Dimensionality Based Scale Selection in 3D Lidar Point Clouds

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Laser Scanning 2011
Tuesday 30 August 2011
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2 Geometrical features
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1 Introduction
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Objective: geometrical feature extraction

- Geometrical features
- Scale selection
- Results
- Conclusion

Geometrical features:
- Normal Vectors
- Geometrical features
- Point Cloud Data
- Segmentation, Classification, Object Matching, Modelling...
- Linearity
- Altitude
- 30 m
- 0 m
- 1
- -1
- 0
- ledge
- parking meter
- trunk
- vehicle
- facade
- ground
- foliage
- pavement

Dimensionality Based Scale Selection
**Objective : geometrical feature extraction**

In any types of 3D Lidar point clouds:

→ Various modalities of acquisition:
  - Airborne (ALS)
  - Terrestrial static (TLS)
  - Acquired with a mobile mapping system (MMS)

→ Various point distributions (density, sweep lines).

→ Various objects (types, shapes, sizes).
Objective: local geometrical feature extraction

For each point, features computed locally: set of neighboring points. ⇒ geometrical features depend on this neighborhood choice.

Example: planarity feature at various growing scales.

Planarity
10 points per neighborhood
Objective: local geometrical feature extraction

For each point, features computed locally: set of neighboring points.

⇒ geometrical features depend on this neighborhood choice.

Example: planarity feature at various growing scales.

Planarity
36 points per neighborhood
Objective: local geometrical feature extraction

For each point, features computed locally: set of neighboring points.  
⇒ geometrical features depend on this neighborhood choice.

Example: planarity feature at various growing scales.
Objective: local geometrical feature extraction

For each point, features computed \textit{locally}: set of neighboring points. 

$\Rightarrow$ geometrical features \textit{depend on this neighborhood choice}.

Example: planarity feature at various growing scales.

Planarity

200 points per neighborhood
Neighborhood choice

- **Shape**: cylinder, hexahedron, sphere, ellipsoid...
- **Size**: fixed size, k nearest neighbors...
- **Orientation**.
- **Adaptative**.
Neighborhood choice

Constant neighborhood: *same volume for all points*
- Unadapted to various contexts.
- Objects mixing.
\[ \pm \] No prior knowledge of point distribution.

Adaptative neighborhood: *adapted to each point*
- Neighborhood consistency.
- Geometrical features well calculated.
- Prior knowledge of point distribution.
Neighborhood choice

Interdependence problem
Neighborhood choice

Interdependence problem

- Geometrical features depend on the choice of the neighborhood.
Neighborhood choice

Interdependence problem

- Geometrical features depend on the choice of the neighborhood.
- A good choice should rely on the local geometry...
Neighborhood choice

Interdependence problem

- Geometrical features depend on the choice of the neighborhood.
- A good choice should rely on the local geometry...
- thus on geometrical features!
Neighborhood choice

Interdependence problem

- Geometrical features depend on the choice of the neighborhood.
- A good choice should rely on the local geometry...
- thus on geometrical features!
Previous works

[Filin & Pfeifer 2005]: Cylindrical adaptative neighborhood.

(a) planimetric distance.
(b) 3 dimensions considered.
(c) Distance measured in the local surface.
Previous works

[Lalonde et al. 2005]: **Optimal support size for normal vectors.**

Spherical neighborhoods + Minimize an error on the normal direction.
Previous works


Ellipsoidal neighborhoods + Merge ellipsoids wrt 2 criteria.
**Proposed method**

For each 3D point:

1. Feature computation on spherical neighborhoods of growing sizes.
2. Selection of an optimal neighborhood size.

Outputs: optimal geometrical features + neighborhood size.
Introduction

Geometrical features

Scale selection

Results

Conclusion
**Choice of a neighborhood**

**Spherical neighborhood**

- Ensure **isotropy** and **rotation invariance**.
- Computed features **not biased** by the neighborhood shape.
- Radius $r$ is the **single parameter** to be optimized.
- No orientation.

**Implementation**

Radius vs $k$ nearest neighbors.
Let a 3D point $P$. 
Principal Component Analysis (PCA)

Set of 3D points

Spherical Neighborhood = \( n \) lidar points \( x_i \).
Let $\bar{x}$ the center of gravity of the $x_i$. 
**Principal Component Analysis (PCA)**

Given \( \mathbf{M} = \begin{pmatrix} x_1 - \bar{x} \\ x_2 - \bar{x} \\ \vdots \\ x_n - \bar{x} \end{pmatrix} \)

Let \( \mathbf{C} = \frac{1}{n} \mathbf{M}^T \mathbf{M} \)

the Covariance matrix or structure tensor of \( \mathbf{M} \)
Principal Component Analysis (PCA)

**Structure Tensor** $\mathbf{C}$: linear function, transforms a sphere into an ellipsoid.

Eigendecomposition: $\mathbf{C} = \mathbf{R} \Lambda \mathbf{R}^T$

$\mathbf{R} = \text{rotation matrix}$  
$\Lambda = \text{diagonal, positive definite matrix}$
**Principal Component Analysis (PCA)**

Eigenvalues: \( \lambda_1 \geq \lambda_2 \geq \lambda_3 > 0 \).

- \( \sigma_j = \sqrt{\lambda_j} \) (\( j \in [1, 3] \))
- \( \sigma_j = \text{the standard deviation} \) along eigenvectors \( \vec{v}_j \).
- \( \sigma_j = \text{lengths of the semi-axes} \).
- \( \sigma_j = \text{geometrical features} \).
Principal Component Analysis (PCA)

Eigenvalues: \( \lambda_1 \geq \lambda_2 \geq \lambda_3 > 0 \).

\[ \sigma_j = \sqrt{\lambda_j} \quad (j \in [1, 3]) \]
\[ \sigma_j = \text{the standard deviation along eigenvectors } \overrightarrow{v_j}. \]
\[ \sigma_j = \text{lengths of the semi-axes.} \]
\[ \sigma_j = \text{geometrical features.} \quad \rightarrow \text{dimensionality features.} \]
Dimensionality features

1 dimension

$$\sigma_1 \gg \sigma_2, \sigma_3 \approx 0$$

$$a_{1D} \leq 1$$

$$a_{2D} \leq 0$$

$$a_{3D} \leq 0$$

2 dimensions

$$\sigma_1, \sigma_2 \gg \sigma_3 \approx 0$$

$$a_{1D} \leq 0$$

$$a_{2D} \leq 1$$

$$a_{3D} \leq 0$$

3 dimensions

$$\sigma_1 \approx \sigma_2 \approx \sigma_3$$

$$a_{1D} \leq 0$$

$$a_{2D} \leq 0$$

$$a_{3D} \leq 1$$
Dimensionality features...
Dimensionality features and labelling

Geometrical features

Scale selection

Results

Conclusion

Dimensionality Based Scale Selection

Jérôme Demantké (IGN-Matis)

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d* : Dimensionality of the 3D point.

\[ d^* = \arg \max_{d \in [1,3]} [a_{dD}] \]
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TLS: Samarina Church, Kalamata (Greece)

East position
Dataset of ISPRS WG V/3

13 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

25 points per neighborhood
TLS : Samarina Church, Kalamata (Greece)

East position

Dataset of ISPRS WG V/3

45 points per neighborhood

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TLS: Samarina Church, Kalamata (Greece)

East position
Dataset of ISPRS WG V/3

73 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

East position

Dataset of ISPRS WG V/3

109 points per neighborhood

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TLS: Samarina Church, Kalamata (Greece)

East position Dataset of ISPRS WG V/3

152 points per neighborhood
TLS : Samarina Church, Kalamata (Greece)

East position

Dataset of ISPRS WG V/3

204 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

East position

Dataset of ISPRS WG V/3

263 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

330 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

406 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

East position
Dataset of ISPRS WG V/3

489 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

580 points per neighborhood

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East position

Dataset of ISPRS WG V/3

679 points per neighborhood
TLS: Samarina Church, Kalamata (Greece)

786 points per neighborhood

East position

Dataset of ISPRS WG V/3

1D
2D
3D
TLS : Samarina Church, Kalamata (Greece)

East position

Dataset of ISPRS WG V/3

901 points per neighborhood
TLS : Samarina Church, Kalamata (Greece)

1024 points per neighborhood
Scale selection

For each 3D point:

Define a criterion \( E_f \) that selects an "optimal" neighborhood size.
Scale selection

Probability axioms:
\[ 0 \leq a_{1D} \leq 1 \]
\[ 0 \leq a_{2D} \leq 1 \]
\[ 0 \leq a_{3D} \leq 1 \]
\[ a_{1D} + a_{2D} + a_{3D} = 1 \]

Uncertainty of labelling measured by entropy:
\[ E_f = -a_{1D} \ln(a_{1D}) - a_{2D} \ln(a_{2D}) - a_{3D} \ln(a_{3D}) \]
Scale selection

\[ E_f = \text{Uncertainty of labelling.} \]

\[ E_f = -a_{1D} \ln(a_{1D}) - a_{2D} \ln(a_{2D}) - a_{3D} \ln(a_{3D}) \]

East position Dataset of ISPRS WG V/3

580 points per neighborhood
Scale selection

For each 3D point: neighborhood size minimizing $E_f$.

Labelling with constant neighborhoods (50-nearest-neighbors).
Scale selection

For each 3D point: neighborhood size minimizing $E_f$.

Labelling with adaptative neighborhoods (scale selection between 10 and 50 neighbors using $E_f$).
TLS : Samarina Church Kalamata (Greece)

Dimensionalities

Radii

East position

I 1D 2D 3D

40 cm

0

Jérôme Demantké (IGN-Matis)

Dimensionality Based Scale Selection
ALS: GML dataset (Russia)

Dimensionality Based Scale Selection

[Shapovalov et al. 2010]
MMS : Oakland dataset (US)

[Munoz et al. 2009]
Proportion of 1D, 2D and 3D points in each class

ALS : GML dataset.

MMS : Oakland dataset.

<table>
<thead>
<tr>
<th>Class</th>
<th>ALS (1D)</th>
<th>ALS (2D)</th>
<th>ALS (3D)</th>
<th>MMS (1D)</th>
<th>MMS (2D)</th>
<th>MMS (3D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground (992581)</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>62%</td>
<td>38%</td>
<td>0%</td>
</tr>
<tr>
<td>Buildings (117264)</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>81%</td>
<td>19%</td>
<td>0%</td>
</tr>
<tr>
<td>Cars (5048)</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>81%</td>
<td>19%</td>
<td>0%</td>
</tr>
<tr>
<td>Low vegetation (42738)</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>81%</td>
<td>19%</td>
<td>0%</td>
</tr>
<tr>
<td>High vegetation (911969)</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>81%</td>
<td>19%</td>
<td>0%</td>
</tr>
<tr>
<td>Chutter (26952)</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>65%</td>
<td>35%</td>
<td>0%</td>
</tr>
<tr>
<td>1D objects (20520)</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>65%</td>
<td>35%</td>
<td>0%</td>
</tr>
<tr>
<td>2D objects (1264320)</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>65%</td>
<td>35%</td>
<td>0%</td>
</tr>
<tr>
<td>3D objects (302824)</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
<td>65%</td>
<td>35%</td>
<td>0%</td>
</tr>
</tbody>
</table>
ALS : Amiens (France)
ALS: Biberach (Germany)

Altitude

Labelling

$E_f$

Radius
STEREOPOLIS mobile mapping system (IGN).
TLS : Samarina Church, Kalamata (Greece)

North and North-East positions

$\alpha_{1D}$
TLS : Samarina Church, Kalamata (Greece)

North and North-East positions

\[ a_{2D} \]
TLS: Samarina Church, Kalamata (Greece)

North and North-East positions

$\alpha_{3D}$
TLS: Samarina Church, Kalamata (Greece)

North and North-East positions

Dimensionalities

1D
2D
3D
TLS : Saint Mandé (France)
TLS : Saint Mandé (France)
Conclusion

Contributions:
- Low level approach.
- Tested on various datasets (density, scales, sweeping method...).
- **Dimensionality** → Synthetic description.
- Automatic scale-selection (parameter free).

Future works:
- Use the adaptative sizes to compute other geometrical features. (normal vectors, cylindricity...)
- **Classification** using \( a_{1D}, a_{2D}, a_{3D} + E_f + \text{radius} + \text{other features.} \)
- **Edge** detection.
Thank you! Any questions?

Bottom view of a tree.

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