IMPROVED TARGET DETECTION IN URBAN AREA USING COMBINED LIDAR AND APEX DATA

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**Light Detection And Ranging (LiDAR)**

Determines the distance between ground objects and sensors by measuring the time a pulse of transmitted energy takes to return to the LiDAR sensor.

LiDAR technology is primary technique to generate Digital Elevation Models (DEMs).

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**Hyperspectral Imaging (HSI)**

A passive technique which collects and processes information from across the electromagnetic spectrum using large number and contiguous spectral bands.

Hyperspectral imaging allows to discriminate, classify, identify as well as quantify materials present in the image using their unique spectral signature.
MAIN OBJECTIVE

Detection of objects in urban scene using combined LiDAR and APEX data.

SPECIFICALLY:
- Improve automatic detection of trees;
- Improve automatic detection of buildings;
- Improve shadow detection in HSI data.

DATA SET OVER THE CITY AND HARBOUR OF ZEEBRUGES (BE)

<table>
<thead>
<tr>
<th>LiDAR</th>
<th>HSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>Date, hour</td>
</tr>
<tr>
<td>13 March 2011</td>
<td>14 June 2011, 14h09</td>
</tr>
<tr>
<td>Scanning altitude</td>
<td>Scanning altitude</td>
</tr>
<tr>
<td>300 m AGL</td>
<td>3500 m AGL</td>
</tr>
<tr>
<td>Strip distance</td>
<td>Spectral range</td>
</tr>
<tr>
<td>100 m</td>
<td>VNIR: 380.5-917.7 nm</td>
</tr>
<tr>
<td>Laser scan rate</td>
<td>SWIR: 941.1-2501.5 nm</td>
</tr>
<tr>
<td>125 Hz</td>
<td>Spectral bands</td>
</tr>
<tr>
<td>Scan angle</td>
<td>288</td>
</tr>
<tr>
<td>20 deg</td>
<td>FWHM</td>
</tr>
<tr>
<td>Scan Frequency</td>
<td>VNIR: 0.7-9.7 nm</td>
</tr>
<tr>
<td>49 Hz</td>
<td>SWIR: 6.2-12 nm</td>
</tr>
<tr>
<td>Scanning mode</td>
<td>FOV</td>
</tr>
<tr>
<td>Last, first &amp; intermediate</td>
<td>28 deg</td>
</tr>
<tr>
<td>Point density</td>
<td>Ground resolution</td>
</tr>
<tr>
<td>~65 points m²</td>
<td>2.14 m</td>
</tr>
<tr>
<td>Point spacing</td>
<td></td>
</tr>
<tr>
<td>10-12 cm</td>
<td></td>
</tr>
</tbody>
</table>
In LiDAR data, the ground points are the measurements from bare-earth terrain that are usually the lowest surface features in a local area. Non-ground points are the measurements from the objects above the bare-earth terrain (i.e. trees, buildings and shrubs).

Surfaces can be divided into four physical categories:

*Elevations, Elevation differences, Surface slopes, Surface homogeneity.*
**LiDAR SEGMENTATION – GROUND and NON-GROUND POINTS**

**One-dimensional bi-directional filter**: 

\[
\forall P_i: \begin{cases} 
\text{if } (S_v > S_T \text{ and } Z_i > Z_T) \text{ non-ground point} \\
\text{otherwise } \text{ground point}
\end{cases}
\]  

(1)

where \( P_i \) is any LiDAR point, \( S_v \) slope vicinity, \( S_T \) is a defined slope threshold, \( Z_i \) is the elevation and \( Z_T \) is an adaptive elevation threshold.

\[
S_i = \arctan\left( \frac{Z_i - Z_{i-1}}{\sqrt{(X_i - X_{i-1})^2 + (Y_i - Y_{i-1})^2}} \right) \quad S_i \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right]
\]

(2)

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**3D Spatial distribution of Non-ground points:**

![3D Spatial distribution of Non-ground points](image)

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**3D Texture filters***:

A 3D cuboid neighborhood is created using a defined radius (1.25m). All points located within the cell volume are counted as the neighbors.

- **\( \Delta Z \):** Height difference between the highest and lowest points within the cuboid neighborhood.
- **\( \sigma Z \):** height standard deviation of points within the cuboid neighborhood.

**E (Entropy):**

\[
E = \sum_{k=1}^{k} \left[ (-I_k \cdot \log_2 I_k) \right]
\]

where \( k \) being the number of neighbors and \( I \) the intensity.

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BruHyp, Bruges, Belgium, 04 September 2012
LiDAR SEGMENTATION – TREES and BUILDINGS (RESULTS)
LiDAR SEGMENTATION – TREES and BUILDINGS (RESULTS)
Normalized Difference Vegetation Index (NDVI$_{705}$)

$$NDVI_{705} = \frac{750 - 705}{750 + 705}$$

Modified Red Edge Simple Ratio (mSR$_{705}$) index

$$mSR_{705} = \frac{750 - 445}{705 + 445}$$

Modified Red Edge Normalized Difference Vegetation Index (mNDVI$_{705}$)

$$mNDVI_{705} = \frac{750 - 705}{705 + 705 - 445}$$
SEGMENTING TREES USING LIDAR AND APEX DATA

LiDAR DATA

One dimensional bi-directional filter

GROUND POINT

NON-GROUND POINT

3D Textural filter

VEGETATION

DTM, DSM

APEX DATA

Greenness indices

VEGETATION

Grid net of 0.5 x 0.5 m

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\[A \forall G_i : \begin{cases} 
\text{if } (C_L = 1 \text{ and } C_A = 1 \text{ and } A_L = 1) & 1 \\
\text{if } (C_L = C_H \neq A_L) & 2 \\
\text{if } (C_L \neq C_H \text{ and } C_H = A_L) & 3 \\
\text{otherwise} & 2 
\end{cases} \]

Points segment as trees
- Green

Points send back for non-ground
- Red

Points segment as non-ground low
- Light pink
HSI SEGMENTATION – BUILDINGS

APEX DATA

Greenness indices

VEGETATION

Mask out vegetation

PCA

Unmixing using VCA

Object detection (ACE, CEM)

Vertex Component Analysis (VCA)

Two basic rules:
1. the endmembers are the vertices of a simplex and;
2. The affine transformation of a simplex is also a simplex.


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HSI SEGMENTATION – BUILDINGS

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Adaptive Coherence Estimator (ACE)*:

\[ T_{ACE}(x) = \frac{(d^T \Sigma^{-1} x)^2}{(d^T \Sigma^{-1} d)(x^T \Sigma^{-1} x)} \]

where \( d \) is the target spectrum, \( x \) is the pixel spectrum, and \( \Sigma \) is the background covariance matrix.

Constrained Energy Minimization (CEM) **:

\[ T_{CEM}(x) = \frac{d^T R^{-1} x}{d^T R^{-1} d} \]

where \( d \) is the target spectrum, \( x \) is the pixel spectrum, and \( R \) is the background correlation matrix.


BUILDING SEGMENTATION USING LIDAR AND APEX DATA

Object detection (ACE, CEM)

Threshold >90%

Resampling

Merging rule (1)

BUILDINGS \(B_A\)

Merging rule (2)

LiDAR DATA

DSM

Non-ground points & not trees

Fused building segmentation

ACE > 90%

CEM > 90%

Region growing algorithm for building separation

Improving DSM

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BUILDING SEGMENTATION USING LIDAR AND APEX DATA

Merging rule (1)

BUILDINGS \( (B_A) \)

Merging rule (2)

Fused building segmentation

\[
\forall P_i : \begin{cases} 
    \text{if } (U = 1 \text{ and } B_L = 1) & 1 \\
    \text{otherwise} & 2
\end{cases}
\]

1 = Non-ground points are buildings
2 = Non-ground points are other high man-made objects

\[
\forall U_i : \begin{cases} 
    \text{if } (B_{ACE} = 1 \text{ and } B_{CEM} = 1 \text{ and } A_L > 2m) & 1 \\
    \text{otherwise} & 0
\end{cases}
\]
3D View of the buildings model
SHADOW DETECTION USING LIDAR AND APEX DATA

APEX scene (R, G, B: b69, b46, b14)

Shadow detection using APEX

Reflectance (%)

Wavelength (µm)

Deep shadow
Target
Semi shadow
Detect shadow in LiDAR DSM using Line-of-sight

LiDAR DSM

Shadow detection using LiDAR DSM
A. RGB image of HSI

B. Shadows estimated through line-of-sight in the LiDAR data

C. Interior of large regions used for training the SVM classifier

D. Shadows detection - final

Detect shadow in LiDAR DSM using Line-of-sight

Detect the interior of large area using distance transformation

Training area

SVM
SHADOW DETECTION USING LIDAR AND APEX DATA

RGB image of HSI

Shadows estimated through line-of-sight in the LiDAR data

Fusion based shadows detection

Zoom to building

Interior of large regions used for training the SVM classifier
CONCLUSIONS

In an effort to overcome the limitations of the segmentation processes in LiDAR, APEX data was combined to provide additional insight about a particular scene and specifically of the detection of trees and buildings.

Fusing a hyperspectral data set with LiDAR has been shown to improve detection and segmentation performances.

The proposed automatic process uses both HSI and LiDAR information and allows for targets as trees and buildings to be discriminated in various heterogeneous background elevations.

A shadow detection method which was developed for VHR HSI was successfully applied also for moderate APEX spatial resolution. The results obtained show that the proposed method can distinguish dark objects from shadows and to improve the shadow segmentation.