Low Complexity Real-Time Simultaneous Localization and Mapping Using Velodyne LiDAR Sensor

Dr. Kiran Gunnam/Algorithms Group
Director of Algorithms, Velodyne LiDAR, Inc.

Outline

- All about LiDAR
- SLAM formulation
- Results (SLAM Demo)
- Benchmarking results on Jetson TX2
About Velodyne LiDAR

Based in Silicon Valley.

Evolved after founder/inventor David Hall developed the HDL-64 Solid-State Hybrid LiDAR sensor in 2005. Leading developer, manufacturer, and supplier of 3D real-time perception systems. Used in a variety of commercial applications including autonomous vehicles, vehicle safety systems, 3D mobile mapping, 3D aerial mapping, and security.

For more information, visit http://www.velodynelidar.com.

My group is hiring experienced mapping and CV engineers. Please contact me at kgunnam@velodyne.com
ROADMAP TO AUTOMATION

LiDAR Covers All Levels of ADAS
Automated Safety

- **Level 0**: LiDAR is essential part for ADAS
  - No intervening vehicle system active

- **Level 1**: System handles lane holding and lane changes
  - System handles the other function

- **Level 2**: System handles lane holding and lane changes in a specific application case
  - System detects limits of system and asks the driver to take over

- **Level 3**: System handles lane system can handle all situations automatically in the specific application case
  - Sufficient warning

- **Level 4**: System handles lane system need no longer continuously monitor the system, must potentially be available to take over
  - Fully automated

- **Level 5**: System can handle all solutions automatically throughout the trip, no driver needed
  - Driverless

Roadmap to Automation - Driver Driven to Driverless Vehicles

Source: Frost & Sullivan; VDA Automotive SYS Konferenz 2014
ULTRA PUCK™ (VLP-32C)

A GROUNDBREAKING LIDAR SENSOR COMBINING BEST-IN-CLASS PERFORMANCE WITH A SMALL FORM FACTOR
HIGH DEFINITION REAL TIME 3D LIDAR FOR AUTOMOTIVE APPLICATION

KEY FEATURES

• Best-in-class performance with a small form factor
• 32 Channels
• Dual Returns
• Up to 200m Range
[Improved algorithms for detection, 2x range improvement from 100m]
• ~1.2M Points per Second
• +15° to -25° Vertical FOV
• 360° Horizontal FOV
• Calibrated reflectivity
• Low Power Consumption (12 Watts!)
• Protective Design
• Connectors: RJ45 / M12
10 times more powerful but a third the size and weight of the sensor it’s replacing, the HDL-64.

128 has our new auto-alignment technology.
Solid-state Velarray™ LiDAR

cost-effective & high-performance
rugged automotive product
Very small form factor (125mm x 50mm x 55mm)
Can be embedded into the front, sides, and corners of vehicles
Provides up to a 120-degree horizontal and 35-degree vertical field-of-view,
200-meter range even for low-reflectivity objects.
Automotive integrity safety level rating of ASIL B.
Ensures safe operation in L4 and L5 autonomous vehicles but also in ADAS-enabled cars.
Target price in the hundreds of dollars when produced in mass volumes.
SLAM overview

- Simultaneous Localization and Mapping
- Localization: vehicle pose estimation "Where am I?"
  Mapping: 3D environment reconstruction
- Centimeter accuracy in real time for car applications

Maximum a Posteriori (MAP) Estimation

SLAM estimate

Front-end:
- Feature extraction
- Data association:
  - Short-term (feature tracking)
  - Long-term (loop closure)

Back-end:
- MAP estimation
Problem described as a graph
- Every node corresponds to a robot position and to a laser measurement
- An edge between two nodes represents a data-dependent spatial constraint between the nodes

Given
- \( u_t \): control command, or **odometry**
- \( z_{t,i} \): the \( i \)th **landmark** from the measurement

**estimate**
- \( s_t \): robot **pose** \((x, y, \theta)\)
- \( m \): **map**, various representations
  - \( l_{c_t,i} \): the \( c_t,i \)th landmark in map, (3D coordinates), can be other parameters
- \( c_{t,i} \): data association, the \( i \)th observed landmark matched to landmark \( c_{t,i} \) in the map (**assume known for algorithms in this talk**)

Yuncong Chen, Algorithms for Simultaneous Localization and Mapping
Online SLAM: Filtering

Estimate map and **current** pose

\[
\arg \max_{s_t, m} P(s_t, m | z_{1:t}, u_{1:t})
\]

Recursive update

\[
\underbrace{p(s_t, m | z_{1:t}, u_{1:t})}_{\text{posterior}_t} \propto \underbrace{p(z_t | s_t, m)}_{\text{measurement model}} \int \underbrace{p(s_t | s_{t-1}, u_t)}_{\text{motion model}} \underbrace{p(s_{t-1}, m | z_{1:t-1}, u_{1:t-1})}_{\text{posterior}_{t-1}} ds_{t-1}.
\]

- first marginalize over previous pose
- then conditioning on new measurement
- have closed form update rules for Gaussian models (Kalman filter)
Full SLAM: Smoothing

Estimate map and **entire trajectory**

\[
\arg \max_{s_{1:t}, m} P(s_{1:t}, m | z_{1:t}, u_{1:t})
\]

Factorize the posterior

\[
p(s_{1:t}, m | z_{1:t}, u_{1:t}) = \prod_{\tau=1}^{t} p(s_{\tau} | s_{\tau-1}, u_{\tau}) p(z_{\tau} | s_{\tau}, m)
\]

\[
= \prod_{\tau=1}^{t} p(s_{\tau} | s_{\tau-1}, u_{\tau}) \prod_{i=1}^{N_{\tau}} p(z_{\tau,i} | s_{\tau}, l_{\tau,i})
\]

- factor graph
Motion Model and Measurement Model

**Motion Model**

\[
s_t = f(s_{t-1}, u_t) + \mathcal{N}(0, \Lambda_u)
\]

\[
p(s_t | s_{t-1}, u_t) = \mathcal{N}(f(s_{t-1}, u_t), \Lambda_u)
\]

- orientation introduces **nonlinearity**
- assume **Gaussian** noise

**Measurement Model**

\[
z_t = h(s_t, m_t) + \mathcal{N}(0, \Lambda_z)
\]

\[
p(z_t | s_t, m_t) = \mathcal{N}(h(s_t, m_t), \Lambda_z)
\]
Nonlinear least squares formulation of full SLAM

Minimize

\[- \log p(s_{1:t}, m | z_{1:t}, u_{1:t})\]

\[= - \log \prod_{\tau=1}^{t} p(s_{\tau} | s_{\tau-1}, u_{\tau}) \prod_{i=1}^{N_{r}} p(z_{\tau,i} | s_{\tau}, l_{c_{\tau,i}})\]

\[\propto \sum_{\tau=1}^{t} \left( \| f(s_{\tau-1}, u_{\tau}) - s_{\tau} \|_{A_{u}}^2 \right) + \sum_{i=1}^{N_{r}} \left( \| h(s_{\tau}, l_{c_{\tau,i}}) - z_{\tau,i} \|_{A_{z}}^2 \right)\]

Unify these two kinds of constraints with generic term

\[e(x_{i}, x_{j}, d_{ij}) \triangleq e_{ij}(x)\]

the goal is then to minimize nonlinear quadratic function:

\[\chi^2(x) \triangleq \sum_{(i,j) \in G} \| e_{ij}(x) \|_{\Omega_{ij}}\]
Feature Detector

The key to reduce the complexity is feature detector so that the backend needs to solve less equations. Our solution is about finding the features fast and also using less number of features. While the sensor can give 1M points per second, we need to decide which points are key to solve 6DOF problem.

Optimal 6DOF estimation with 8 measurements when sensor and target frames are unknown to each other. Target frame contains 16 active Lasers/LEDs and chase frame contains the detector in autonomous aerial refueling application.

Summary

Graph-/optimization-based approaches draw ideas from the intersection of numerical methods and graph theory.

They are getting more and more favored over filtering approaches, partly due to the latter's inherent inconsistency.

Combined with submapping, they show great efficiency.
Results
Benchmarking
Real-time target is 100 ms. Both the mapping and odometry meets the real-time requirement.

Table 1: Execution Time and Power Consumption Analysis

<table>
<thead>
<tr>
<th></th>
<th>Nvidia Jetson TX2 (ARM+Denver)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usage</td>
<td>Using only ARM cores. GPU is not used.</td>
</tr>
<tr>
<td>Execution Time (ms)</td>
<td>Power Consumption (w)</td>
</tr>
<tr>
<td>Mapping</td>
<td>96.1</td>
</tr>
<tr>
<td>Odometry</td>
<td>60.9</td>
</tr>
</tbody>
</table>
References

Yuncong Chen, Algorithms for Simultaneous Localization and Mapping
Backup
<table>
<thead>
<tr>
<th>Features</th>
<th>HDL-64</th>
<th>HDL-32</th>
<th>VL-F-16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels</td>
<td>64</td>
<td>32</td>
<td>16</td>
</tr>
<tr>
<td>Range</td>
<td>100-120 m</td>
<td>80-100 m</td>
<td>100 m</td>
</tr>
<tr>
<td>Accuracy</td>
<td>±1/2 m</td>
<td>±1/2 m</td>
<td>±1/3 m</td>
</tr>
<tr>
<td>Data</td>
<td>Distance/Intensity</td>
<td>Distance/Calibrated Reflectivities</td>
<td>Distance/Calibrated Reflectivities</td>
</tr>
<tr>
<td>Data Rate</td>
<td>1.2 M pts/sec</td>
<td>700,000 pts/sec</td>
<td>300,000 pts/sec</td>
</tr>
<tr>
<td>Vertical FOV</td>
<td>26.8°</td>
<td>40°</td>
<td>30°</td>
</tr>
<tr>
<td>Vertical Resolution</td>
<td>-0.4°</td>
<td>1.3°</td>
<td>-2.0°</td>
</tr>
<tr>
<td>Horizontal FOV</td>
<td>360°</td>
<td>360°</td>
<td>360°</td>
</tr>
<tr>
<td>Horizontal Resolution</td>
<td>5 Hz: 0.98° 10 Hz: 0.17° 20 Hz: 0.35°</td>
<td>5 Hz: 0.98° 10 Hz: 0.17° 20 Hz: 0.35°</td>
<td>5 Hz: 0.1° 10 Hz: 0.2° 20 Hz: 0.4°</td>
</tr>
<tr>
<td>Input Voltage</td>
<td>10-32 VDC</td>
<td>9-32 VDC</td>
<td>9-32 VDC</td>
</tr>
<tr>
<td>Power</td>
<td>60 W</td>
<td>12 W</td>
<td>8 W</td>
</tr>
<tr>
<td>Environmental</td>
<td>IP67</td>
<td>IP67</td>
<td>IP67</td>
</tr>
<tr>
<td>Operating Temperature</td>
<td>-10° to 50° C</td>
<td>-10° to 60° C</td>
<td>-10° to 60° C</td>
</tr>
<tr>
<td>Size</td>
<td>203 mm x 204 mm (7.6” x 8.0”)</td>
<td>89 mm x 145 mm (3.5” x 5.7”)</td>
<td>104 mm x 72 mm (4.1” x 2.8”)</td>
</tr>
<tr>
<td>Weight</td>
<td>15 kg (33 lbs)</td>
<td>1 kg (2.2 lbs)</td>
<td>0.83 kg (1.8 lbs)</td>
</tr>
</tbody>
</table>
Thank You!