Rapid Extraction and Updating Road Network from LIDAR Data

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• Road extraction from remotely sensed data is a traditional, but challenging topic
• Challenge: accuracy, confidence, completeness, and automation
• Comparing with 2D imageries, LIDAR data has 3D information attached
• Our goal is to explore the advanced airborne LIDAR sensing data for automated road extraction and road quality mapping
  – grid-structured urban road network
Data preparation

- Oakland LIDAR data

Intensity image

Depth image
Grid-structured road network extraction

Major Steps

1. Ground Object Separation
2. Road Region Detection
3. Intersection Detection
4. Centerline Fitting
5. Road Network Completion

Input: LIDAR data

Data Conversion

2D intensity image  2D depth image

Hierarchical Morphology

Ground objects  Elevated objects

EM Classification

Road candidate image

Radius-Rotating

Sliced candidate image

TLS Line Fitting

Road centerlines

Vote-based Removal & Missing Line Inference

Output: Vectorized road network
1. Ground objects separation

• **Goal:** separate elevated and ground objects from depth image

• **Method:**

  ➢ Hierarchical Morphological Opening

    ✓ Approximate DTM

    ✓ Elevated objects = depth image – approximate DTM

    ✓ Ground objects = (Elevated objects)ᶜ
1. Ground objects separation

Oakland

-depth image

DTM

elevated objects

grounded objects
1. Ground objects separation

Denver

depth image
DTM

elevated objects
grounded objects
2. Road feature classification

- **Goal**: road candidate extraction from ground objects mask and LIDAR intensity image

  ✓ Instead of classifying the whole intensity image, we carry out classification on grounded objects only

  ✓ Assume intensity distribution of ground objects to be Gaussian Mixture

  \[
p(x) = \sum_z p(z) p(x|z) = \sum_{k=1}^{K} \pi_k N(\mu_k, \Sigma_k)
\]

  ✓ Employ Expectation-Maximization(EM) algorithm to find the maximum likelihood solution for Gaussian Mixture models

  ✓ Each pixel is classified according to their posterior probability
2. Road feature classification
3. Road intersection detection

• After EM classification, *ground road candidates* (binary image) are separated. From this raster image, we proceed to detect road centerlines.

• Here, we develop our approach. First we propose a *Radius-Rotating* method to find road intersections, and cut roads apart from these intersections. Now originally continuous roads are sliced into disconnected segments. Afterwards, *total least squares* fitting is employed to estimate centerlines for each segment.
• **Radius-Rotating**: Unlike template matching methods, in which various shape models like T, +, L shapes are defined, here we only have to put a radius on the candidate point, rotate it and count the number of road regions it goes across.

• **Radius-Rotating** method is illustrated in the following figure:
3. Road intersection detection

a) ≥ 3 branches: intersection candidate point;
b) 2 branches: further check the angle between the two directions.
3. Road intersection detection

- EM segmentation
- Intersection candidates
- Intersections
- Slicing
3. Road intersection detection
4. TLS road centerline fitting

• For each separated segment, we use total least squares (TLS) to fit a center line.

• Given the line equation $ax + by + c = 0$, the criterion of TLS is to minimize the sum of perpendicular distances between points and the line, i.e. we need to minimize:

$$
\sum_i \left( ax_i + by_i + c \right)^2
$$
4. TLS road centerline fitting

Road candidate image

TLS line fitting
5. Road network completion

- After TLS line fitting, there can be many false positives (non-road centerlines). Before proceeding to missing road inference, we’d better remove these false positives as many as possible.

- In general, false positives have random directions, while true road centerlines share several main directions. Based on this observation, we propose the *direction-based cumulative voting* process to pre-remove those centerlines with minor directions (small voted values).
5. Road network completion

**Major direction:** 5 green lines and 5 blue lines, each of them is voted by other 4 with similar direction. So each has *cumulative voted value 4*;

**Minor direction:** randomly distributed (red, orange and black), there is no vote for them. So each has *cumulative voted value 0*. 
5. Road network completion

TLS line fitting

cumulative voting result

Minor direction: removed
5. Road network completion

• After preliminary cumulative-voting based segments removal, we adopt the following procedure for network inference and validation:
  – Geometrical constraints guided gap filling
  – Hypothesis test (back-projection validation)

• **Geometrical constraints:**
  – 1) Collinearity
  – 2) Gap
  – 3) Curvature
  – 4) Length.

• **Hypothesis test:**
  – After inference of these possible gaps, we back-project them onto the intensity and depth image, and perform the validation using intensity and elevation within the regions.
5. Road network completion

Based on these 4 measures, we define failing-link-rate by linear combination:

\[ \text{flr} = \alpha A + \beta D + \mu C + \nu L \]

**the smaller, the more possible**

**a) Collinearity:** direction difference

\[ A = \begin{cases} \frac{|A_1 - A_2|}{A_{max}} & \text{if } (|A_1 - A_2| < A_{max}) \\ \infty & \text{otherwise} \end{cases} \]

**b) Gap:** gap length

\[ D = \begin{cases} \frac{\text{gap}}{G_{max}} & \text{gap} < G_{max} \\ \infty & \text{otherwise} \end{cases} \]

**c) Curvature:** direction variance

\[ C = \frac{\|T_2 - T_1\|_2^2 + \|T_3 - T_2\|_2^2}{4} \]

**d) Length:** longer road first

\[ L = \frac{L_{\text{min}}}{\min(L_1, L_2)} \]
5. Road network completion

Road network completion based on geometrical constraints and back-projection validation
5. Road network completion

Denver

*Visual Quality:* there are 12 $45^0$ and 7 $135^0$ roads. 10.5 $45^0$ and 6 $135^0$ roads are extracted.
5. Road network completion

Denver

Visual Quality: there are 10 vertical and 5 horizontal roads. 8 vertical and 4 horizontal roads are extracted.
5. Road network completion

**Oakland**

Visual Quality: there are 8 450 and 12 1350 roads. 7.5 450 and 11.5 1350 roads are extracted.
5. Road network completion

Atlanta

**Visual Quality:** there are 7 vertical and 6 horizontal roads. 5 vertical and 4 horizontal roads are extracted.
Thank you!