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]
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]

\[ \lambda_0 \approx \lambda_1 \approx \lambda_2 \]

- 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
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

\[ \lambda_0 \approx \lambda_1 > > \lambda_2 \]

\[ \mathbf{F}_{\text{planar}} = (\lambda_1 - \lambda_2) \cdot e_2 \]

  – Closely related to normal estimation

• Extend method for optimal scale selection for normal estimation [Mitra-IJCGA05]

Optimal scale selection for normal estimation [Mitra-IJCGA05]

- Analytic expression for optimal scale

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

- \( r \): Estimated scale
- \( \kappa \): Estimated local curvature*
- \( \rho \): Estimated local density
- \( \sigma_n \): Sensor noise

* 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 \( r^{(i+1)} \)
Algorithm [Mitra-IJCGA05]

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

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

Ladar data
Real-world data, normal estimation

Avg. error = 22 deg.
Real-world data, convergence

Avg. error = 22 deg.
Proposed algorithm

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

\[
\gamma \\
\text{Dampening factor}
\]
Effect of dampening on convergence

Original method (no dampening)

With dampening
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