Automatic Building Extraction from UAV data

Introduction

There is a need to quickly and accurately identify buildings in unplanned settlements to characterize the settlement, support the detailed design of infrastructure interventions, and inspection. The state-of-the-art in building identification from sub-meter-remotely-sensed imagery or point clouds have limited performance in areas where buildings are (1) small, (2) irregular, and (3) closely packed together on sloped terrain. These are all characteristic of unplanned settlements in the City of Kigali. In May 2015, a low-cost UAV acquired imagery over approximately 150 ha of unplanned settlements in the City of Kigali, Rwanda. This provided detailed geospatial data in the form of a dense point cloud as well as a 3 cm ortho-image and Digital Surface Model. We demonstrate how to combine radiometric, textural, and geometric features obtained from UAV data to accurately identify and characterize buildings in the challenging setting of unplanned settlements on steep slopes in the City of Kigali.

Methodology

One thousand reference pixels were labelled and used to train an SVM classifier. A reference dataset of ten 30 x 30 m tiles representing different building typologies was used to test the method.

As input for the classifier, the following features were calculated:

- **Radiometric features:** The Red, Green, and Blue channels of the orthomosaic, the normalized r,g,b and a vegetation index (ExG = 2g r b) [1].
- **Texture features:** Local Binary Patterns (LBP) [2] were used, a rotationally invariant texture feature which describes which of the pixels around a central pixel have a higher value. This helps identify edges and corners in the images.
- **Point cloud features:** such as the number of points per pixel and their maximal height difference [4], planar segment features to help identify building roofs [5] when different colors of corrugated iron are used, and geometrical features describing the 3D shape of objects [6].
- **Segment features:** a Mean Shift segmentation [3] was used to group similar pixels, smoothing the classification output and helping identify roof edges.

Conclusions

- The proposed methodology correctly classifies 91% of the dataset.
- Buildings have a completeness of 94% and correctness of 98%.
- Structures such as walls are more difficult to identify.

Table 1: The confusion matrix of the final classification.

<table>
<thead>
<tr>
<th>Predicted class</th>
<th>Buildings</th>
<th>Vegetation</th>
<th>Structures</th>
<th>Outlier</th>
<th>Completeness</th>
<th>Correctness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td>2406</td>
<td>330</td>
<td>40</td>
<td>0</td>
<td>94%</td>
<td>94%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>150</td>
<td>2277</td>
<td>0</td>
<td>0</td>
<td>35%</td>
<td>0%</td>
</tr>
<tr>
<td>Structures</td>
<td>0</td>
<td>30</td>
<td>497</td>
<td>0</td>
<td>55%</td>
<td>0%</td>
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<tr>
<td>Outlier</td>
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<td>10</td>
<td>0</td>
<td>1749</td>
<td>0%</td>
<td>45%</td>
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<tr>
<td>Completeness</td>
<td>94%</td>
<td>35%</td>
<td>55%</td>
<td>0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correctness</td>
<td>94%</td>
<td>0%</td>
<td>0%</td>
<td>45%</td>
<td></td>
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</tbody>
</table>

References


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