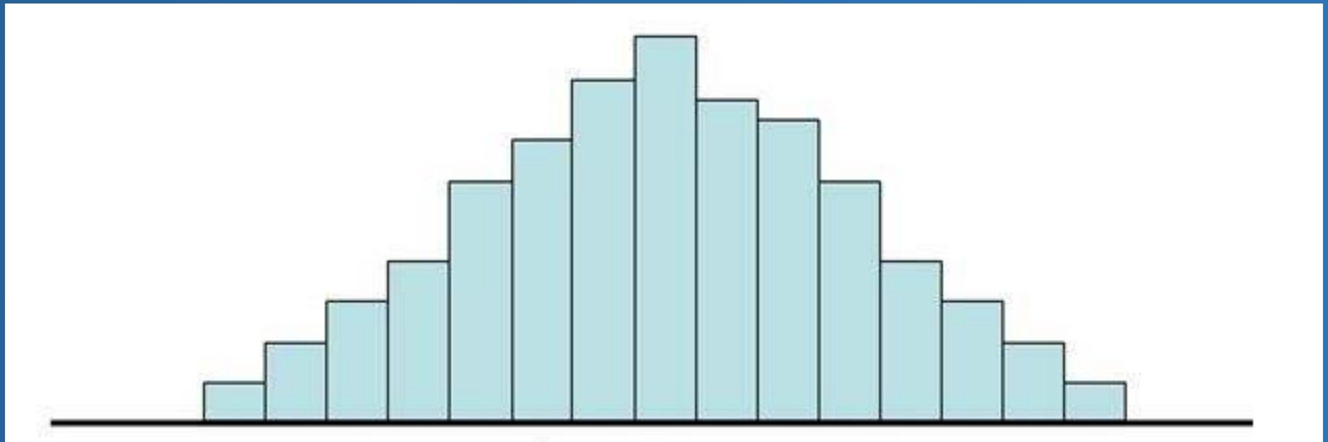
Surface-shape histograms

$$\vec{f} = \Bigg[\underbrace{f_1, \ldots, f_{n_s}}_{\text{spherical classes}}, \underbrace{f_{n_s+1}, \ldots, f_{n_s+n_p}}_{\text{planar classes}}, \underbrace{f_{n_s+n_p+1}, \ldots, f_{n_s+n_p+n_l}}_{\text{linear classes}}\Bigg]^{\mathrm{T}} = \begin{bmatrix} \vec{S} \\ \vec{P} \\ \vec{L} \end{bmatrix},$$



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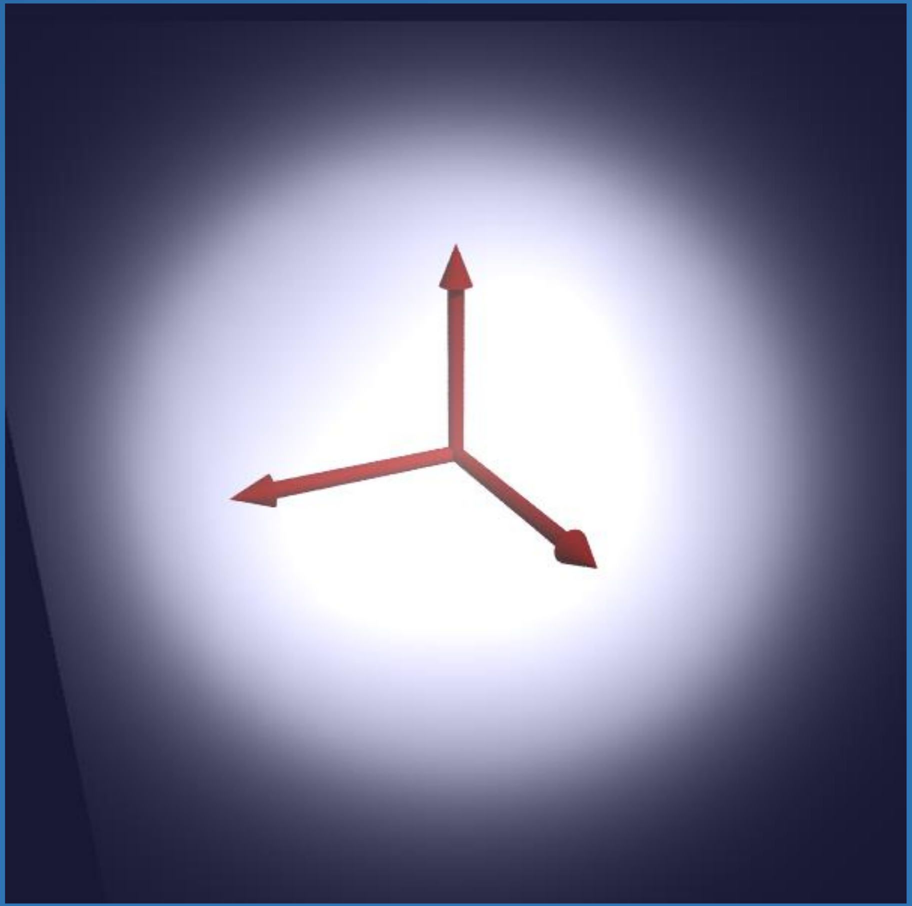
Spherical subclasses

the “roundness” ratio λ_2/λ_3

$$i = \left\lceil n_s \frac{\lambda_2/\lambda_3 - t_e}{1 - t_e} \right\rceil .$$

larger values of i = distributions with more variance

$$t_e > \lambda_2/\lambda_3 \geq 1, so\ 1 \leq i \leq n_s$$



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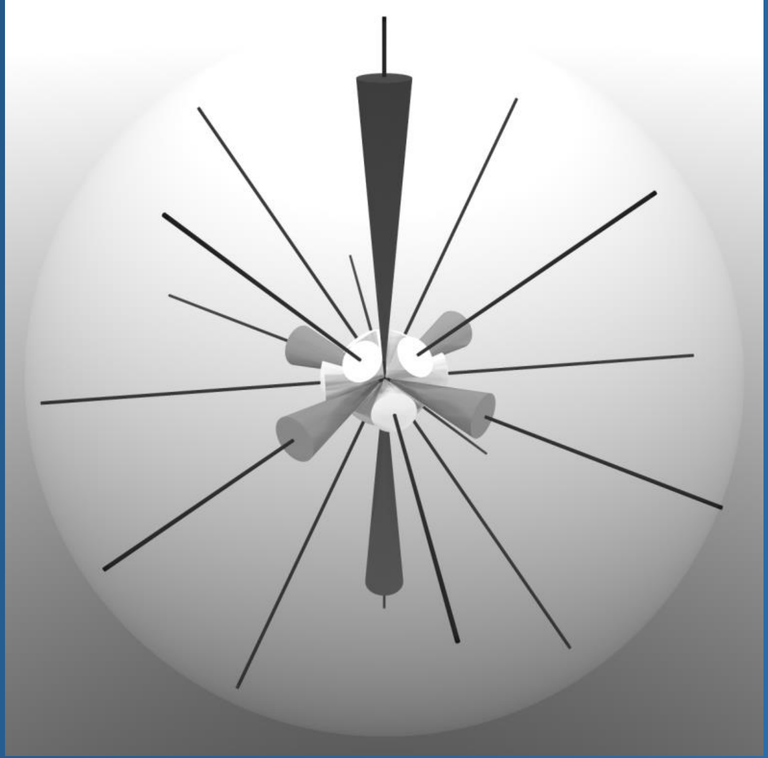
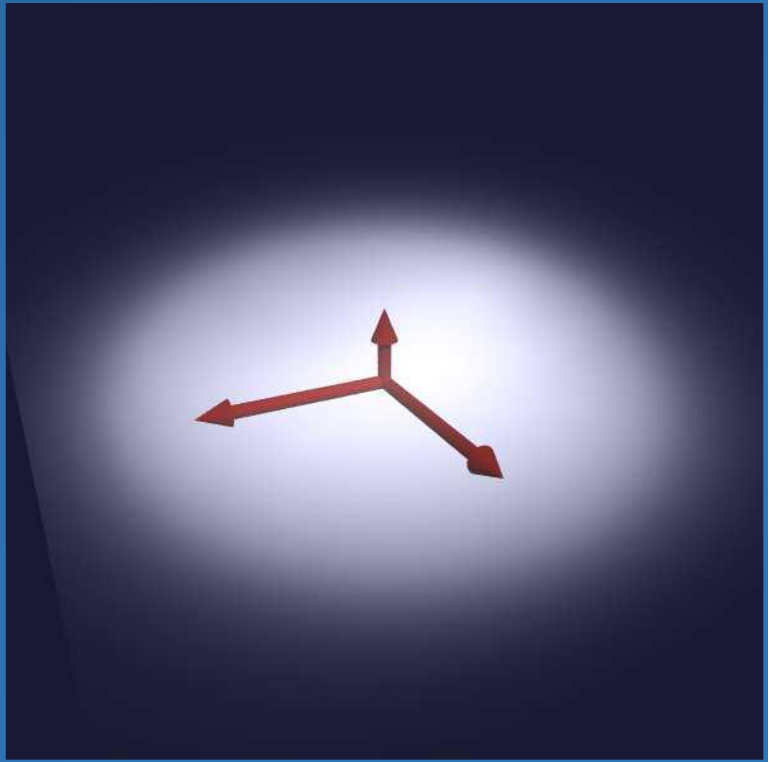
planar subclasses

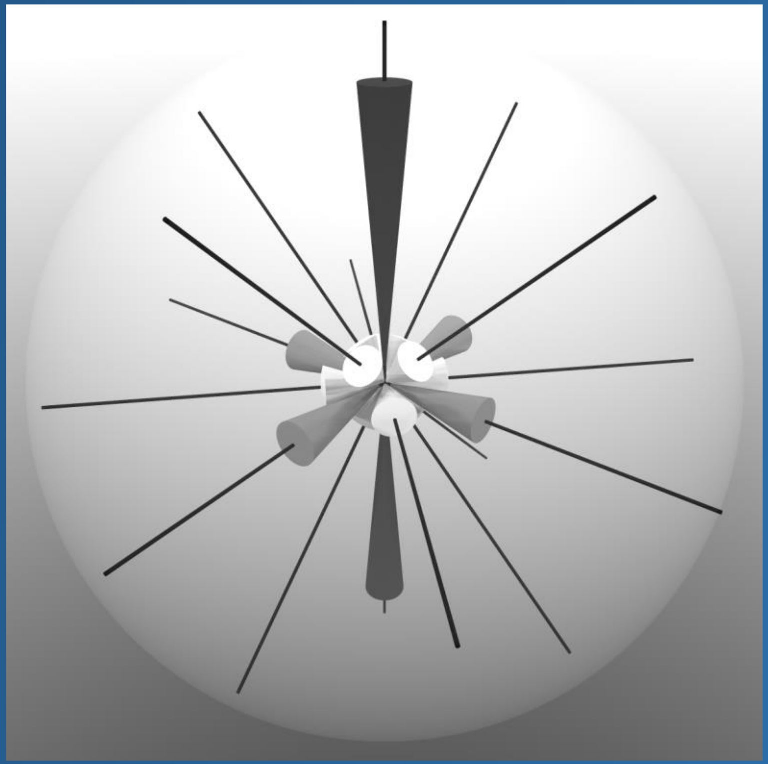


$$P = \{\pi_1, \ldots, \pi_{n_p}\}$$

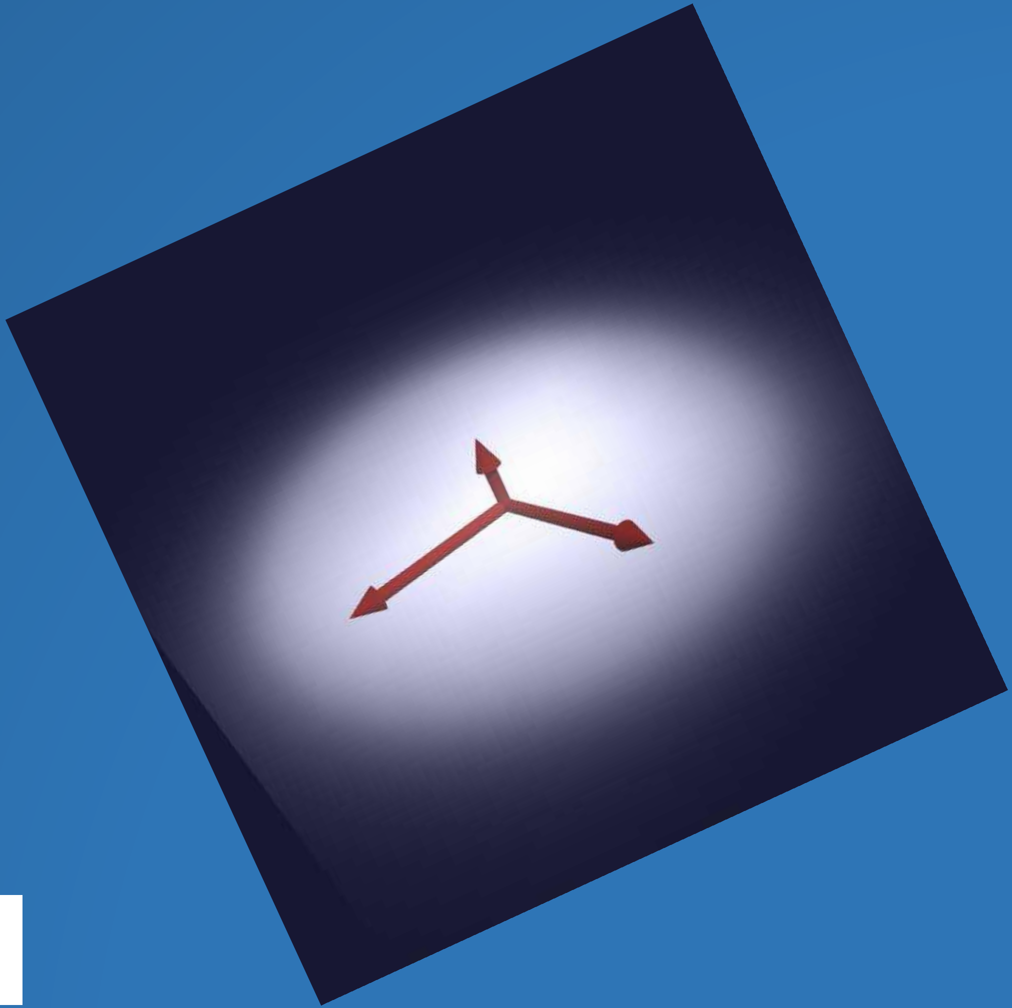


$$i = n_s + \arg\min_j d(\vec{e}_1, \boldsymbol{\pi}_j),$$

Is it rotation invariant?



Nope



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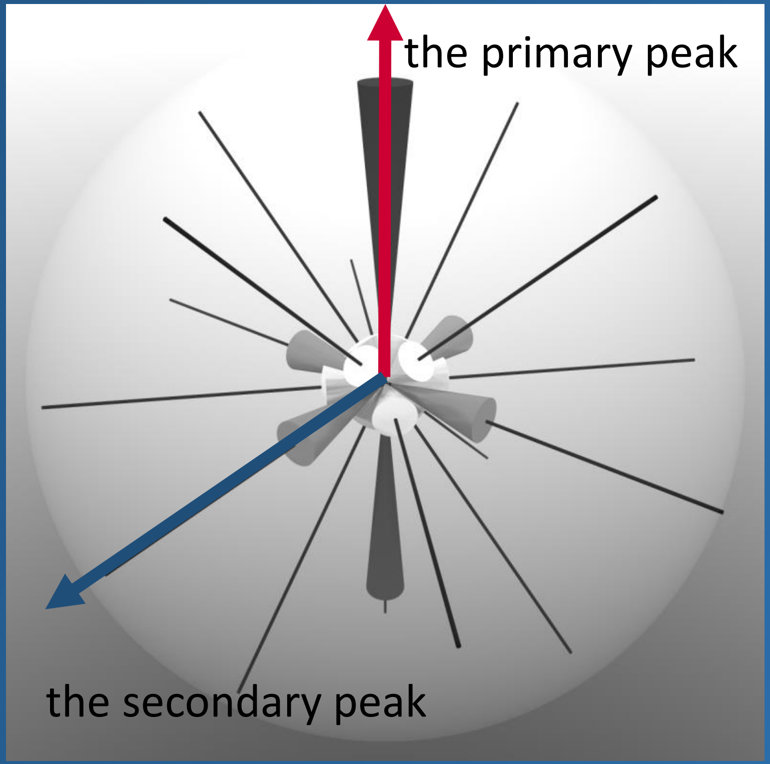
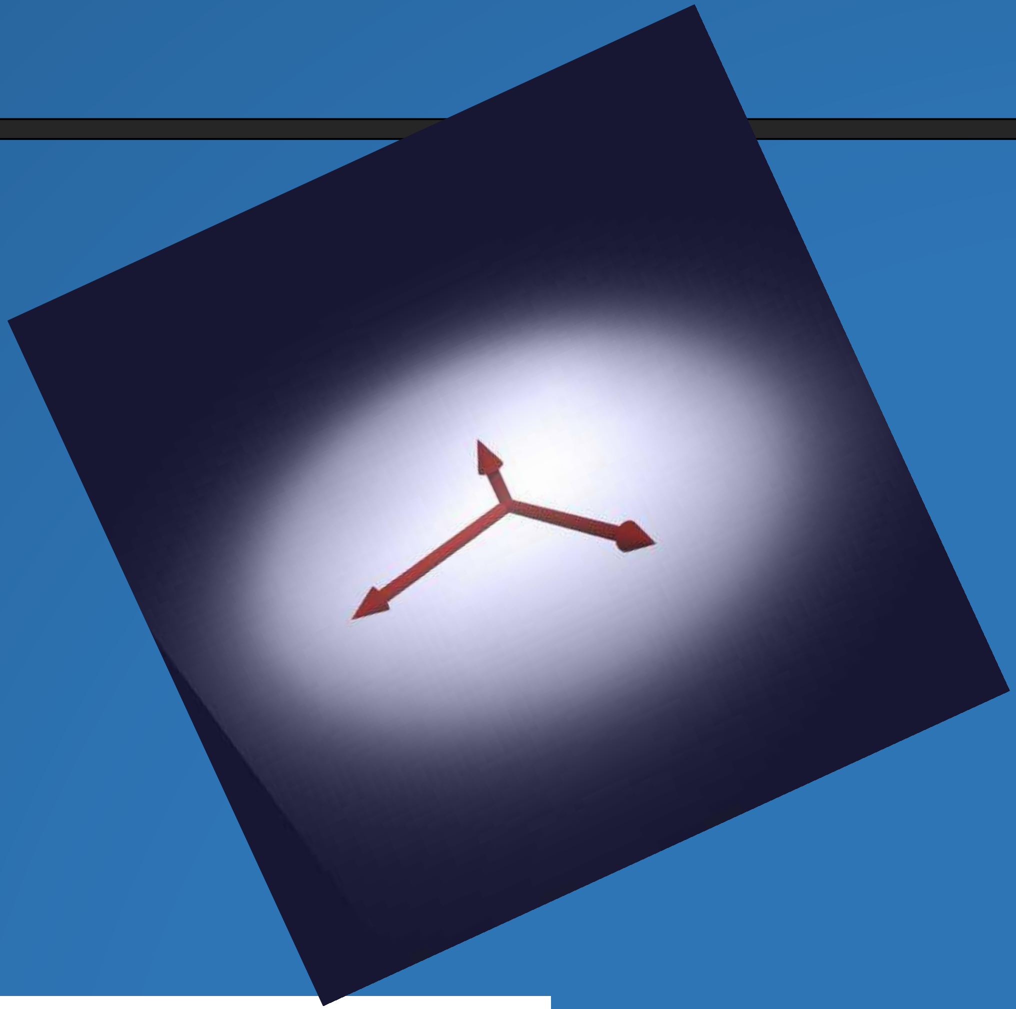
Rotation invariance





$$R_z = \left(\vec{\pi}_i \times \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, -\arccos\left(\vec{\pi}_i \cdot \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right) \right),$$

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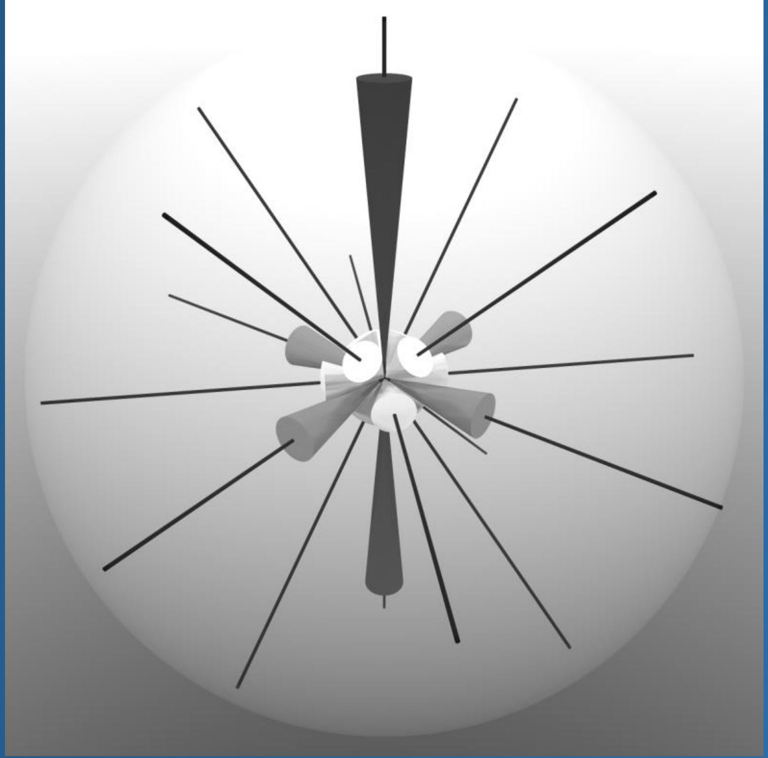
linear subclasses



$$L = \{l_1, \dots, l_{n_l}\}$$

$$i = n_s + n_l + \arg\min_j d(\vec{e}_3, \boldsymbol{\lambda}_j).$$

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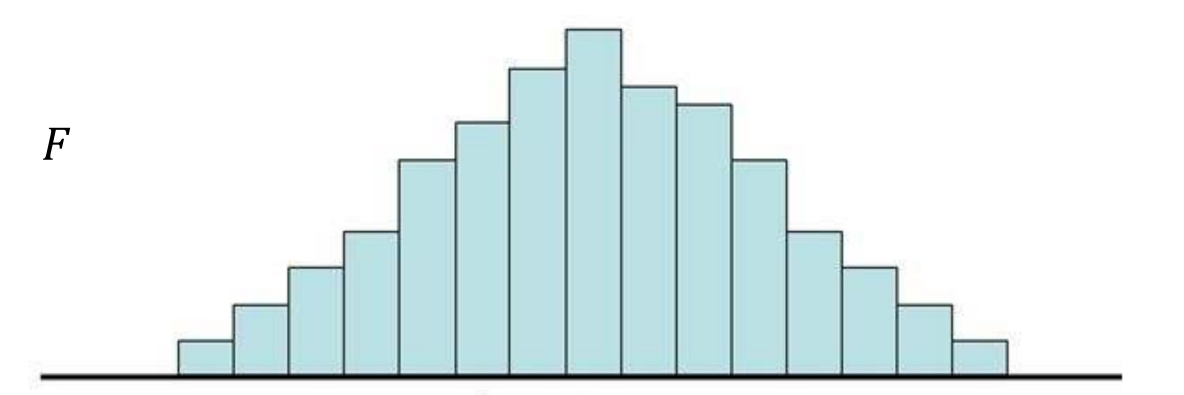
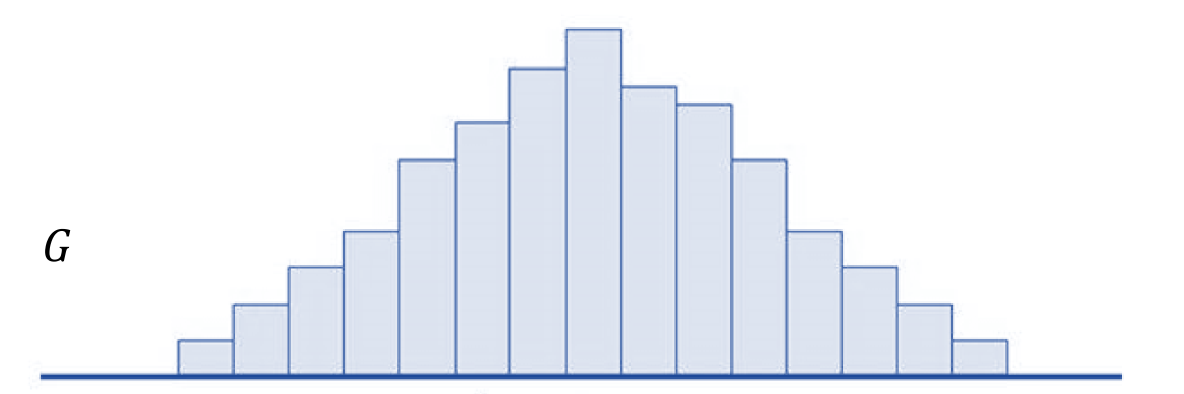
planar distributions are more descriptive than linear ones

Difference measure

$$\delta(\mathbf{F},\mathbf{G}) = \sum_{i=1}^{n_r} \left(\left\| \frac{\vec{f}_i}{\|\mathbf{F}\|_1} - \frac{\vec{g}_i}{\|\mathbf{G}\|_1} \right\|_2 \right) \frac{\max\left(\|\mathbf{F}\|_1 , \|\mathbf{G}\|_1 \right)}{\min\left(\|\mathbf{F}\|_1 , \|\mathbf{G}\|_1 \right)}$$





$$\Delta(\mathcal{X}_1, \mathcal{X}_2) = \min_{i,j} \delta(\mathbf{F}_i, \mathbf{G}_j) \qquad \mathbf{F}_i \in \mathcal{F},\ \mathbf{G}_j \in \mathcal{G}$$

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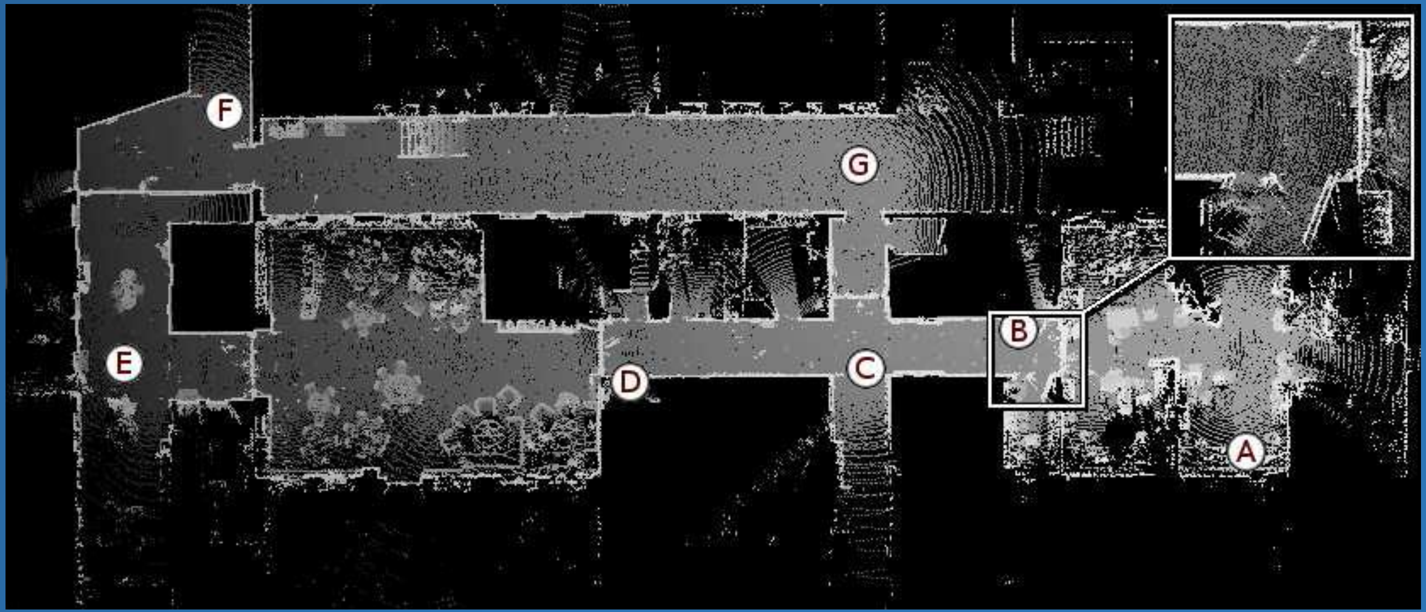
Parameters

- NDT cell size $B = 0.5$ m,
- range limits $\boxed{\mathcal{R} = \{[0, 3), [3, 6), [6, 9), [9, 15), [15, \infty)\} \text{ m},}$
- spherical class count $n_s = 1$,
- planar class count $n_p = 9$,
- linear class count $n_l = 1$,
- eigenvalue-ratio threshold $t_e = 0.10$,
- ambiguity-ratio threshold $t_a = 0.60$.

Results

Data sets

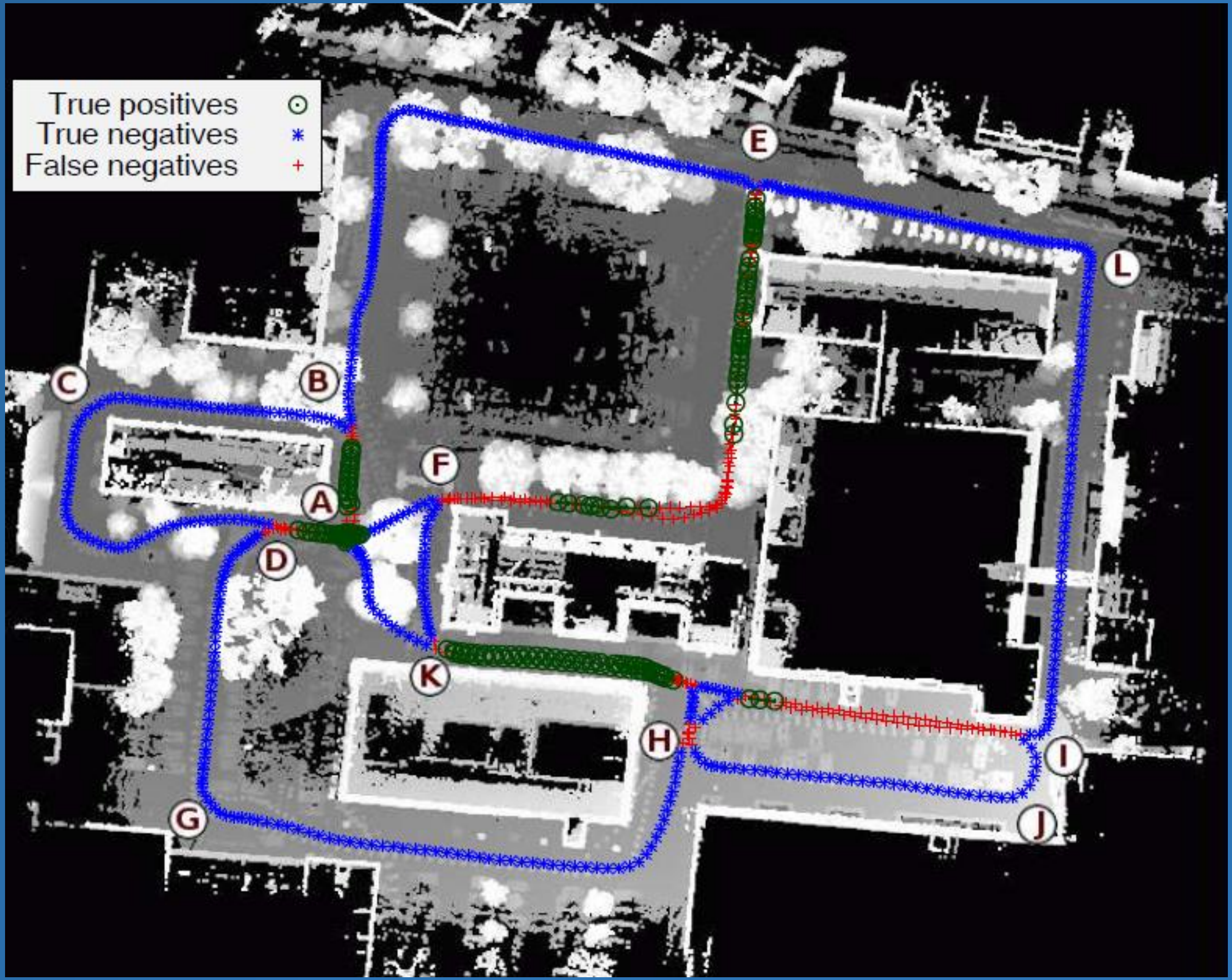
Hannover-2



AASS-Loop

Detection Results

A-B-C-D-A-B-E-F-A-D-G-H-I-J-H-K-F-E-L-I-K-A



True positives

False positives ×

True negatives

False negatives

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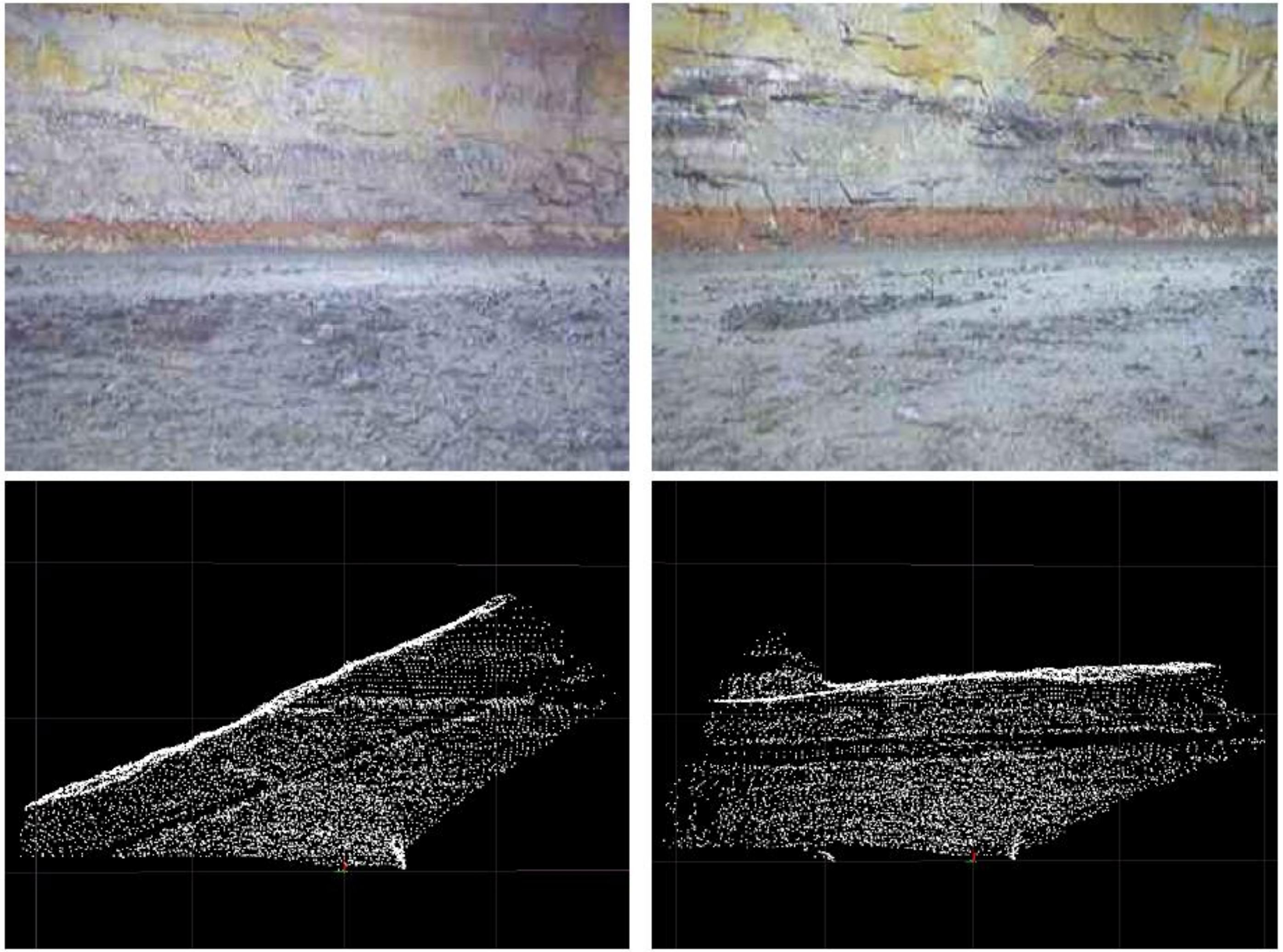
Problem encountered

$$\Delta(X, \hat{X}) < t_d$$

What is the best difference threshold?



(a) Location F (b) Location H

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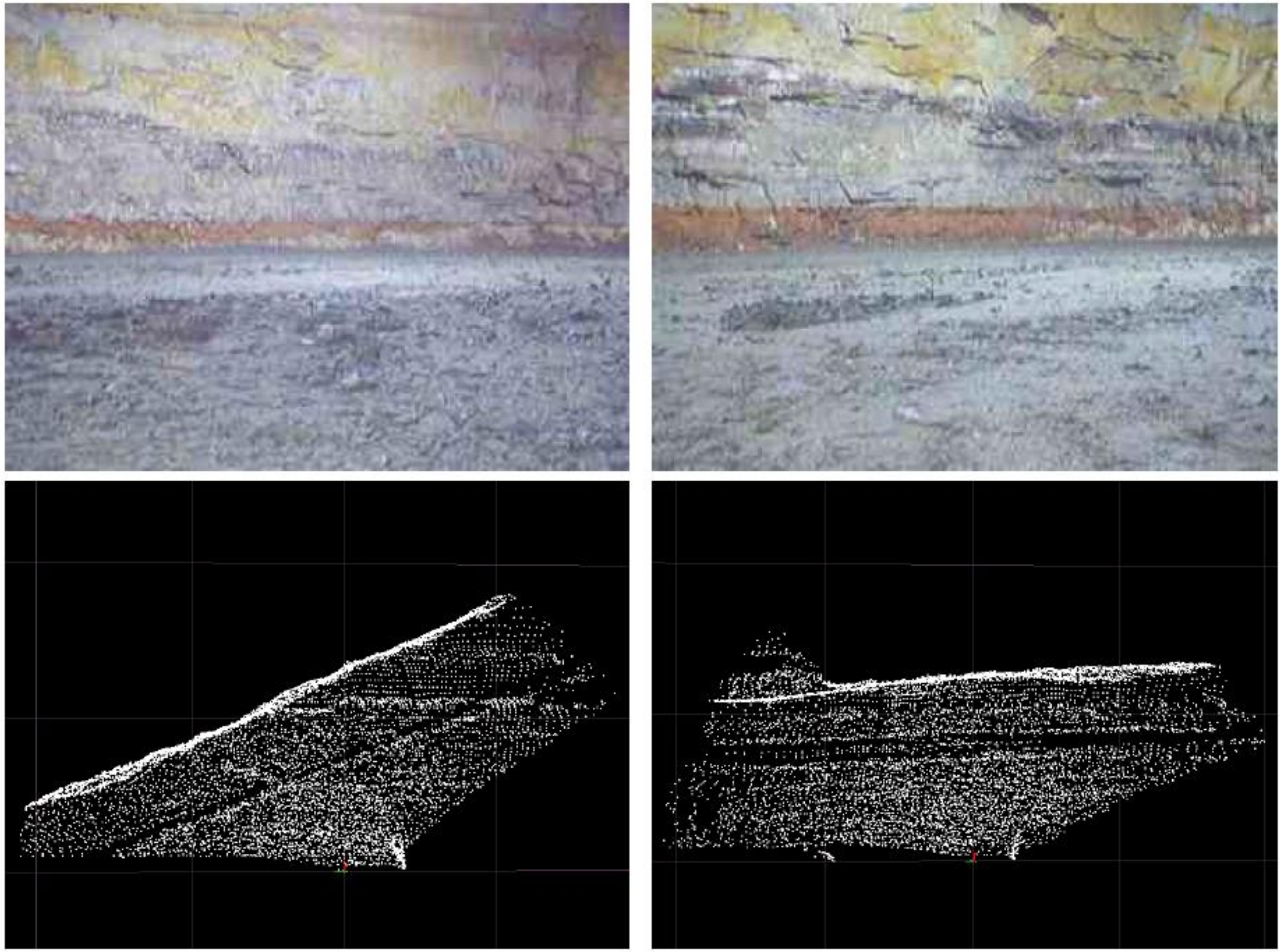
Problem encountered

$$\Delta(X, \hat{X}) < t_d$$

What is the best difference threshold?



(a) Location F (b) Location H

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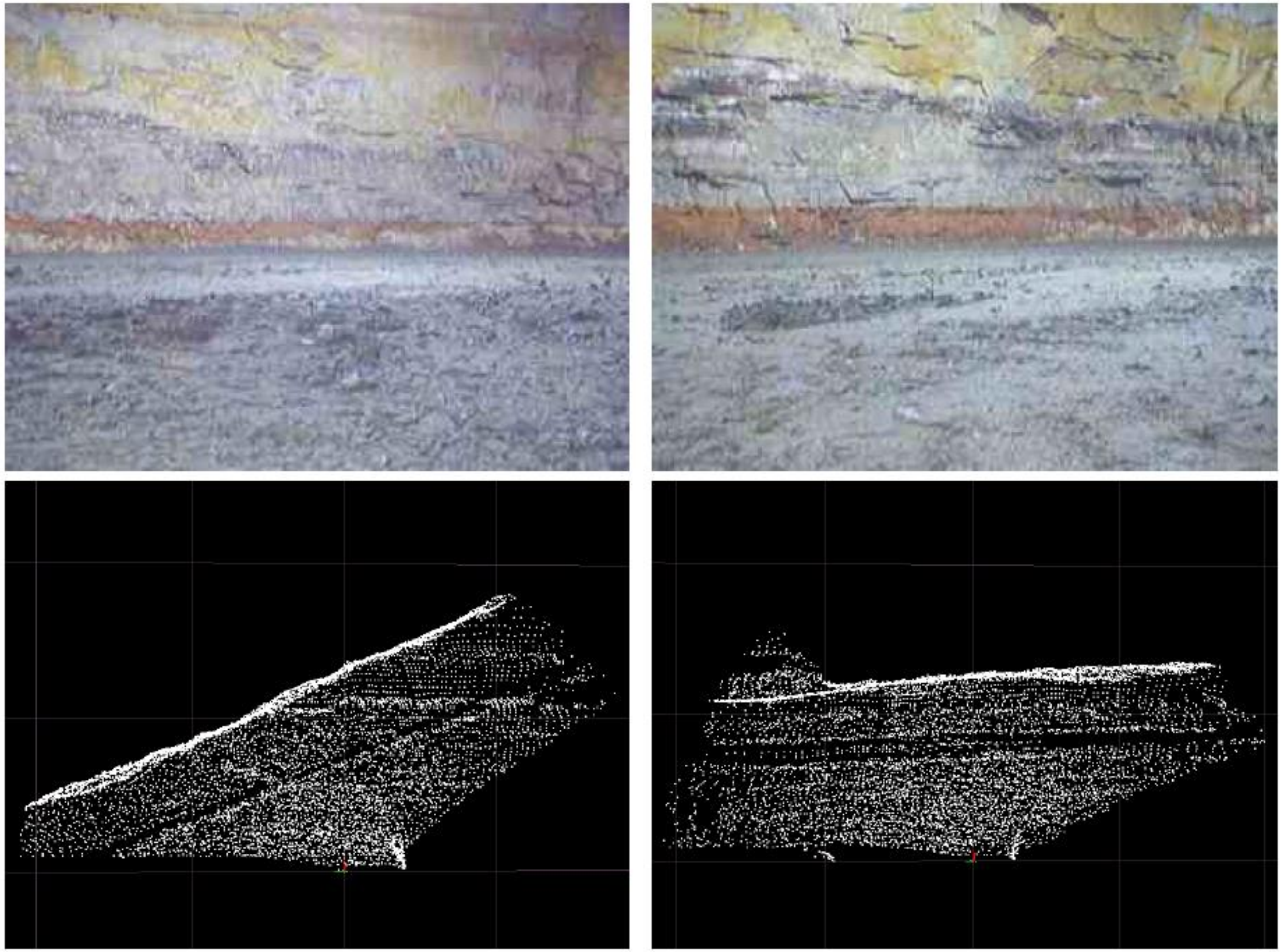
Problem encountered

$$\Delta(X, \hat{X}) < t_d$$

What is the best difference threshold?

10m below the threshold = Positive



(a) Location F (b) Location H

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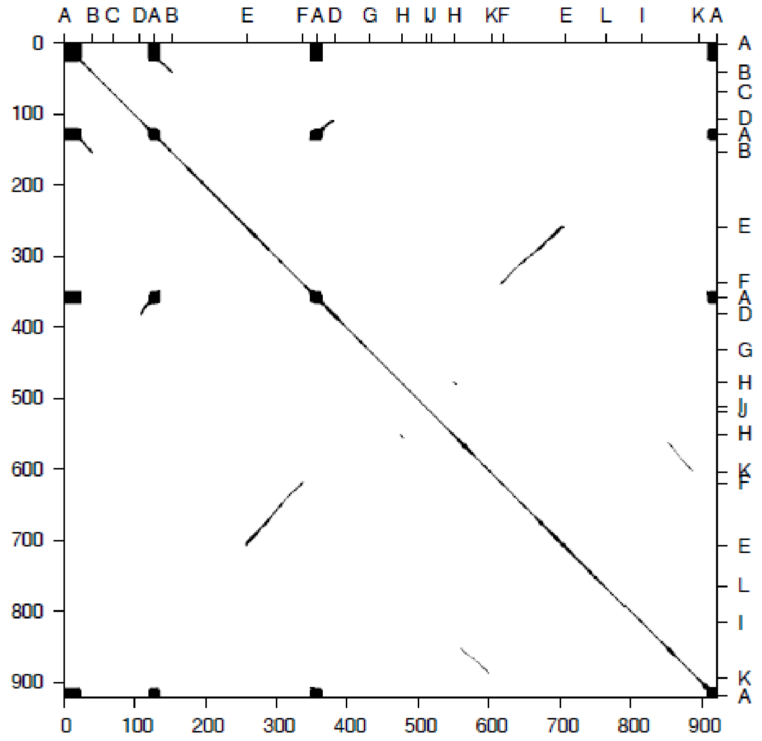
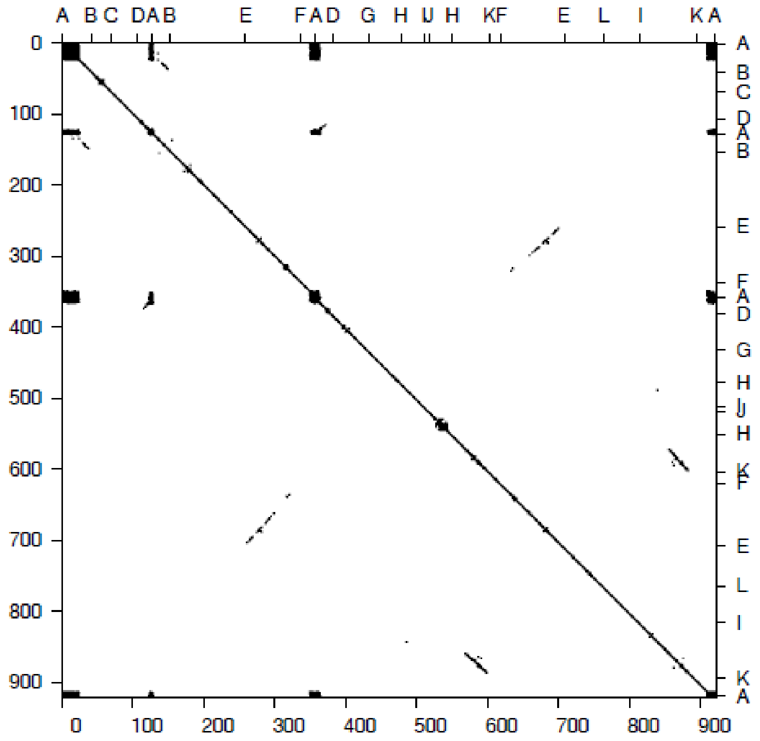
Final results



(a) Thresholded ground-truth distance matrix of Hannover-2, showing all scan pairs taken less than 3 m apart.



(b) Similarity matrix of Hannover-2, showing all scan pairs whose difference value $\Delta < 0.0737$.

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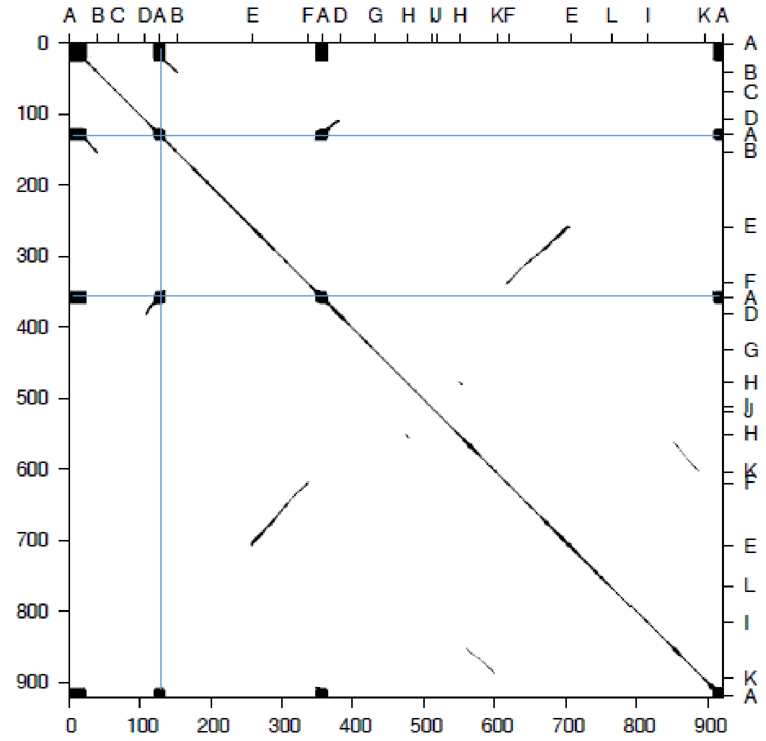
Final results



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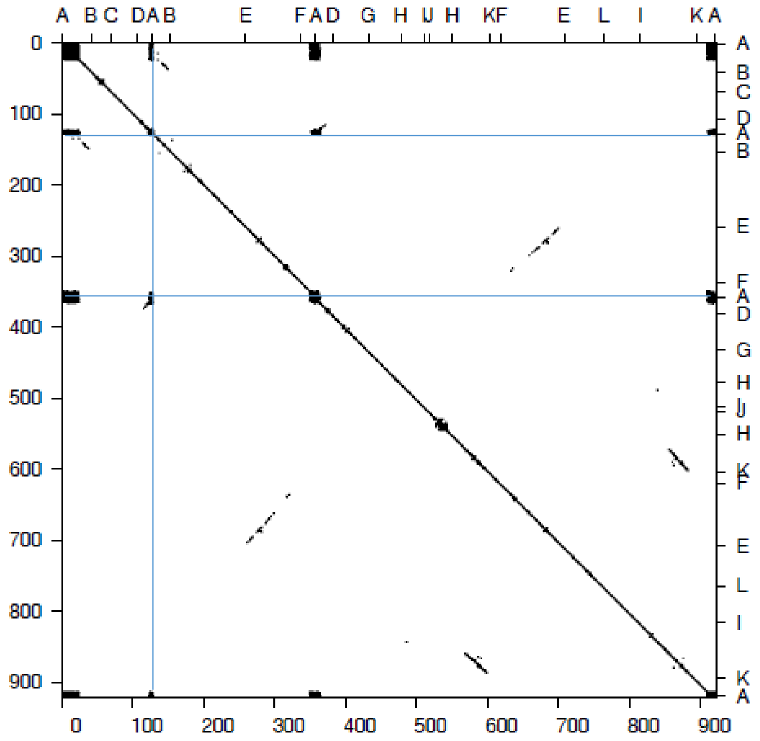

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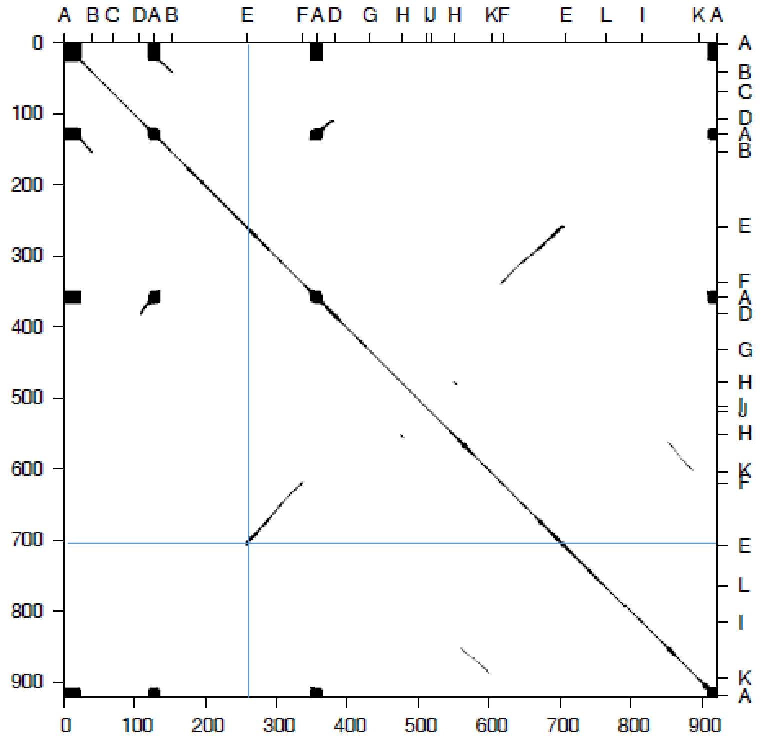
Final results



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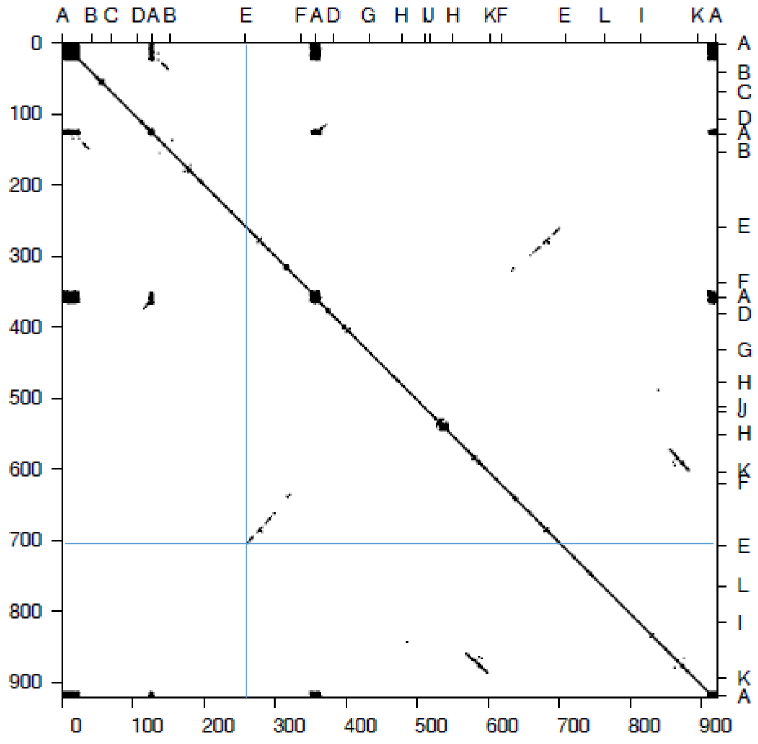

(b) Similarity matrix of Hannover-2, showing all scan pairs whose difference value $\Delta < 0.0737$.

Future Expectation

The author's expectation

1. Different methods（automatic parameter）
2. Different data sets
3. Improving performance
4. Substituting a simple threshold with similarity matrix

Conclusion

1. A typical method of histogram based method
2. Main problems of loop closure detection

Tks!

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To be continued…