Vehicle Localization based on Lane Marking Detection

Yuncong Chen
UCSD
HRI intern 2014
Overview

Input

- Odometry (noisy GPS / IMU for now)
- Monocular camera
- Lane level map

Goal

- lateral localization on highway
- give correct estimate on merge / split points

Assumptions

- road surface is flat
Coordinate System

GPS
Longitude / Latitude

Map
California State Plane

Algorithm
North / East / Down

Local plane origin = first gps position
Map

no semantic information, interpolate
Particle Filter

- **Motion model**
  \[ P(x_t|x_{t-1}, u_t) \]
  - previous pose
  - current pose
  - GPS / odometry

- **Observation model**
  \[ P(o_t|x_t, m) \]
  - current image
  - map

\( \text{pose} = (\text{north, east, yaw}) \)
\( \text{map} = \text{a set of points labeled by marking groups} \)
Particle Filter

- **propagate** using motion model
- weight each particle by its likelihood computed from observation model
- resample particles according to their weights

all with same weight here
Motion Model \[ P(x_t | x_{t-1}, u_t) \]

- rotations and translation computed from odometry
Observation Model $P(o_t | x_t, m)$

project map points to bird’s-eye view

Given the vehicle pose, our bird’- eye view image is expected to look like this ...
Observation Model \[ P(o_t | x_t, m) \]

project map points to bird’s-eye view

Given the vehicle pose, our bird’- eye view image is expected to look like this ...
Observation Model \( P(o_t | x_t, m) \)

... while what we really observe is ...

inverse perspective transform \[ \rightarrow \]

filter \[ \rightarrow \]

Hough line fitting
Observation Model  \( P(o_t|x_t, m) \)
Maximum Bipartite Matching

expected

observed
... not so simple

some map lines may not be detected in the image

order must be consistent

matches cannot be too far away

# candidate matchings
Likelihood Score

$$P(\text{detected lines} \mid \text{map lines}) = \prod_{i \in \text{matched}} P(l_i \mid m_i) \cdot \prod_{i \in \text{unmatched}} p_0$$

$$P(l_i \mid m_i) = e^{-\eta d(l_i,m_i)}$$

score = $\frac{1}{m} \log P(\text{detected lines} \mid \text{map lines})$
Speed Up Matching

- Sample to obtain a very small set of candidate matchings
- For the rest of the particles, only evaluate these candidate matchings
- Exploit spatial correlation of matchings among nearby particles
- Preferable to sample particles spread out in space.
Speed Up Matching search in previous map lines’ extent

- Keep track of extent of every map line
- For a new set of detected lines, search matchings for each map line only within its extent
- Exploit **temporal invariance** of matchings for a single particle at different times
Process Images

$P(o_t | x_t, m)$

- inverse perspective transform
- filter
- Hough line fitting
Inverse Perspective Mapping

Lane Map, NED coordinate system

pitch

height

yaw

measured by hand
Inverse Perspective Mapping
Inverse Perspective Mapping
Inverse Perspective Mapping
Top-hat Filter

high response if one side of an edge is very dark
Top-hat Filter

- High response if one side of an edge is very dark.
- More robust for detecting dark-bright-dark patterns.

Threshold &
Steerable Filter  Second derivative of Gaussian

\[ G_\theta = \cos^2(\theta) \cdot \frac{\partial^2 G}{\partial x^2} + \sin^2(\theta) \cdot \frac{\partial^2 G}{\partial y^2} - 2\cos(\theta)\sin(\theta) \cdot \frac{\partial^2 G}{\partial x \partial y} \]
Map-guided Filtering

SC

logic OR
Steerable vs. Top-hat noisy image
Take Advantage of Map

Observation model
- map-guided image filtering
- map-guided line fitting

Motion model
- more likely to go along the current lane
- cannot move beyond road edges
Hough Transform Line Fitting

25 line segments detected by OpenCV’s probabilistic Hough transform

6 lines remains after merging
Experiments on straight lanes

avg lateral error: 0.22, max: 1.35
Straight lanes
Deal with Curved Lanes

avg lateral error: 0.25, max: 0.98
Deal with Curved Lanes

- detect whether the line is a curve (i.e. residual of a linear regression is large)
- if so, match only the bottom segment
Steerable vs. Top-hat

**Steerable**
- Avg lateral error: 0.23
- Max lateral error: 1.15

**Top-hat**
- Avg lateral error: 0.2
- Max lateral error: 0.86
Steerable vs. Top-hat

**Steerable**
- Avg lateral error: 0.3, max 0.79
- Avg lon. error: 0.7, max 1.55

**Top-hat**
- Avg lateral error: 0.47, max 1.8
- Avg lon. error: 0.67, max 2.83
Effect of the Number of Particles
Issues and Extensions

- shadows
- more general markings (urban environment)
  - stop-lines (longitudinal correction)
  - curved lanes
  - model-free
- investigate how number of particle affects performance