Semantic Alignment of LiDAR Data at City Scale

Fisher Yu    Jianxiong Xiao    Thomas Funkhouser
Princeton University
Motivation

Multiple efforts to scan the cities

Applications

Reconstruction

Virtual Reality
Google Street View

Image based method
+ A lot of pixels
- Adversarial textureless buildings
- Incomplete model
Google Street View

Image based method
Google Street View

Vertical laser line scanner
Google Street View

Laser Measurement + Pose Estimation = 3D Point Cloud
Problem

• Inconsistent pose estimation
• Large scale data
Goal

Robust methods to perform registration of LiDAR scans
Goal

Robust methods to perform registration of LiDAR scans

Before Alignment

Different colors represent different scan runs
Previous Methods

Features
Previous Methods
Previous Methods

Problem

• Primitive features are indistinctive
• Too many to optimize

Desired feature properties

• repeatable
• stable
• view-independent

• sparse
• distinctive
• universal coverage
Approach

Semantic Features
Semantic Features

(a) Facade
(b) Road
(c) Pole
(d) Car
(e) Segment
(f) Line
Poles

- Tree trunks, signs, road lamps
- Reliably matched across runs
Poles
Poles
Facades and Roads

- Point on large planar surface
- Reliably matched across runs
Facades and Roads
Facades and Roads
Vehicles

- Detect HOG features on LiDAR images
- Train SVM with labeled bounding boxes
- Use mean-shift to get foreground
Vehicles
Small Object Segmentation

- Hierarchical clustering by proximity
Small Object Segmentation
Small Object Segmentation
Lines

- Abundant but pairs are hard to distinguish
- Good at fine adjustment
Semantic Features

- repeatable
- stable
- view-independent

- distinctive
- sparse
- universal coverage

Different features have different properties

<table>
<thead>
<tr>
<th>Sparser</th>
<th>Easier to find correspondences</th>
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</thead>
<tbody>
<tr>
<td>Denser</td>
<td>More observation and better accuracy</td>
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</tbody>
</table>
Overview

Semantic Features

Optimization
Overview

Semantic Features

Multiscale Optimization
Overview

Semantic Features

Multiscale Optimization
Multiscale Optimization
Multiscale Optimization
Multiscale Optimization

Use all the features
Multiscale Optimization

Use all the features
Multiscale Optimization

Use sparse features first
Multiscale Optimization

Use sparse features first
Multiscale Optimization

Refine
Multiscale Optimization

ICP

Closest Update

Smaller Tolerance

Multiscale
Pole
Facade
Vehicle
Objects
Line
Experiments

Test data

• **Data set:** NYC
• **Ground truth:** 589 manually-specified point correspondences scattered throughout city

Goal

• Understand how different features contribute to the alignment
Experiments

Test data
• Data set: NYC
• Ground truth: 589 manually-specified point correspondences scattered throughout city

Goal
• Understand how different features contribute to the alignment
Feature Order

Pole  Facade  Vehicle  Objects  Line

Finer  Sparser
Initial Alignment

![Graph showing the percentage of correspondences versus correspondence errors in meters. The graph has a yellow line labeled 'Initial'.]
Poles

Correspondence Errors in Meters

Percentage of Correspondences

Correspondence Errors in Meters

- Poles
- Initial
Facades and Roads

![Graph showing correspondence errors in meters versus percentage of correspondences for different categories: Poles, facades, roads (blue), Poles (pink), and Initial (yellow). The graph indicates an increase in percentage of correspondences with increasing correspondence errors in meters.](image-url)
Vehicles

Correspondence Errors in Meters

- Add cars
- Poles, facades, roads
- Poles
- Initial
Small Object Segmentation

![Graph showing correspondence errors in meters against percentage of correspondences.](image)
Results for NYC
Results for Other Cities

(a) New York City

(b) San Francisco

(c) Paris

(d) Rome
Visual Comparison
Acknowledgment

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