From 3D Point Clouds to Objects

Dr.-Ing. Martin Weinmann
From 3D Point Clouds to **Semantic** Objects

Dr.-Ing. Martin Weinmann
Motivation

Façades

Traffic signs, street lights, etc.

Cars

Vegetation

Ground
Literature

1. Introduction
2. Preliminaries of 3D Point Cloud Processing
3. A Brief Survey on 2D and 3D Feature Extraction
4. Point Cloud Registration
5. Co-Registration of 2D Imagery and 3D Point Cloud Data
6. **3D Scene Analysis**
7. Conclusions and Future Work
Outline

1. Introduction
2. Methodology
3. Experimental Results
4. Conclusions & Future Work
1. Introduction

- Semantic interpretation of 3D point cloud data
  - Unique assignment of a semantic class label to each 3D point (e.g. ground, building or vegetation)
  - General applicability (e.g. for TLS / MLS / ALS or MVS point cloud data)
  - Desired properties
    - Fully automated and efficient approaches
    - Accurate results (without including prior knowledge?)
1. Introduction

Main challenges

- Single-scale representation vs. multi-scale representation
- Complex features vs. interpretable features
- All features vs. relevant features
- Individual classification vs. contextual classification
1. Introduction

2. Methodology

3. Experimental Results

4. Conclusions & Future Work
2. Methodology

- Neighborhood Definition
- Feature Extraction
- Feature Selection
- Supervised Classification

3D Point Cloud

?
2. Methodology

- Recovery of local 3D neighborhoods
  - Spherical neighborhood with fixed radius
    - Which radius?
  - Cylindrical neighborhood with fixed radius
    - Which radius?
  - $k$ closest neighbors in 3D (flexible neighborhood size)
    - Which $k$?

- Neighborhood Definition
  - Feature Extraction
  - Feature Selection
  - Supervised Classification
2. Methodology

- Recovery of an optimal value for $k$
- Consideration of neighboring 3D points

$\rightarrow$ 3D structure tensor
  $\quad= 3D$ covariance matrix

$$S_{3D} = \frac{1}{k+1} \sum_{i=0}^{k} (x_i - \bar{X}) (x_i - \bar{X})^T$$
2. Methodology

- Recovery of an optimal value for $k$
  - Consideration of neighboring 3D points

→ 3D structure tensor
   = 3D covariance matrix

→ Eigenvalues represent the extent of a 3D ellipsoid along its principal axes
2. Methodology

- Recovery of an optimal value for $k$
  - Dimensionality-based scale selection
    [Demantké et al., 2011]
    \[
    k_{\text{min}} = 10 \quad E_{\text{dim}} = -L_{\lambda} \ln(L_{\lambda}) - P_{\lambda} \ln(P_{\lambda}) - S_{\lambda} \ln(S_{\lambda})
    \]
    \[
    k_{\text{max}} = 100 \quad L_{\lambda} = \frac{\lambda_1 - \lambda_2}{\lambda_1} \quad P_{\lambda} = \frac{\lambda_2 - \lambda_3}{\lambda_1} \quad S_{\lambda} = \frac{\lambda_3}{\lambda_1}
    \]
  - Idea: favor 1D, 2D or 3D structure and minimize
  
  - Eigenentropy-based scale selection
    [Weinmann et al., PCV 2014]
    \[
    k_{\text{min}} = 10 \quad E_{\lambda} = -\lambda_1 \ln(\lambda_1) - \lambda_2 \ln(\lambda_2) - \lambda_3 \ln(\lambda_3)
    \]
    \[
    k_{\text{max}} = 100 \quad \Delta k = 1
    \]
    \[
    \text{ Idea: favor the minimal disorder of 3D points and minimize}
    \]
2. Methodology

- **Recovery of local 3D neighborhoods**
  - Multi-scale neighborhood
e.g. [Niemeyer et al., IJPRS 2014]
  - Consider local 3D structure at different scales
  - Describe geometric behavior across different scales

- **Multi-scale, multi-type neighborhood**
e.g. [Blomley et al., ISPRS Congress 2016]
  - Consider local 3D structure at different scales
  - Describe geometric behavior across different scales and different neighborhood types
2. Methodology

- Multi-scale, multi-type neighborhood
e.g. [Blomley et al., ISPRS Congress 2016]

→ Consider local 3D structure at
different scales

→ Describe geometric behavior
across different scales and
different neighborhood types
2. Methodology

- Extraction of 3D features \((8)\)

- Eigenvector-based features \(\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0\)

- Linearity: \(L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1}\)

- Planarity: \(P_\lambda = \frac{\lambda_2 - \lambda_3}{\lambda_1}\)

- Scattering: \(S_\lambda = \frac{\lambda_3}{\lambda_1}\)

- Omnivariance: \(O_\lambda = \frac{3}{\sqrt[3]{\lambda_1 \lambda_2 \lambda_3}}\)

- Anisotropy: \(A_\lambda = \frac{\lambda_1 - \lambda_3}{\lambda_1^{3/2}}\)

- Eigenentropy: \(E_\lambda = -\sum_{i=1}^{3} \lambda_i \ln(\lambda_i)\)

- Sum of eigenvalues: \(\Sigma_\lambda = \lambda_1 + \lambda_2 + \lambda_3\)

- Change of curvature: \(C_\lambda = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}\)
2. Methodology

- Extraction of 3D features (8)
- Dimensionality features

Feature: Linearity (1D)

Feature: Planarity (2D)

Feature: Scattering (3D)
Feature: Planarity (2D)
2. Methodology

- Extraction of 3D features (8 + 6)
  - Geometric 3D properties
    - Radius of $k$-NN: $r_{k-NN,3D}$
    - Local point density: $D_{3D} = \frac{k + 1}{\frac{4}{3} \pi r_{k-NN,3D}^3}$
    - Verticality: $V = 1 - n_Z$
    - Absolute height: $H$
    - Height difference: $\Delta H_{k-NN,3D}$
    - Std.dev. of height values: $\sigma_{H,k-NN,3D}$
2. Methodology

- Extraction of 2D features \((2 + 2 + 3)\)
  - Geometric 2D properties
    - Radius of \(k\)-NN: \(r_{k,2D}\)
    - Local point density: \(D_{2D}\)
  - Eigenvalue-based features
    - Sum of eigenvalues: \(\Sigma_{\lambda,2D}\)
    - Ratio of eigenvalues: \(R_{\lambda,2D} = \frac{\lambda_{2,2D}}{\lambda_{1,2D}}\)
  - Discretization (e.g. bins of 0.25m x 0.25m)
    - # points per bin: \(M\)
    - Properties of a bin: \(\Delta H, \sigma_H\)
Façades

Border

street/sidewalk

Feature: # points per bin
2. Methodology

- Extraction of more complex features

- 3D Shape Context descriptor
  [Frome et al., ECCV 2004]

- Signature of Histograms of OrienTations (SHOT) descriptor
  [Tombari et al., ECCV 2010]

- Point Feature Histograms (PFHs)
  [Rusu et al., ICRA 2009]

- Shape Distributions
  [Osada et al., 2002]
2. Methodology

- Selection of “suitable” features
  - Relevant, irrelevant and redundant features
  - Hughes phenomenon [Hughes, 1968]

![Graph showing the relationship between number of features and accuracy](image)

- Neighborhood Definition
- Feature Extraction
- Feature Selection
- Supervised Classification
2. Methodology

- Selection of “suitable” features
  - Filter-based methods
    - Classifier-independent
    - Simple and efficient
    - Consideration of intrinsic properties of the given (training) data
    - Different criteria
  - Alternative strategies:
    - Wrapper-based methods
    - Embedded methods

Diagram:
- Neighborhood Definition
  - Feature Extraction
  - Feature Selection
  - Supervised Classification
2. Methodology

- Filter-based methods
  - Univariate methods
    - “Evaluate” feature–class relations
      - Correlation coefficient

\[ c_{\text{Pearson}}(x_i) = \frac{\text{Cov}(x_i, l)}{\sigma(x_i) \cdot \sigma(l)} \]

- Multivariate methods
  - “Evaluate” feature–class relations and feature–feature relations
    - Correlation-based Feature Selection [Hall, 1999]

\[ R(X_{1\ldots n}, C) = \frac{n \bar{\rho}_{XC}}{\sqrt{n + n(n - 1) \bar{\rho}_{XX}}} \]
## 2. Methodology

### Individual classification

<table>
<thead>
<tr>
<th>Learning principle</th>
<th>Involved classifiers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instance-based learning</td>
<td>- Nearest Neighbor (NN) classifier</td>
</tr>
<tr>
<td>Rule-based learning</td>
<td>- Decision Tree (DT)</td>
</tr>
<tr>
<td>Probabilistic learning</td>
<td>- Naïve Bayesian (NB) classifier</td>
</tr>
<tr>
<td></td>
<td>- Linear Discriminant Analysis (LDA)</td>
</tr>
<tr>
<td></td>
<td>- Quadratic Discriminant Analysis (QDA)</td>
</tr>
<tr>
<td>Max-margin learning</td>
<td>- Support Vector Machine (SVM)</td>
</tr>
<tr>
<td>Ensemble learning</td>
<td>- Random Forest (RF)</td>
</tr>
<tr>
<td></td>
<td>- Random Fern (RFe)</td>
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<tr>
<td></td>
<td>- AdaBoost (AB)</td>
</tr>
<tr>
<td>Deep learning</td>
<td>- Multi-Layer Perceptron (MLP)</td>
</tr>
</tbody>
</table>
1. Introduction

2. Methodology

3. Experimental Results

4. Conclusions & Future Work
3. Experimental Results

- **Oakland 3D Point Cloud Dataset** [Munoz et al., 2008, 2009]
  - 5 semantic classes: *Wire, Pole/Trunk, Façade, Ground, Vegetation*

<table>
<thead>
<tr>
<th></th>
<th>Training</th>
<th>Validation</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td># 3D points</td>
<td>5,000</td>
<td>91,515</td>
<td>1,324,310</td>
</tr>
<tr>
<td>Min. class size</td>
<td>1,000</td>
<td>899</td>
<td>3,794</td>
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<tr>
<td>Max. class size</td>
<td>11,000</td>
<td>67,419</td>
<td>934,146</td>
</tr>
</tbody>
</table>

Reduction of training data
3. Experimental Results

A. Insights w.r.t. the selection of optimal neighborhoods

B. Impact of optimal neighborhood size selection

C. Impact of the selection of relevant features

D. Extension towards data-intensive processing
3. Experimental Results (A)

- **Oakland 3D Point Cloud Dataset**

- Distribution of $k$ across all 3D points of the dataset:

$$\sim 758 \text{ s} \quad (\text{Intel Core i7-3829, 3.6GHz, 64GB RAM})$$
3. Experimental Results (A)

Class-specific distribution of $k$:

- $k$(Wire)
- $k$(Pole/Trunk)
- $k$(Façade)
- $k$(Ground)
- $k$(Vegetation)
3. Experimental Results

A. Insights w.r.t. the selection of optimal neighborhoods

B. Impact of optimal neighborhood size selection

C. Impact of the selection of relevant features

D. Extension towards data-intensive processing


3. Experimental Results (B)

- *Oakland 3D Point Cloud Dataset*, all 21 low-level features:

  - Feature extraction based on different neighborhood definitions

  - Classification: *Random Forest* (100 decision trees)

<table>
<thead>
<tr>
<th>Mean class recall:</th>
<th>Wire</th>
<th>Pole/Trunk</th>
<th>Façade</th>
<th>Ground</th>
<th>Vegetation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{N}_{10}$</td>
<td>70.46</td>
<td>68.49</td>
<td>50.29</td>
<td>98.23</td>
<td>66.45</td>
</tr>
<tr>
<td>$\mathcal{N}_{25}$</td>
<td>69.48</td>
<td>69.59</td>
<td>60.98</td>
<td>98.91</td>
<td>74.29</td>
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<tr>
<td>$\mathcal{N}_{50}$</td>
<td>56.86</td>
<td>62.64</td>
<td>68.13</td>
<td>98.84</td>
<td>77.10</td>
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<tr>
<td>$\mathcal{N}_{75}$</td>
<td>49.71</td>
<td>58.63</td>
<td>67.51</td>
<td>98.81</td>
<td>75.31</td>
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<tr>
<td>$\mathcal{N}_{100}$</td>
<td>49.67</td>
<td>58.27</td>
<td>62.69</td>
<td>98.71</td>
<td>73.20</td>
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<tr>
<td>$\mathcal{N}_{\text{opt,dim}}$</td>
<td>85.16</td>
<td>78.90</td>
<td>65.90</td>
<td>98.52</td>
<td>79.99</td>
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<tr>
<td>$\mathcal{N}_{\text{opt,\lambda}}$</td>
<td>86.05</td>
<td>79.99</td>
<td>67.01</td>
<td>98.48</td>
<td>81.41</td>
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</table>

<table>
<thead>
<tr>
<th>Overall accuracy:</th>
<th>Wire</th>
<th>Pole/Trunk</th>
<th>Façade</th>
<th>Ground</th>
<th>Vegetation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{N}_{10}$</td>
<td>5.51</td>
<td>7.99</td>
<td>77.62</td>
<td>96.82</td>
<td>94.79</td>
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<td>$\mathcal{N}_{25}$</td>
<td>7.12</td>
<td>9.46</td>
<td>83.88</td>
<td>98.58</td>
<td>94.87</td>
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<td>$\mathcal{N}_{50}$</td>
<td>4.81</td>
<td>19.47</td>
<td>83.43</td>
<td>97.77</td>
<td>94.40</td>
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<td>$\mathcal{N}_{75}$</td>
<td>4.00</td>
<td>18.25</td>
<td>80.28</td>
<td>97.86</td>
<td>93.84</td>
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<td>$\mathcal{N}_{100}$</td>
<td>3.98</td>
<td>13.55</td>
<td>76.19</td>
<td>97.92</td>
<td>93.55</td>
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<tr>
<td>$\mathcal{N}_{\text{opt,dim}}$</td>
<td>7.98</td>
<td>22.09</td>
<td>83.71</td>
<td>97.67</td>
<td>94.97</td>
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<tr>
<td>$\mathcal{N}_{\text{opt,\lambda}}$</td>
<td>9.03</td>
<td>24.13</td>
<td>84.69</td>
<td>97.18</td>
<td>95.87</td>
</tr>
</tbody>
</table>
3. Experimental Results (B)

- **Oakland 3D Point Cloud Dataset**, all 21 low-level features:

  - **Overall accuracy**:

    | \(N\)  | NN   | DT   | NB   | LDA  | QDA  | SVM  | RF   | RFe  | AB   | MLP  |
    |------|------|------|------|------|------|------|------|------|------|------|
    | \(N_{10}\) | 73.86 | 65.64 | 78.88 | 87.38 | 78.93 | 82.93 | 87.53 | 81.94 | 86.78 | 80.54 |
    | \(N_{25}\)  | 86.25 | 69.30 | 83.64 | 90.08 | 83.62 | 88.88 | 90.50 | 88.77 | 89.99 | 78.59 |
    | \(N_{50}\)  | 88.89 | 75.47 | 85.03 | 92.83 | 84.95 | 92.00 | 91.54 | 90.42 | 91.80 | 85.68 |
    | \(N_{75}\)  | 89.97 | 76.87 | 85.00 | 93.05 | 84.99 | 91.99 | 91.06 | 91.16 | 90.56 | 87.07 |
    | \(N_{100}\) | 89.90 | 84.45 | 84.33 | 92.60 | 84.43 | 91.76 | 90.16 | 90.59 | 87.01 | 84.39 |
    | \(N_{\text{opt, dim}}\) | 79.34 | 70.71 | 83.75 | 91.01 | 83.80 | 90.15 | 91.89 | 90.12 | 91.62 | 85.69 |
    | \(N_{\text{opt, \lambda}}\) | 79.87 | 75.76 | 85.63 | 90.39 | 85.69 | 89.10 | 92.25 | 90.45 | 92.28 | 87.20 |

  - **Mean class recall**:

    | \(N\)  | NN   | DT   | NB   | LDA  | QDA  | SVM  | RF   | RFe  | AB   | MLP  |
    |------|------|------|------|------|------|------|------|------|------|------|
    | \(N_{10}\) | 63.40 | 54.19 | 62.29 | 70.68 | 62.33 | 58.86 | 70.78 | 63.75 | 67.52 | 64.20 |
    | \(N_{25}\)  | 70.01 | 57.41 | 68.46 | 75.54 | 68.47 | 68.50 | 74.65 | 71.48 | 68.64 | 68.03 |
    | \(N_{50}\)  | 69.47 | 59.99 | 67.12 | 72.76 | 66.98 | 68.47 | 72.72 | 69.22 | 71.46 | 69.13 |
    | \(N_{75}\)  | 68.29 | 57.82 | 65.49 | 73.05 | 65.44 | 68.00 | 69.99 | 68.88 | 68.19 | 70.47 |
    | \(N_{100}\) | 66.66 | 57.96 | 63.44 | 72.35 | 63.46 | 64.76 | 68.51 | 67.16 | 59.58 | 68.98 |
    | \(N_{\text{opt, dim}}\) | 74.17 | 62.15 | 74.49 | 81.36 | 74.35 | 79.58 | 81.70 | 78.35 | 77.63 | 78.61 |
    | \(N_{\text{opt, \lambda}}\) | 73.98 | 66.99 | 76.19 | 82.05 | 76.15 | 79.97 | 82.59 | 78.70 | 79.49 | 79.92 |
3. Experimental Results (B)

- Processing time for training and testing:

<table>
<thead>
<tr>
<th>Time</th>
<th>NN</th>
<th>DT</th>
<th>NB</th>
<th>LDA</th>
<th>QDA</th>
<th>SVM</th>
<th>RF</th>
<th>RF e</th>
<th>AB</th>
<th>MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_{train}$ [s]</td>
<td>0.00</td>
<td>0.11</td>
<td>0.01</td>
<td>0.05</td>
<td>0.07</td>
<td>1.39</td>
<td>0.44</td>
<td>0.03</td>
<td>6.20</td>
<td>2.28</td>
</tr>
<tr>
<td>$t_{train}$ [%]</td>
<td>0.00</td>
<td>24.54</td>
<td>3.13</td>
<td>10.74</td>
<td>15.18</td>
<td>317.19</td>
<td>100.00</td>
<td>6.96</td>
<td>1410.66</td>
<td>518.13</td>
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<tr>
<td>$t_{test}$ [s]</td>
<td>167.52</td>
<td>0.65</td>
<td>3.71</td>
<td>4.45</td>
<td>3.92</td>
<td>319.48</td>
<td>6.33</td>
<td>8.12</td>
<td>76.31</td>
<td>1.80</td>
</tr>
<tr>
<td>$t_{test}$ [%]</td>
<td>2645.77</td>
<td>10.22</td>
<td>58.64</td>
<td>70.34</td>
<td>61.96</td>
<td>5045.68</td>
<td>100.00</td>
<td>128.22</td>
<td>1205.24</td>
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</table>

- Overall accuracy:

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</table>
3. Experimental Results

A. Insights w.r.t. the selection of optimal neighborhoods

B. Impact of optimal neighborhood size selection

C. Impact of the selection of relevant features

D. Extension towards data-intensive processing


3. Experimental Results (C)

- **Oakland 3D Point Cloud Dataset**

- Feature extraction based on different neighborhood definitions

- Feature selection:
  - All features (21)
  - Dimensionality features (3)
  - Eigenvalue-based 3D features (8)
  - 5 best-ranked features according to [Weinmann et al., 2013] (5)

- Correlation-based Feature Selection [Hall, 1999] (12-16)
- Fast Correlation-Based Filter [Yu & Liu, 2003] (6-9)
- Minimal-Redundancy-Maximal-Relevance [Peng et al., 2005] (10)

- Classification: **Random Forest** (100 decision trees)
Martin Weinmann

3. Experimental Results (C)

Hughes phenomenon

$R_{3D,2D}$

$V$

$CA$

$\sigma_{H,k-NN,3D}$

$\Delta H_{k-NN,3D}$

$\mathcal{P}_3$

$\Delta H$

$\tau_{k-NN,3D}$

$\tau_{k-NN,2D}$

$D_{2D}$

$A_A$

$\sigma_H$

$H$

$M$

$D_{3D}$

$\Sigma_A$

$\Sigma_{\lambda,2D}$

$L_A$

$E_A$

$k = 50$
3. Experimental Results (C)

- **Overall accuracy:**

<table>
<thead>
<tr>
<th>( N )</th>
<th>( S_{\text{all}} )</th>
<th>( S_{\text{dim}} )</th>
<th>( S_{\lambda,3D} )</th>
<th>( S_5 )</th>
<th>( S_{\text{CFS}} )</th>
<th>( S_{\text{FCBF}} )</th>
<th>( S_{\text{mRMR}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_{10} )</td>
<td>87.50</td>
<td>58.36</td>
<td>74.33</td>
<td>85.66</td>
<td>87.43</td>
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<td>91.71</td>
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<td>69.59</td>
<td>77.69</td>
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<td>91.83</td>
<td>91.55</td>
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<td>63.61</td>
<td><strong>84.88</strong></td>
<td><strong>91.44</strong></td>
<td><strong>92.27</strong></td>
<td><strong>92.78</strong></td>
<td>84.28</td>
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</table>

- **Mean class recall:**

<table>
<thead>
<tr>
<th>( N )</th>
<th>( S_{\text{all}} )</th>
<th>( S_{\text{dim}} )</th>
<th>( S_{\lambda,3D} )</th>
<th>( S_5 )</th>
<th>( S_{\text{CFS}} )</th>
<th>( S_{\text{FCBF}} )</th>
<th>( S_{\text{mRMR}} )</th>
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<td>72.64</td>
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<td>70.19</td>
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<tr>
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<td><strong>61.53</strong></td>
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<td>80.83</td>
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<td>59.48</td>
<td><strong>69.17</strong></td>
<td><strong>78.50</strong></td>
<td><strong>82.39</strong></td>
<td><strong>82.93</strong></td>
<td>69.37</td>
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</tbody>
</table>
3. Experimental Results

A. Insights w.r.t. the selection of optimal neighborhoods

B. Impact of optimal neighborhood size selection

C. Impact of the selection of relevant features

D. Extension towards data-intensive processing

Paris-rue-Madame Database:

- 20M points
- Overall accuracy: 89.03%
- Mean class recall: 84.14%
Paris-rue-Cassette Database:

- 12M points
- Overall accuracy: 89.52%
- Mean class recall: 81.46%
1. Introduction

2. Methodology

3. Experimental Results

4. Conclusions & Future Work
4. Conclusions & Future Work

- Semantic interpretation of 3D point cloud data
  - Selection of individual 3D neighborhoods of optimal size
    → Significant improvement of classification results
  - Selection of relevant features
    → Increase in efficiency w.r.t. processing time and memory consumption
  - Extension towards large-scale 3D scene analysis
    → Parallelized data processing
4. Conclusions & Future Work

- Outlook
  - Extended 3D scene analysis up to object level
    - Segmentation / clustering
    - Spatial context
  - Large-scale 3D scene analysis on point level and on object level
    - >100M points
    - Complex environments
    - Many classes of interest
    - Class hierarchies
4. Conclusions & Future Work

Outlook

- Tree detection, segmentation and localization (→ IQmulus)
  → Binary classification ("tree" vs. "non-tree")
  → Tree individualization via segmentation
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Thank you for your attention!