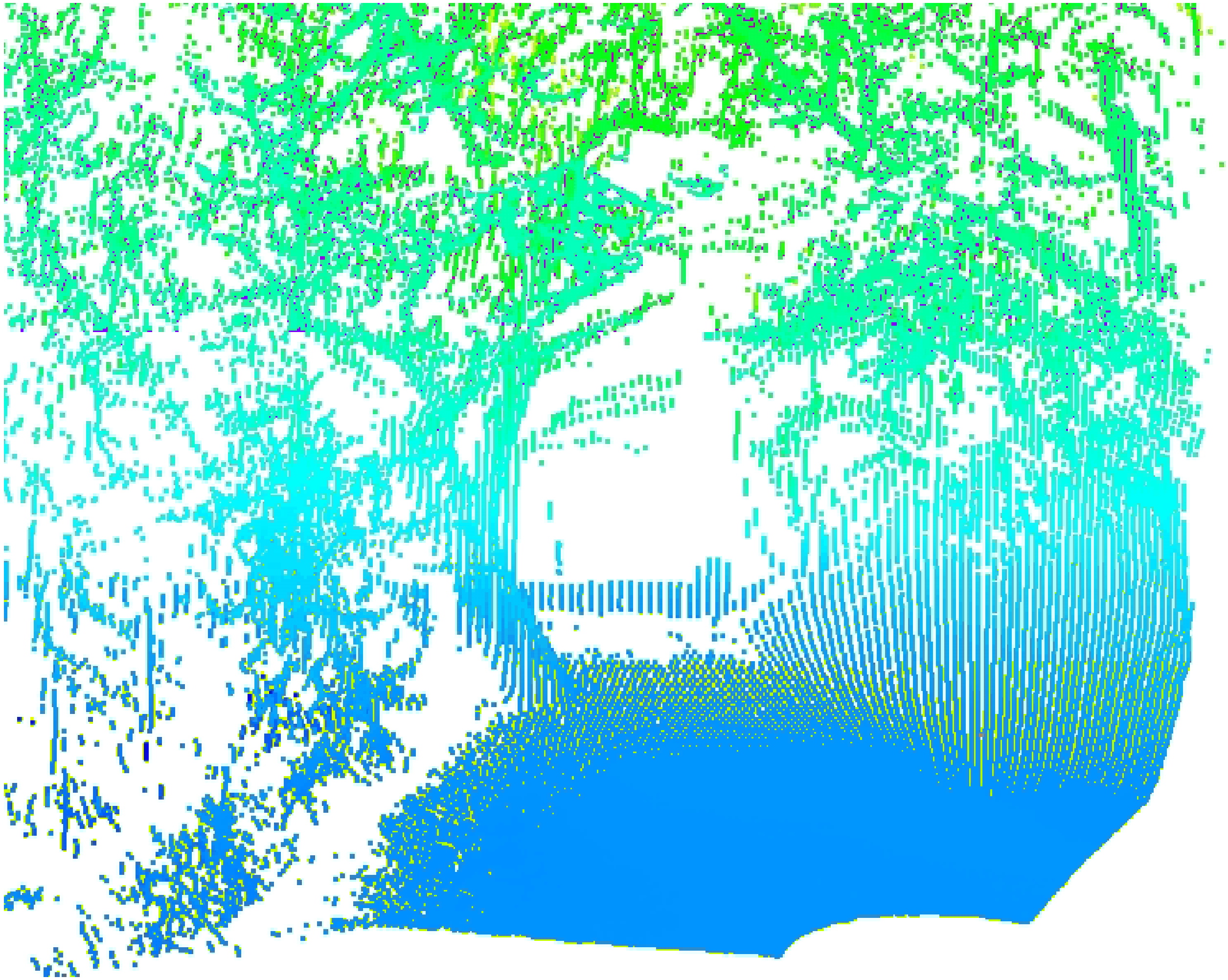
Scale Selection for Classification of Point-sampled 3-D Surfaces

Jean-François Lalonde, Ranjith Unnikrishnan,
Nicolas Vandapel and Martial Hebert

Carnegie Mellon University

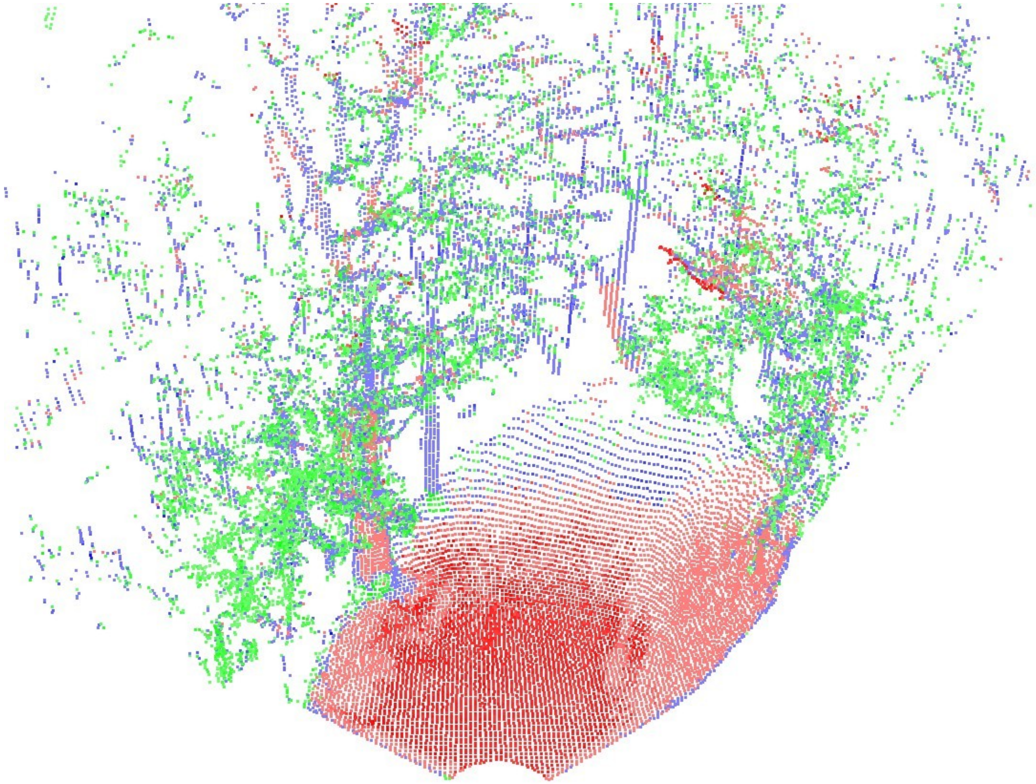
Problem

Processing of large 3-D point cloud data from ladar



Example

- Terrain classification
  - Through local processing [Vandapel-ICRA04]

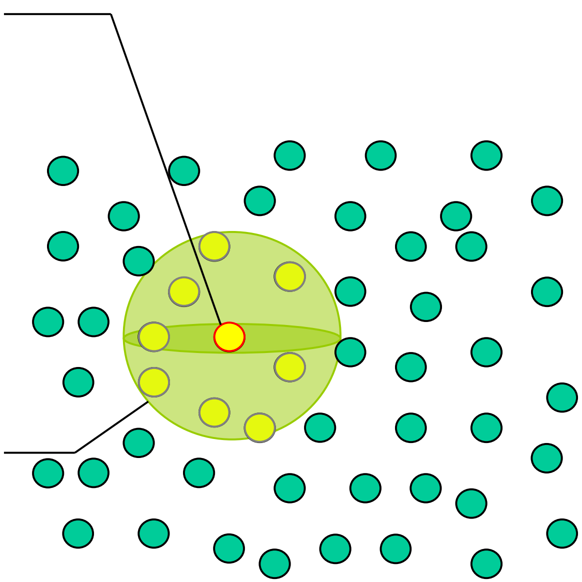


vegetation
linear
surface

Local computation on 3-D point sets

Point of interest
Scan through all points in the dataset

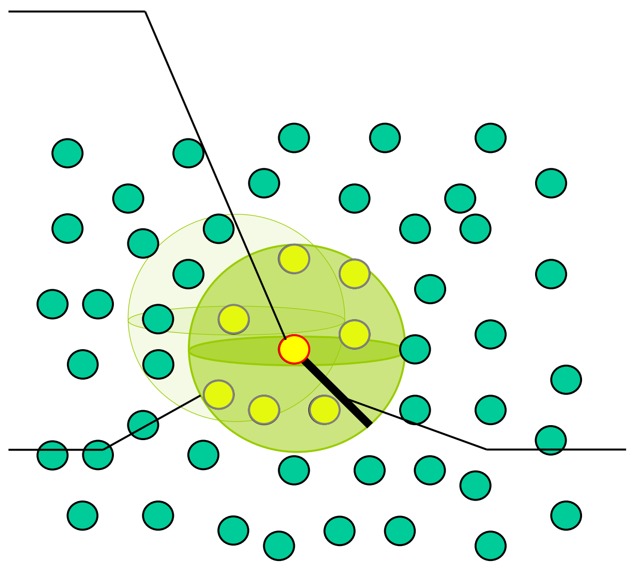
Support region
Local computation on highlighted points



Local computation on 3-D point sets

Point of interest
Scan through all points in the dataset

Support region
Local computation on highlighted points

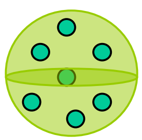


Scale
Radius of support region

Terrain classification

- Compute scatter matrix within support region
- Extract principal components
- Features are linear combination of eigenvalues [Tang-PAMI04]

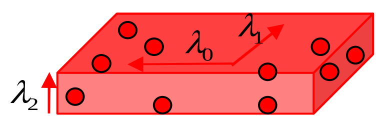
$\lambda_0 \approx \lambda_1 \approx \lambda_2$



$F_{scatter} = \lambda_0$

Scatter

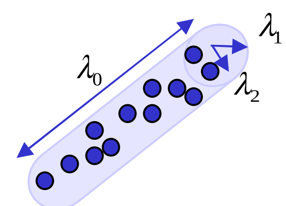
$\lambda_0 \approx \lambda_1 >> \lambda_2$



$F_{planar} = (\lambda_1 - \lambda_2) \cdot e_2$

Planar

$\lambda_0 >> \lambda_1 \approx \lambda_2$

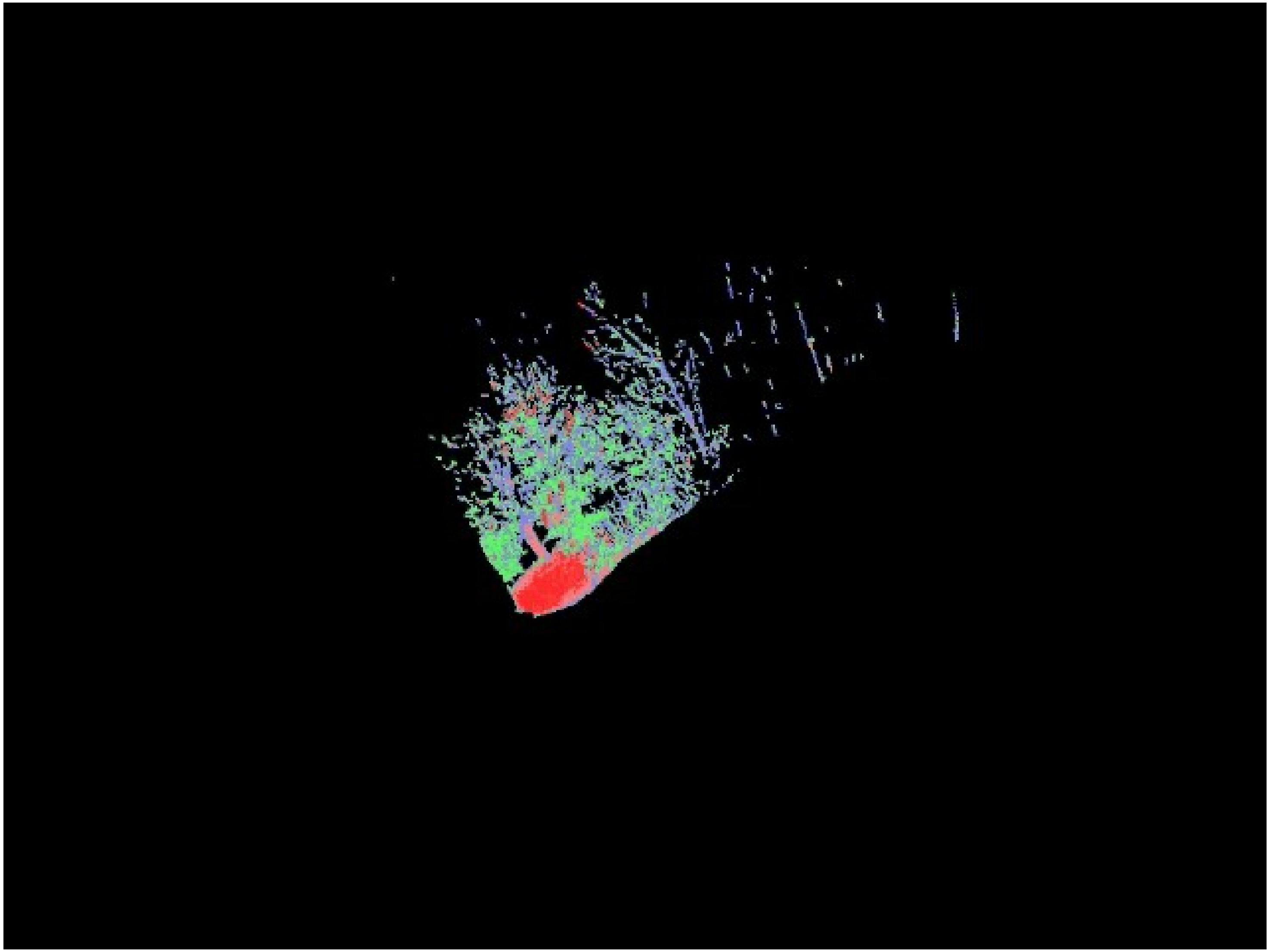


$F_{linear} = (\lambda_0 - \lambda_1) \cdot e_0$

Linear

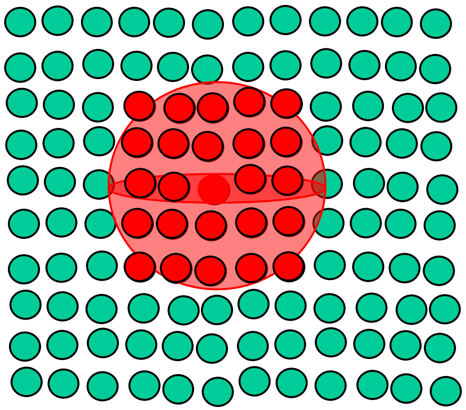
- Train a GMM classifier on hand-labelled data using EM
- Classification: maximum likelihood class
- Scale is fixed

Problems with fixed scale

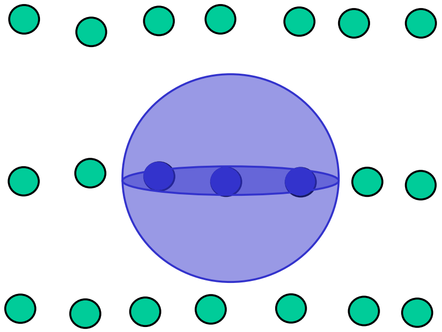


Problems with fixed scale

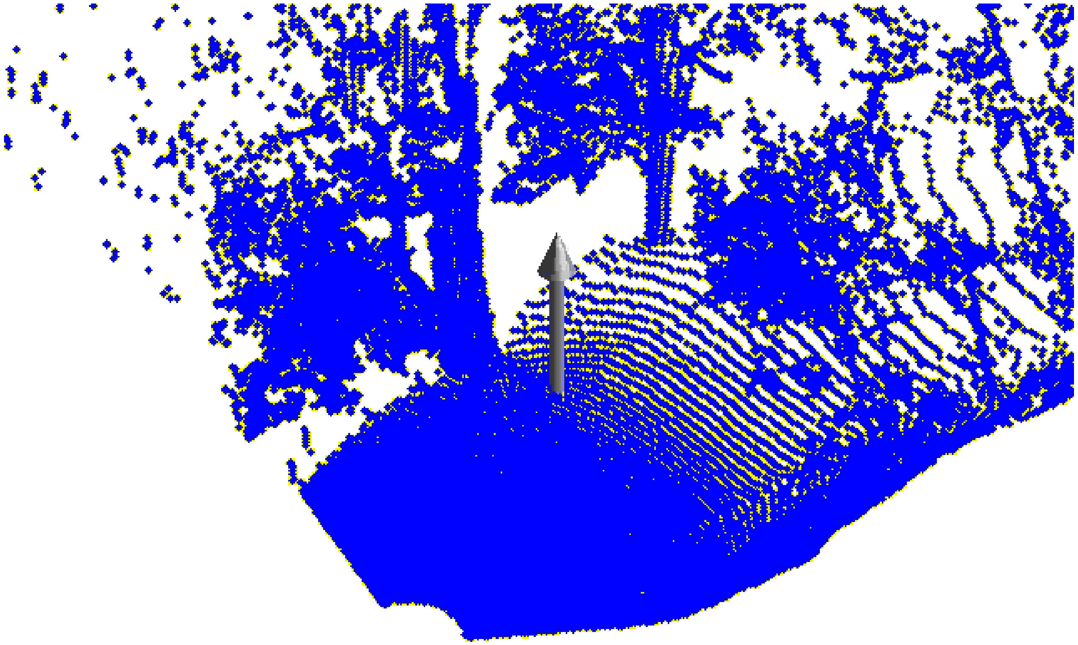
High density



Low density



What is the best support region size?

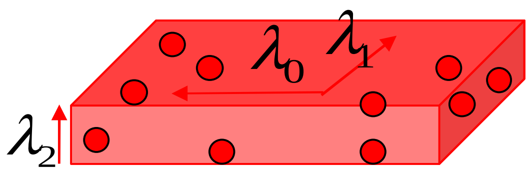


- Scale theory well-known in 2-D [Lindeberg-PAMI90, Lindeberg-JAS94]
- No such theory in 3-D
  - some methods exist [Tang-ICRA04, Pauly-Eurographics03]

Approach

- Focus analysis to surfaces
  - Larger source of errors

$$\lambda_0 \approx \lambda_1 >> \lambda_2$$



$$F_{\text{planar}} = (\lambda_1 - \lambda_2) \cdot e_2$$

  - Closely related to normal estimation
- Extend method for optimal scale selection for normal estimation [Mitra-IJCGA05]

[Mitra-IJCGA05] N. Mitra, A. Nguyen and L. Guibas, Estimating surface normals in noisy point cloud data. *Intl. Journal of Computational Geometry and Applications (to appear)*, 2005.

Optimal scale selection for normal estimation [Mitra-IJCGA05]

- Analytic expression for optimal scale

$$r = \left(\frac{1}{\kappa} \left(\theta_3 \frac{\sigma_n}{\sqrt{\varepsilon\rho}} + \frac{\theta_4}{2} \sigma_n^2 \right) \right)^{\frac{1}{3}}$$

r
Estimated scale

κ
Estimated local curvature*

ρ
Estimated local density

$\boldsymbol{\sigma_n}$
Sensor noise

known
unknown

* Curvature estimation from [Gumhold-01]

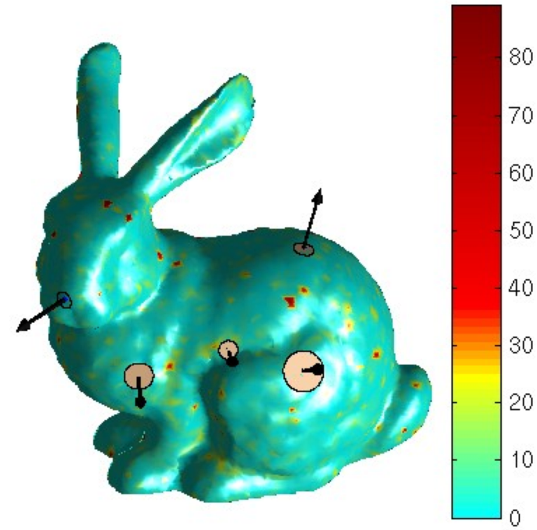
Algorithm [Mitra-IJCGA05]

- Initial value of $k=k^{(i)}$ nearest neighbors
- Iterative procedure
  - Estimate curvature $\kappa^{(i)}$ and density $\rho^{(i)}$
  - Compute $r^{(i+1)}$
  - $k^{(i+1)}$ is number of points in neighborhood of size $r^{(i+1)}$

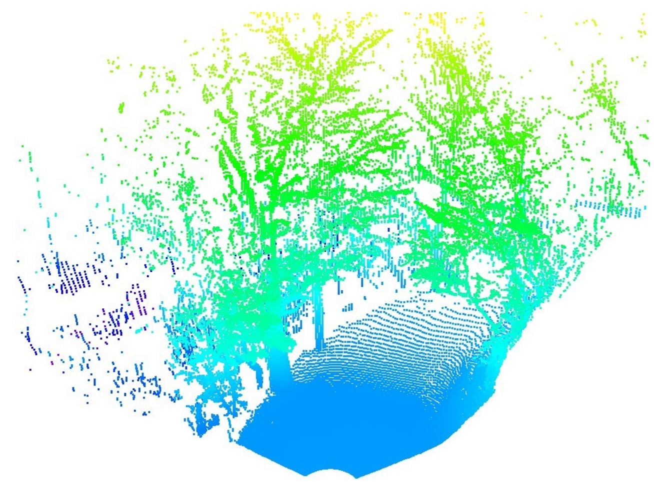
iteration i

Algorithm [Mitra-IJCGA05]

- Works well for
  - Minimum spatial density (no ho
  - No discontinuities
  - Small noise and curvature

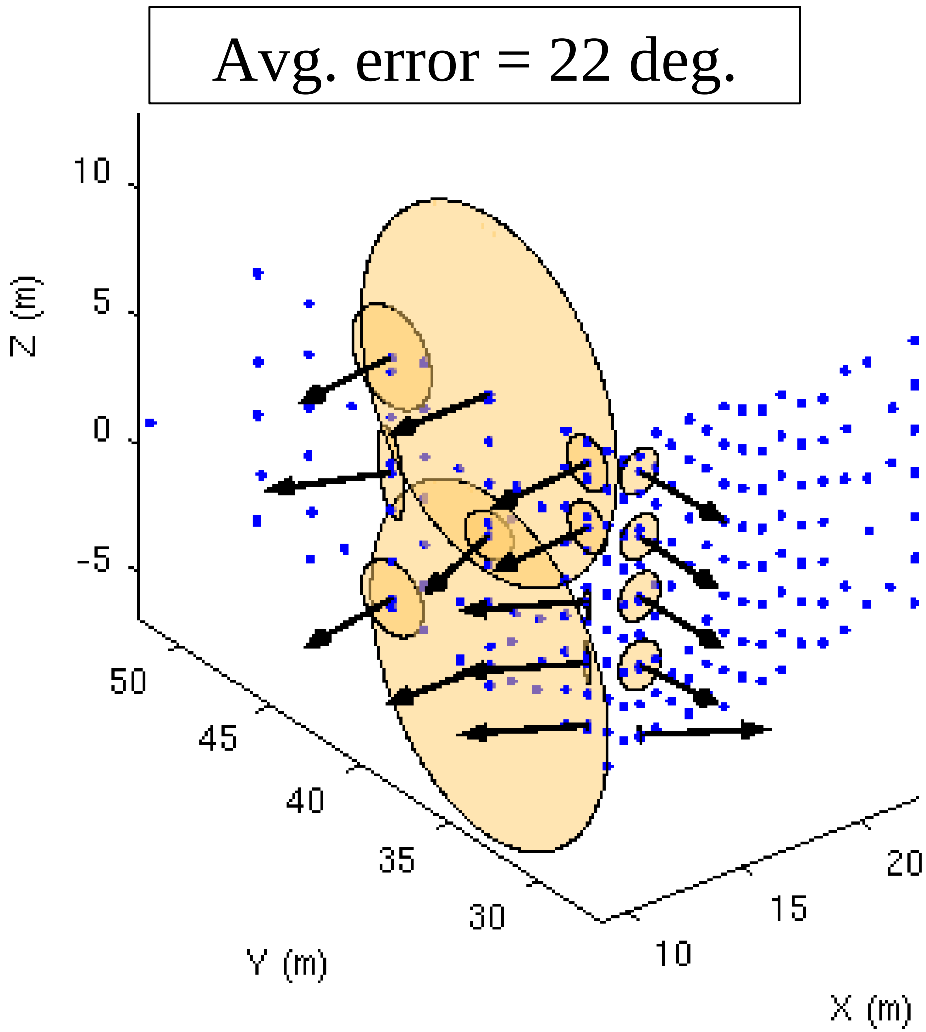


- Real-world data
  - High density variation
  - Holes
  - Unbounded curvature
  - Discontinuities, junctions

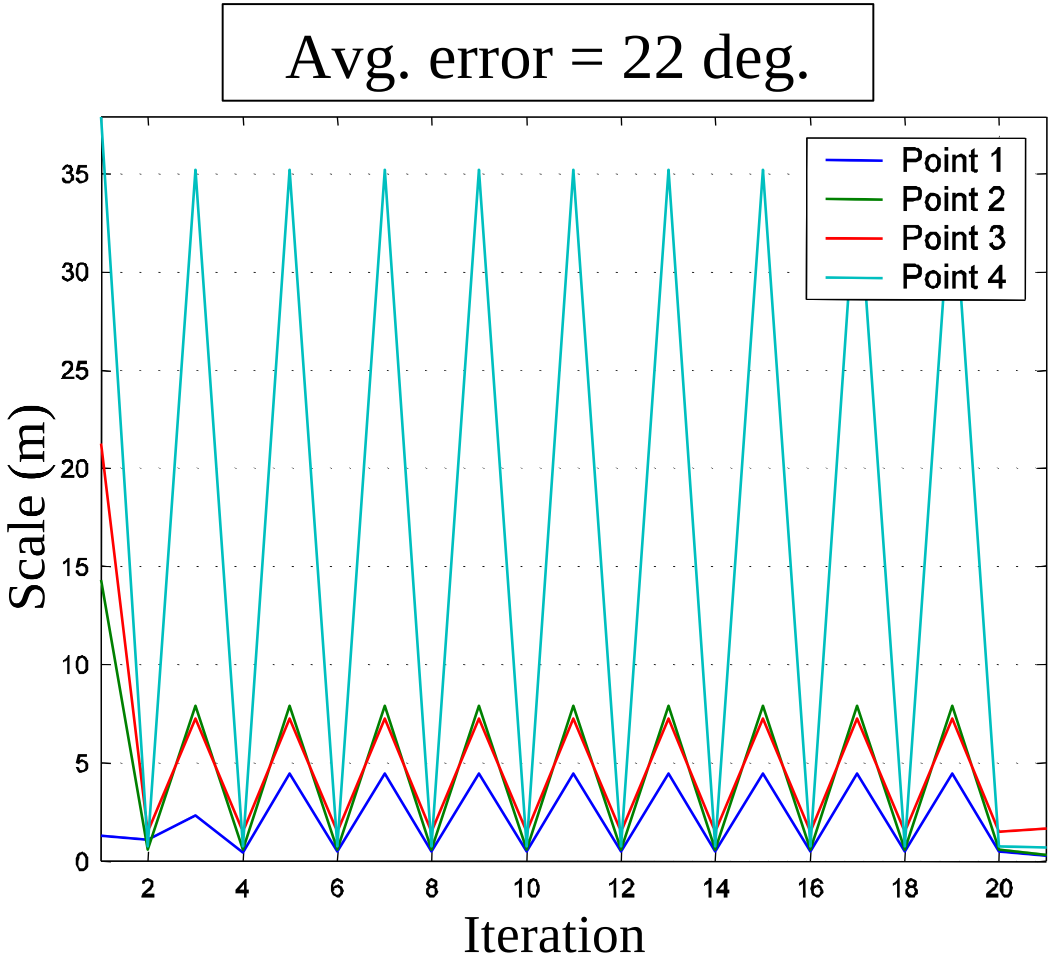


Ladar data

Real-world data, normal estimation



Real-world data, convergence



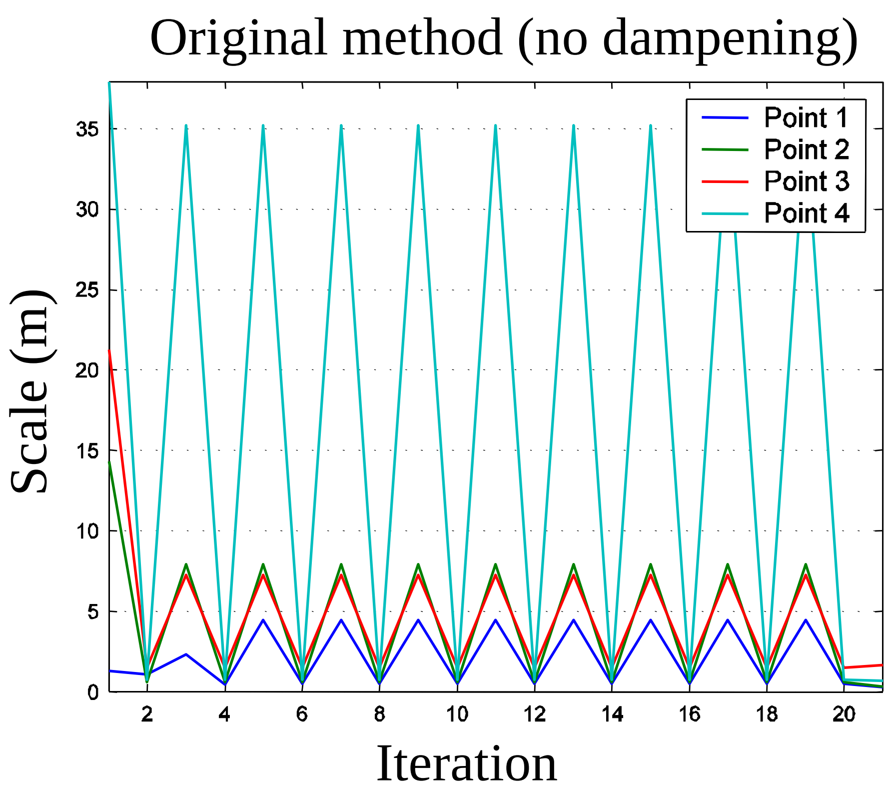
Proposed algorithm

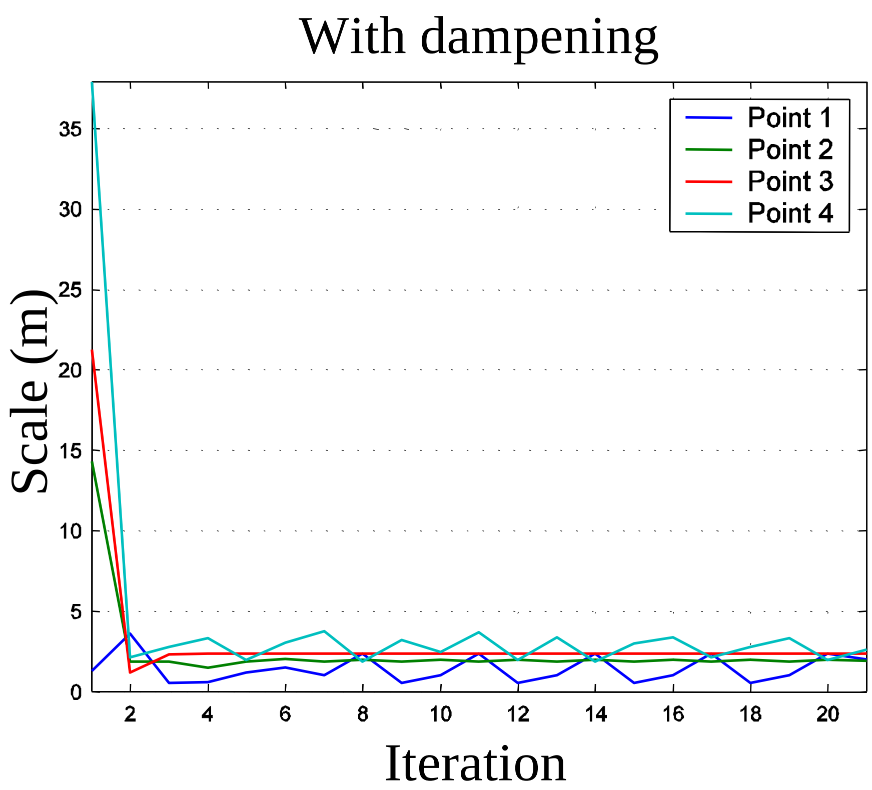
- Initial value of $k=k^{(i)}$
- Iterative procedure
  - Estimate curvature $\kappa^{(i)}$ and density $\rho^{(i)}$
  - Compute $r^{(i+1)}$
  - k_{computed} is number of points in neighborhood of size $r^{(i+1)}$
  - **Dampening on *k*:**

$$k^{(i+1)} = \underbrace{\gamma k_{\text{computed}} + (1-\gamma)}_{} k^{(i)}$$

γ
Dampening factor

Effect of dampening on convergence

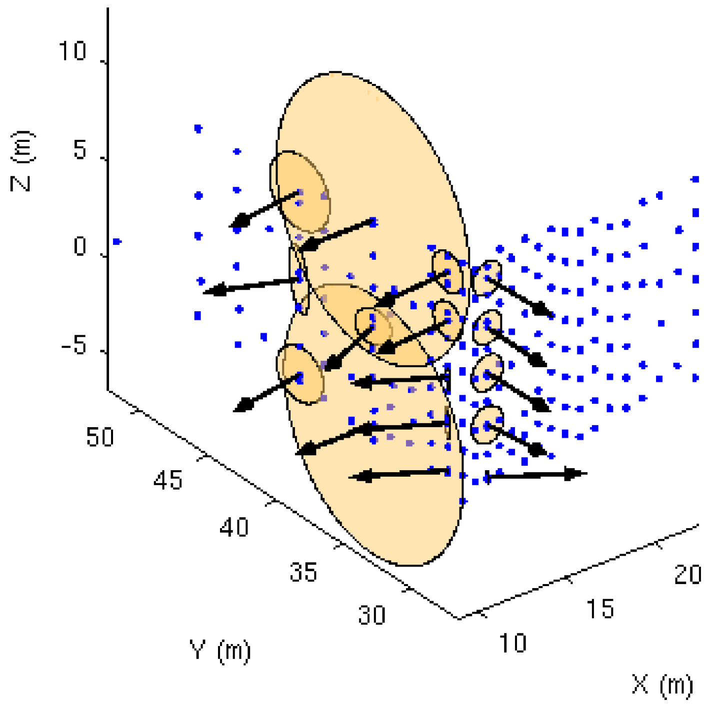




Effect of dampening on normal estimation

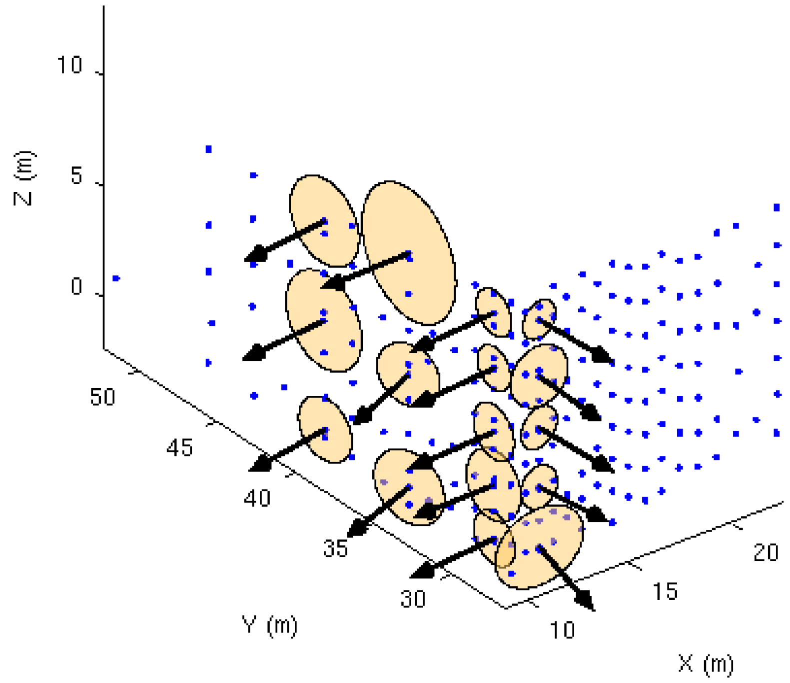
Original method (no dampening)

Avg. error = 22 deg.

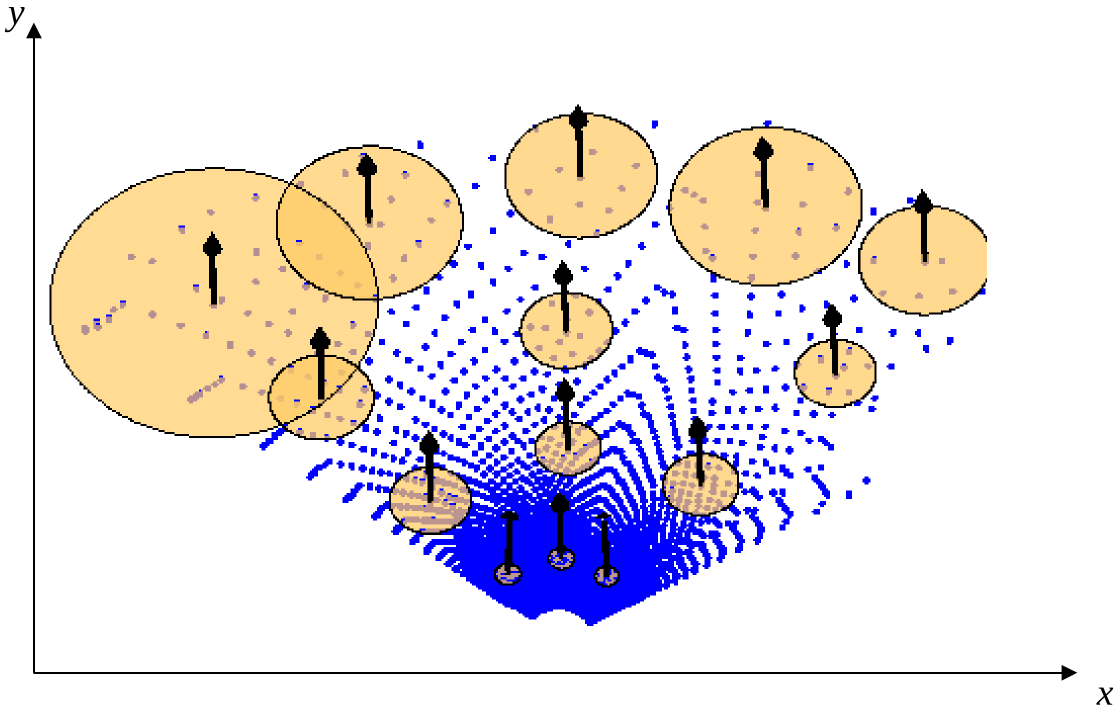


With dampening

Avg. error = 12 deg.



Variation of density

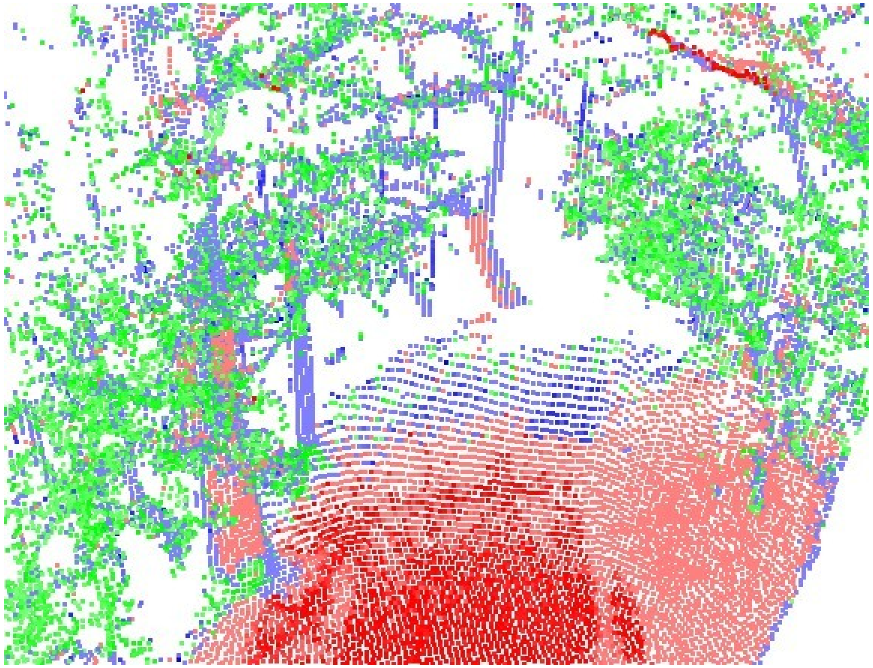


- Data subsampled for clarity
- Normals estimated from support region
- Scale determined by the algorithm

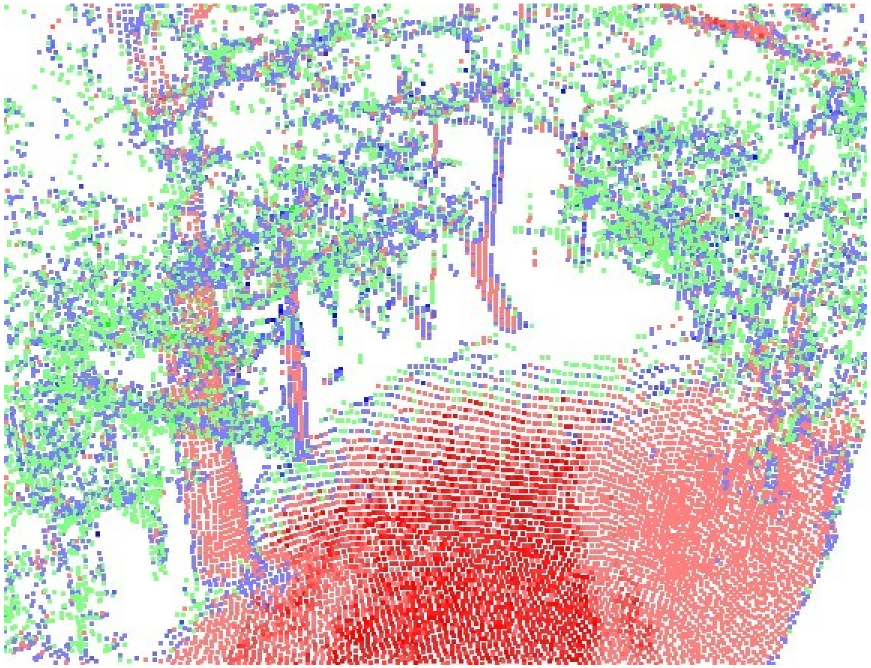
Classification experiments

- SICK scanner

Fixed scale (0.4 m)



Variable scale at each point

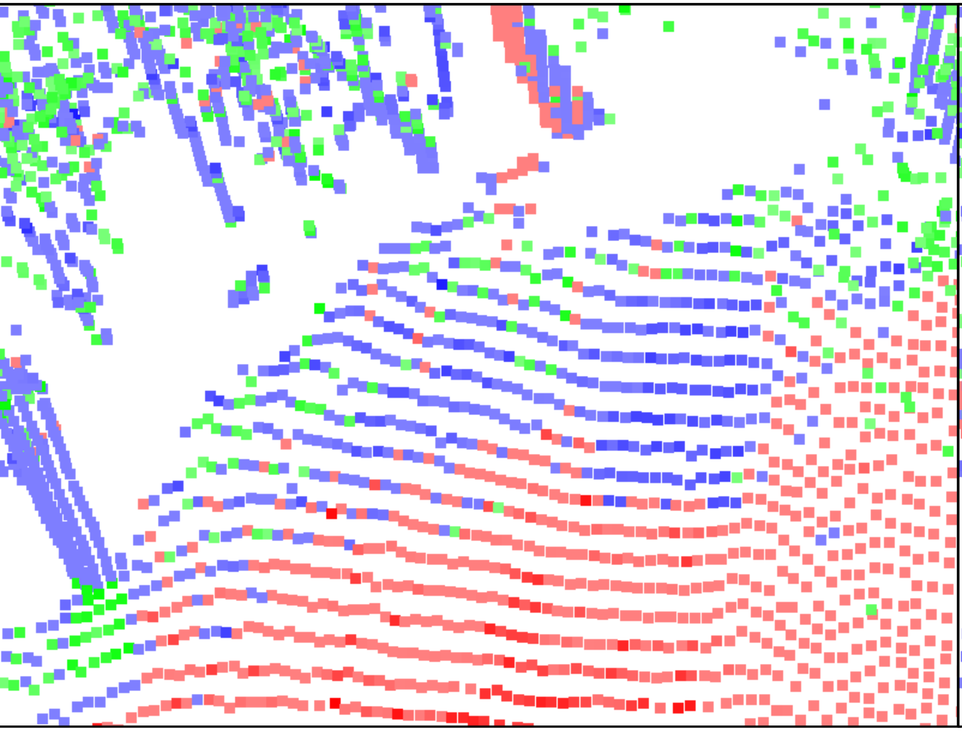


- 0.4m best fixed scale, determined experimentally
- Improvement of 30% for previously misclassified points

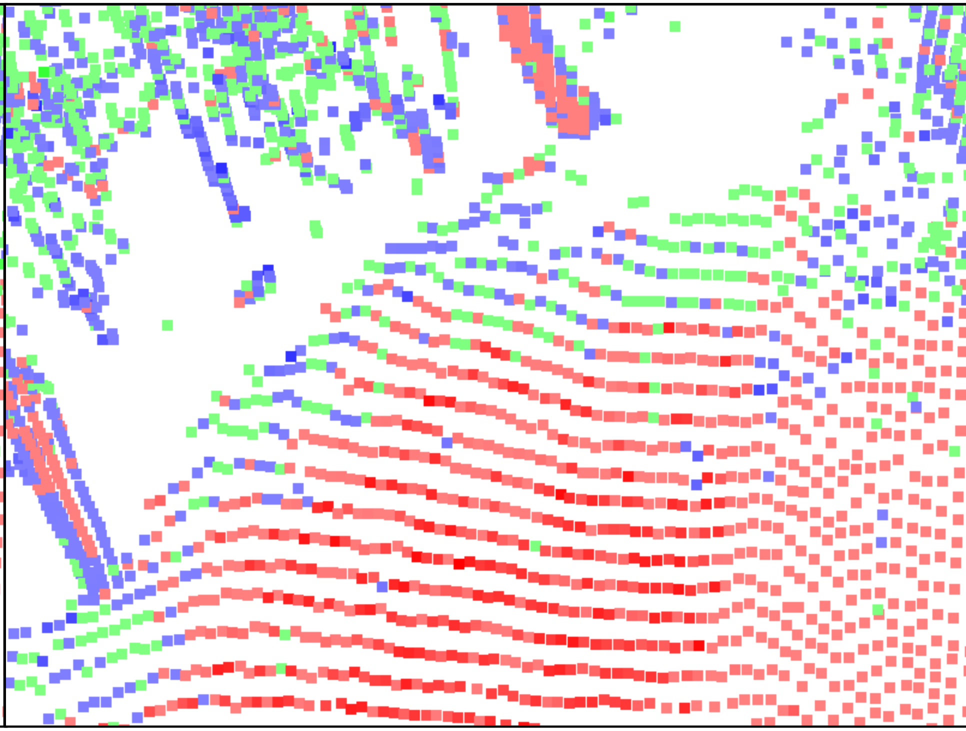
Classification experiments

- SICK scanner

Fixed scale (0.4 m)



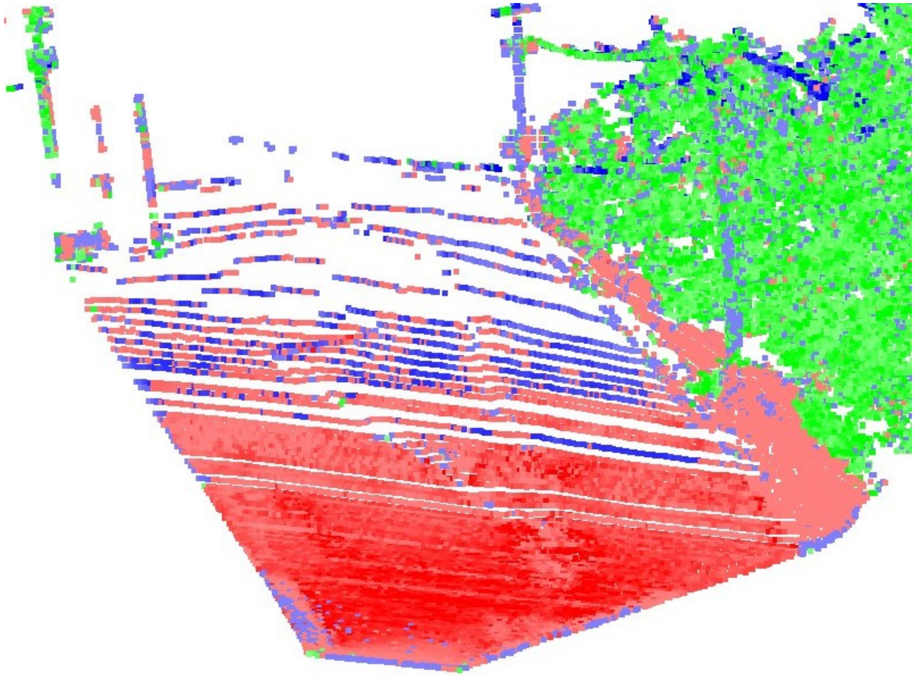
Variable scale at each point



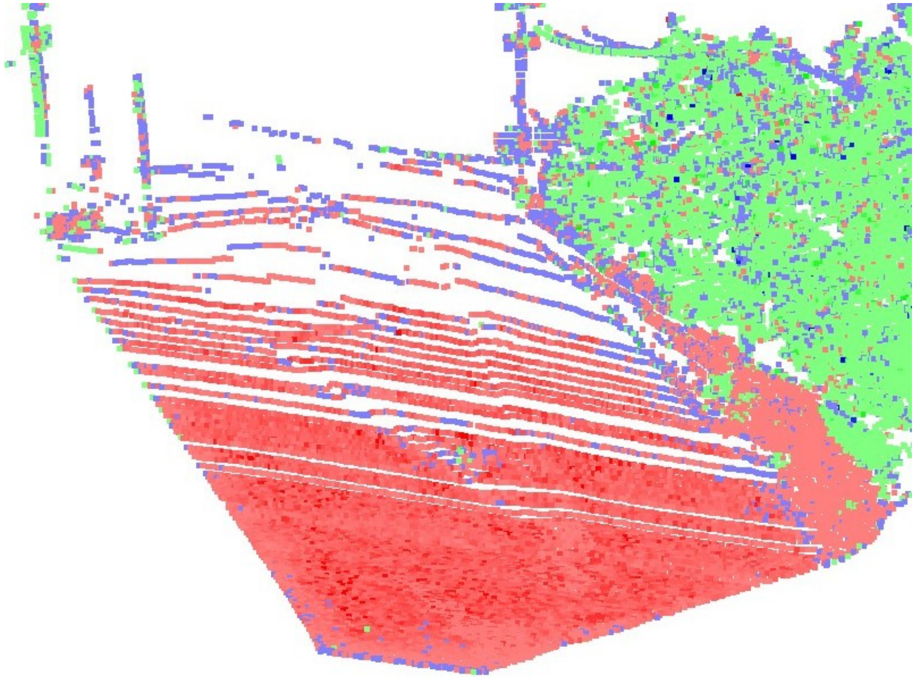
Classification experiments

- RIEGL scanner

Fixed scale (0.4 m)



Variable scale at each point

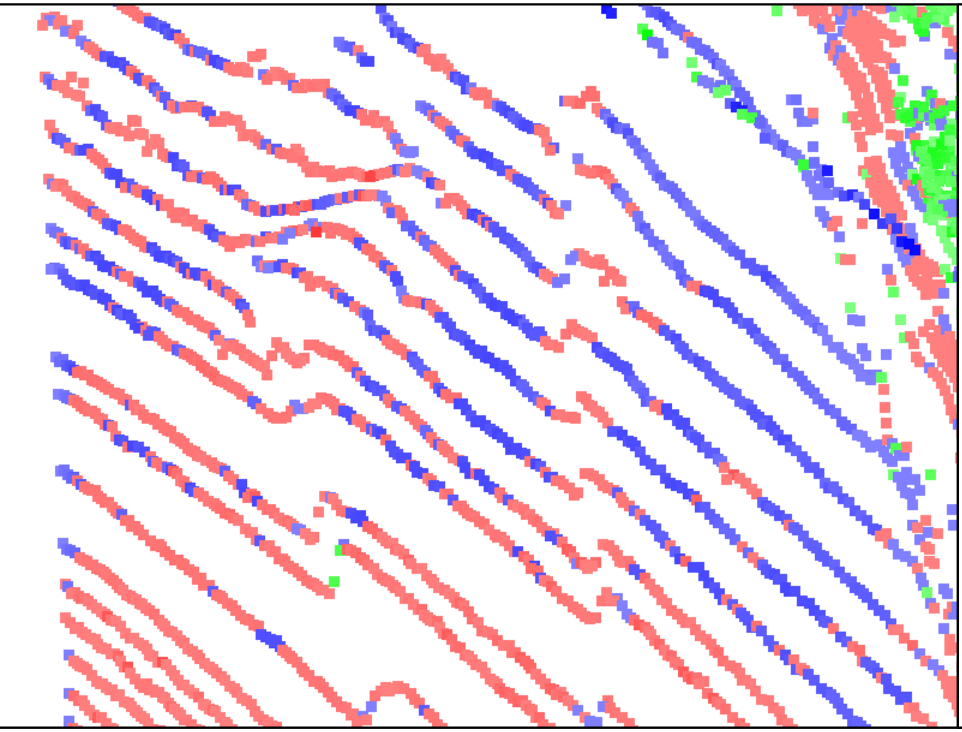


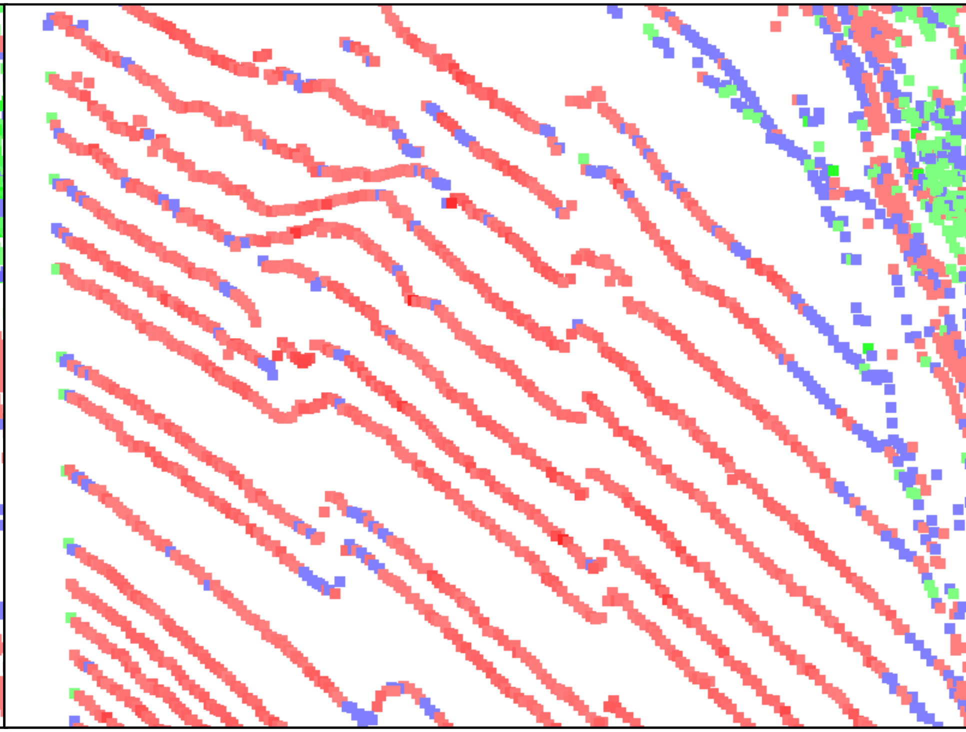
Classification experiments

- RIEGL scanner

Fixed scale (0.4 m)

Variable scale at each point

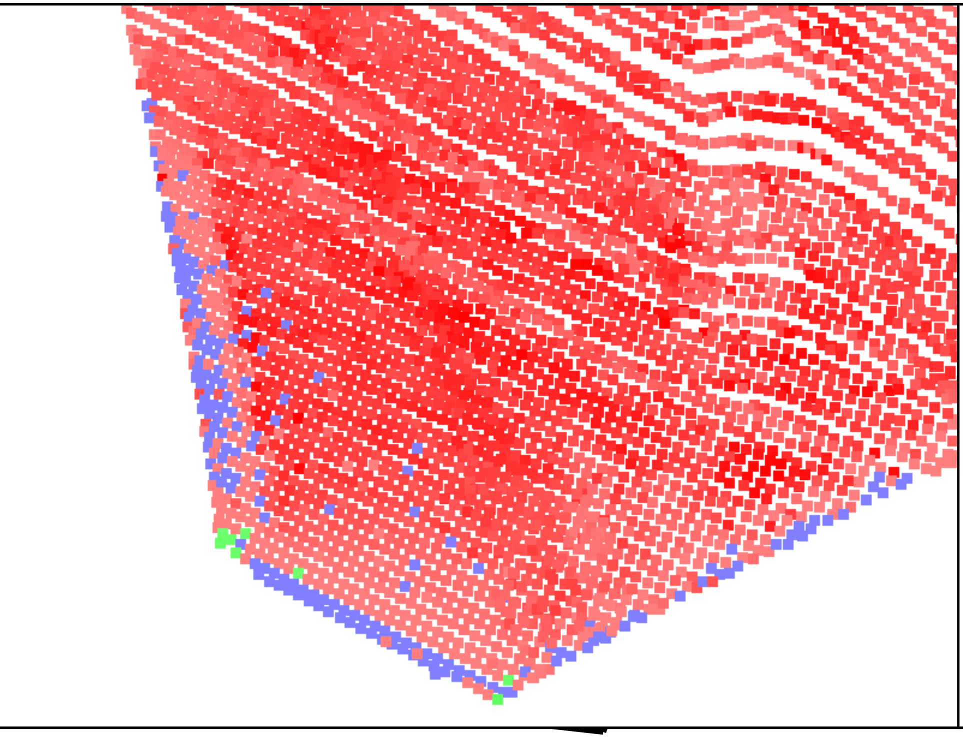




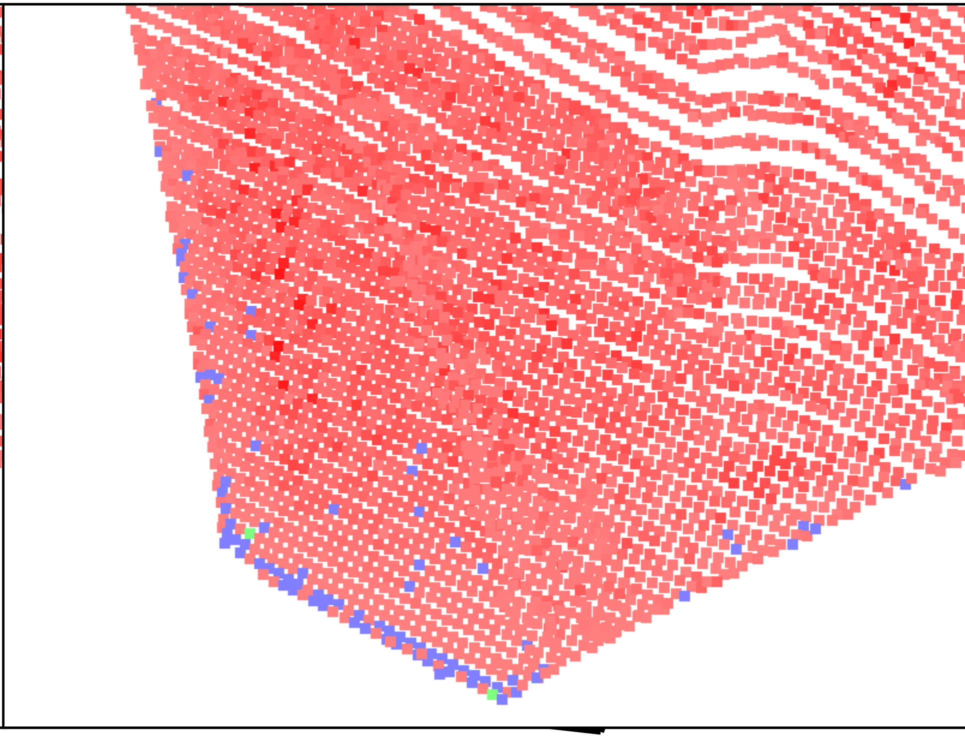
Classification experiments

- RIEGL scanner

Fixed scale (0.4 m)



Variable scale at each point



Conclusion

- Problem
  - Terrain classification errors due to fixed scale
- Contributions
  - Assumptions
    - Minimum spatial density ☑
    - No discontinuities ☑
    - Small curvature ☑
  - Improves convergence / reduce oscillations
  - Apply variable scale to classification
  - Extensive experimental verification shows 30% improvement
- Limitations
  - Points misclassified regardless of scale

Conclusion

- Acknowledgements
  - General Dynamics Robotics Systems
  - U.S. Army Research Laboratory

Thank you