Lane Assignment

2011.11.13

0. Plan

Toy Model:

(1) Fixed Map

(2) One Straight Road Segment

(3) One Less noisy Route

(4) GPS Location Observation

Real World:

(1) Map is noisy → Map Refinement problem

(2) Multiple Roads:

  (a) Conjunctions constraint → inner lane before turning
  (b) Map Matching problem

(3) Multiple Noisy Routes → need systematic correction for some routes

(4) More Dynamics: Yaw rate + Speed

1. Fixed Map, One Road, One Route, GPS Location

Settings:
Map: OSM
Road: Part of Beacon Street, 28 way points, 2 lanes, 9m wide
Route: mfallon mit 2011-08-19 18-44-12-342476 Partition 0 4.rt, 183 way points

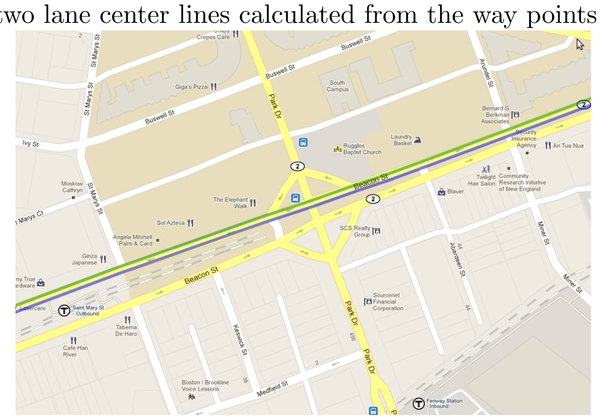
1.1) i.i.d-Gaussian Mixture

Model:
The car is in one of the three states {Left Lane,Changing Lane,Right Lane}
The distance from GPS Location to lane center line follows from normal distribution:
x=(lat,lon)$|z_x \sim \sum_{j=1}^{3} \delta(z_x = j)\mathcal{N}(\mu_j^x, \sigma^2)$
where:
z_x is the lane assignment of x,

μ_j^x is the projection of x onto lane center,
dist is calculated with haversine formula for the sphere

Algo:
Maximum Likelihood $\leftrightarrow$ Greedy Assignment: assign each x to the nearest lane center line
Result:

Figure 1: two lane center lines calculated from the way points from OSM



1.2) Weak-Limit HDP-HMM-Gaussian Mixture

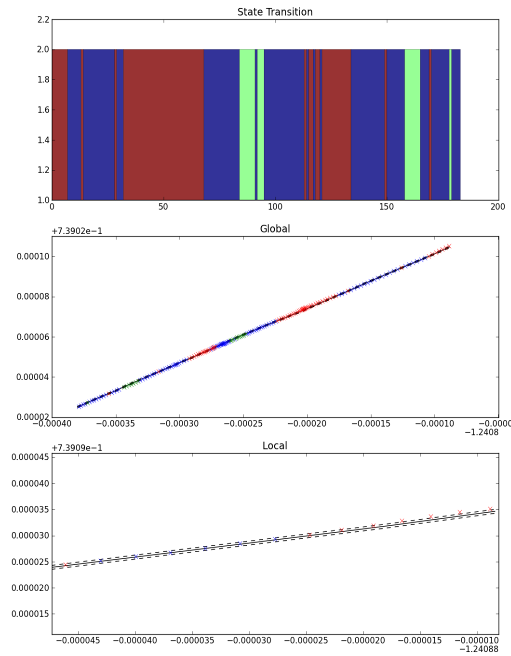
Model:
$\beta \sim Dir(\frac{\gamma}{K}, ..., \frac{\gamma}{K})$
$\pi_0|\rho \sim Dir(\rho, ..., \rho)$
$\pi_j|\beta, \alpha \sim Dir(\alpha\beta_1, ..., \alpha\beta_K)$
$x_t|\{\pi_j\}_{j=1}^{\infty}, x_{t-1} \sim \pi_{x_{t-1}}$
$y_t|\{\theta_j\}_{j=1}^{\infty}, x_t \sim \mathcal{N}(\mu_{x_t}^{y_t}, \sigma_{x_t}^2)$
$\sigma_{x_t}^2 \sim$ Scaled-Inv-$\chi^2(\nu_0, \sigma_0^2)$
$\mu_{x_t}^{y_t}$ is Fixed

where $\lambda = \{\nu_0, \sigma_0^2\}, \theta_t = \{\mu_{x_t}^{y_t}, \sigma_{x_t}^2\}$
Algo:
Gibbs Sampler:

1) parameter:
Discrete Measure β^{new}: $P(\beta^{new}|\vec{x}^{old}, \beta^{old}) \sim Dir(\frac{\gamma}{K} + m_1, ..., \frac{\gamma}{K} + m_K)$
Transition Matrix π_j^{new}: $P(\pi_j^{new}|\vec{x}^{old}, \beta^{new}) \sim Dir(\alpha\beta_1^{new} + n_{j1}, ..., \alpha\beta_K^{new} + n_{jK})$
Initial State π_0^{new}: $P(\pi_0^{new}|x_0^{old}) \sim Dir(\rho + \delta(x_0^{old} = 1), ..., \rho + \delta(x_0^{old} = K))$
Covariance Matrix σ_j^2: $P(\sigma_j^2|\vec{x}^{old}) \sim$ Scaled-Inv-$\chi^2(\nu_0 + n, \frac{\nu_0\sigma_0^2 + (n-1)s^2}{\nu_0 + n})$

where:
n^{ji} is the number of times that transit from state j to state 1
m^j is the simulated number of tables from Chinese Restaraunt Process
s^2 is the sample variance

Figure 2: Up: state transitions, Mid: Global look of the lane assignment, Down: Local look of the lane assignment



2) state assignment:
Backward Sum-Product:
$m(x_N = k) = 1$

$$m(x_n = k) = P(y_{n+1:N}|x_n) = \sum_{x_{n+1}=1}^{K} m(x_{n+1})P(y_{n+1}|x_{n+1})P(x_{n+1}|x_n = k)$$

Forward Sample:
$P(x_1^{new}|y_{1:N}) \propto P(x_1^{new})P(y_{1:N}|x_1) = \pi_0(x_1^{new})P(y_1|x_1^{new})m(x_1)$
$P(x_t^{new}|x_{1:t-1}^{new}, y_{t:N}, \pi_{x_{t-1}^{new}}^{new}) \propto P(x_t^{new}|x_{t-1}^{new})P(y_{t:N}|x_t) = \pi_{x_{t-1}^{new}}(x_t^{new})m(x_t)P(y_t|x_t^{new})$

1.3) HSMM-Gaussian Mixture

Result:

Figure 3: Graphical Model

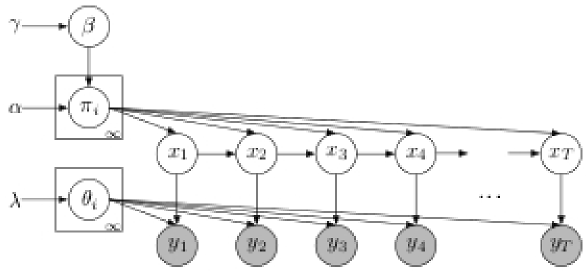


Figure 4: Comparison Result