Generation of Accurate Lane Level Maps from Coarse Prior Maps and LIDAR

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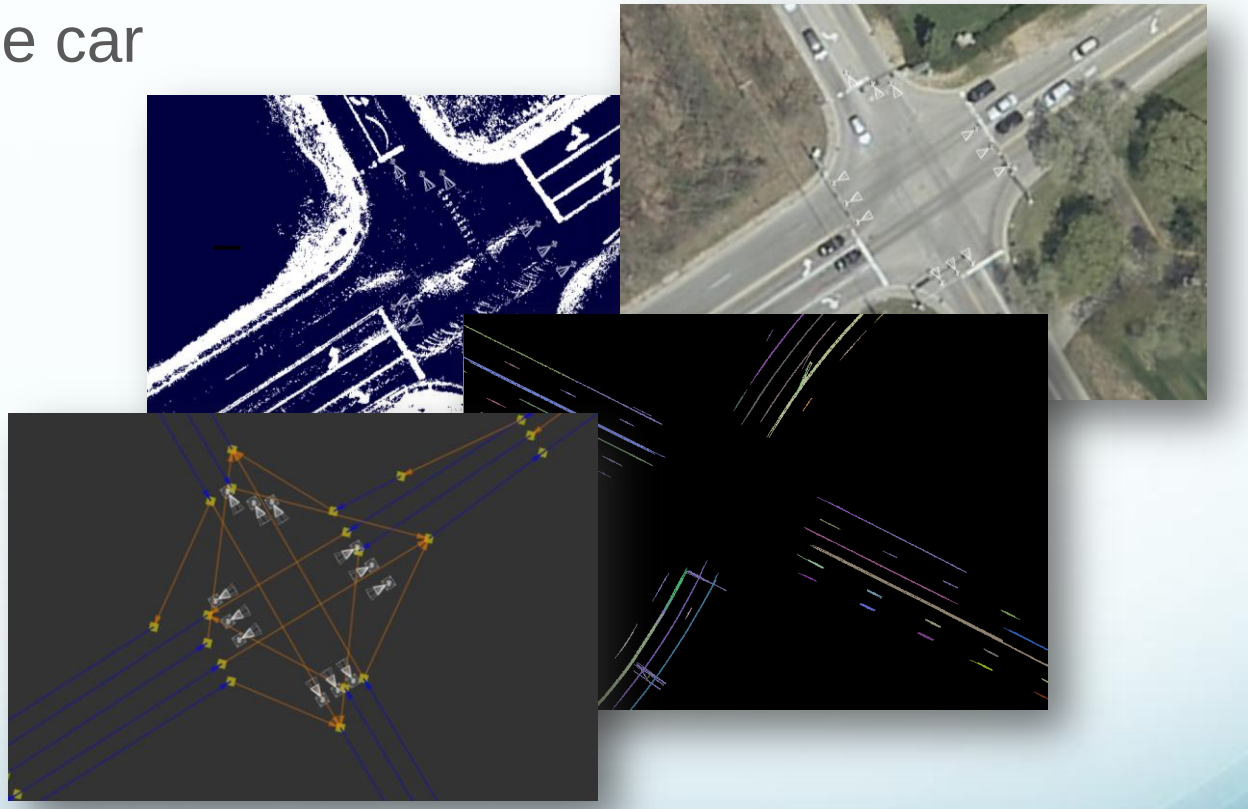
Maps for Autonomous Driving

- Localization of the car
- Planning
- Perception



Add Semantic Information..

Objective

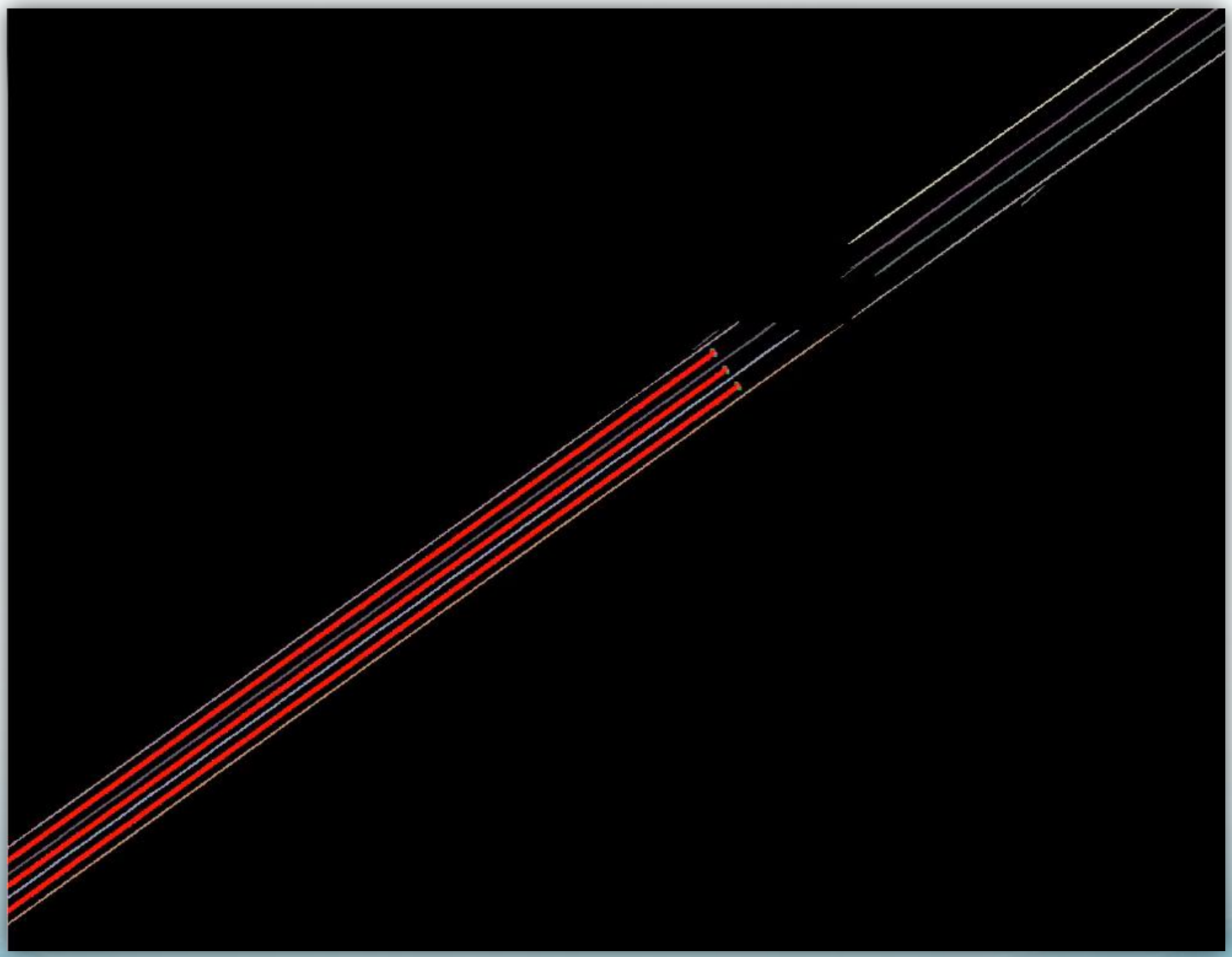
Inaccurate map for coarse structural information

High Precision LIDAR Data

Accurate Semantic Lane Map

Key Contributions

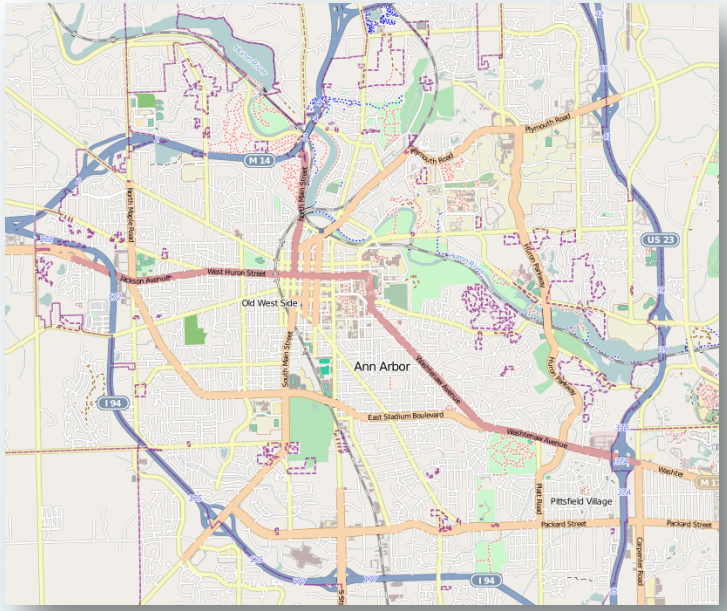
- Design of a probabilistic inference algorithm which can leverage the coarse structural information
- Use of Particle Filter and its variations as a probabilistic inference algorithm
  - Particle Filter is guided along this coarse map to generate lane estimates
  - Filter parameters are modified based on the semantic information in the map



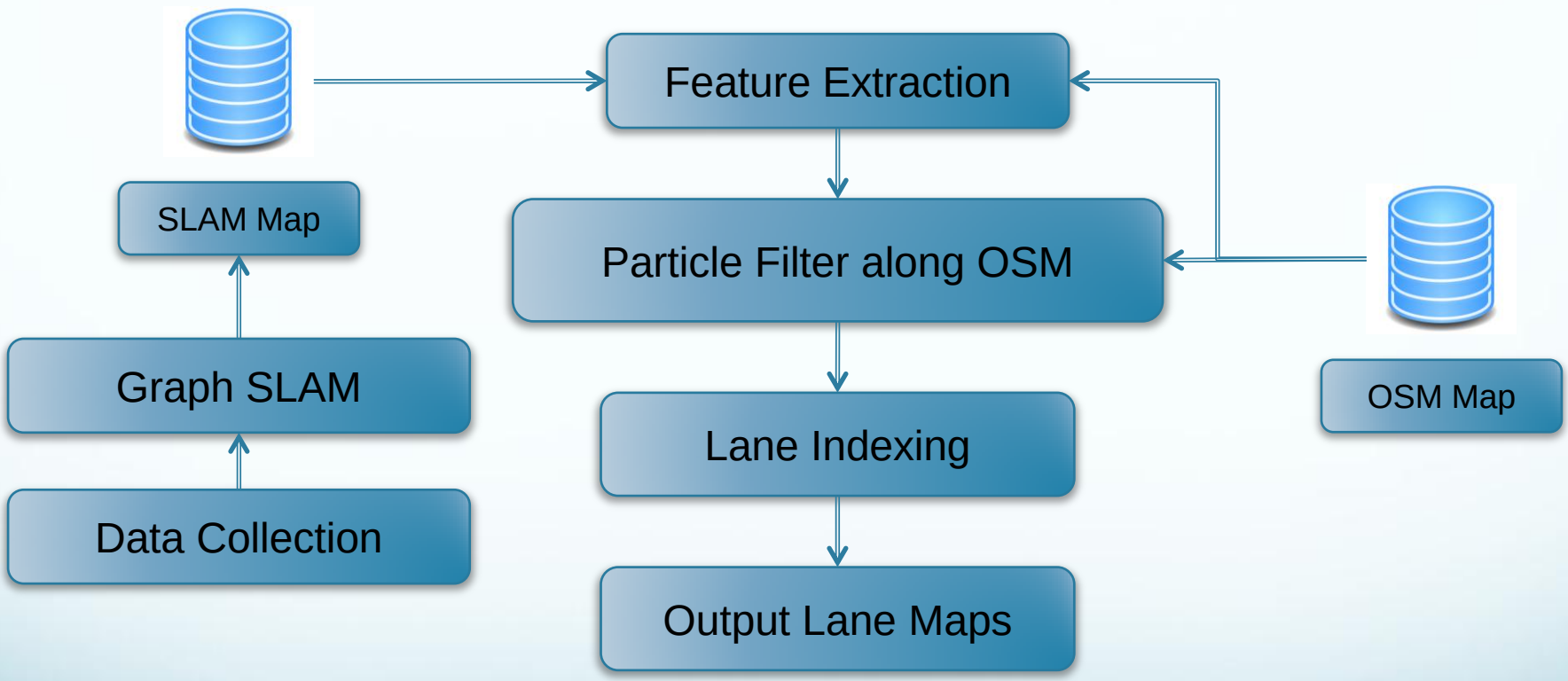
Autonomous Driving

Open Street Map

- The Free Wiki World Map
  - Database of crowd sourced map network
  - More than 33 Million km of roads in the database (as of May 2009)
- Data is not accurate enough for autonomous driving

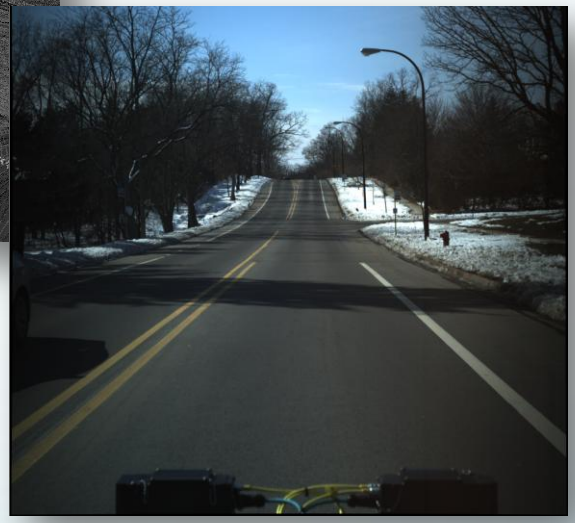


Overview


Feature Extraction
SLAM Map
Particle Filter along OSM
Graph SLAM
OSM Map
Lane Indexing
Data Collection
Output Lane Maps

Data Collection

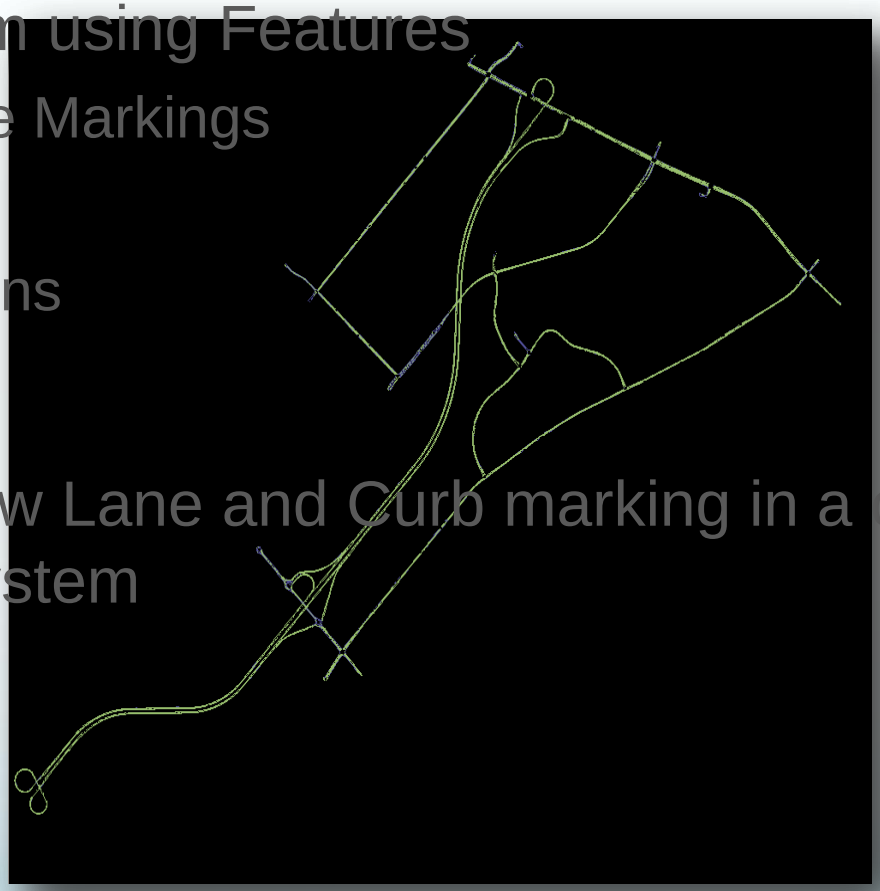
- Sensors
  - Velodyne
  - Camera data
  - Applanix GPS
- Scenes
  - Urban Roads
  - Country Roads
  - Freeways



Data is collected across multiple days in different log files.

Graph SLAM

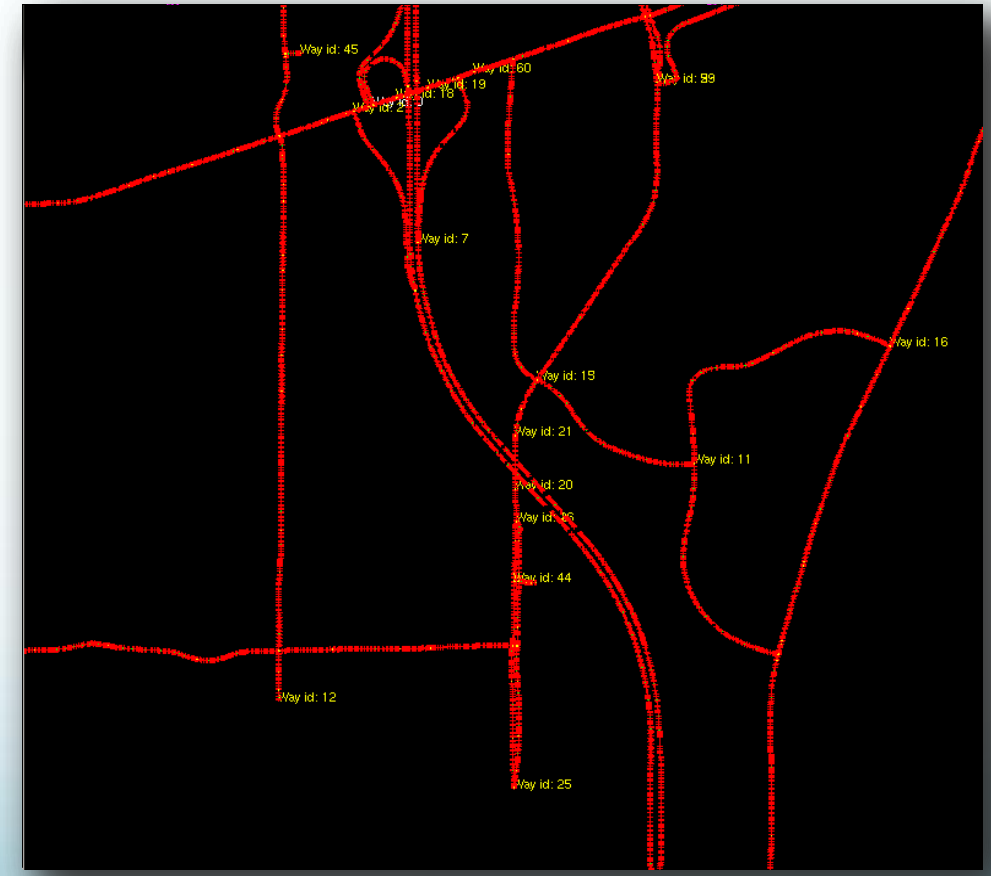
- Graph Slam using Features
  - Lane Line Markings
  - Curbs
  - Road Signs
  - Poles
- Output: Raw Lane and Curb marking in a consistent co-ordinate system



Highway with an overpass

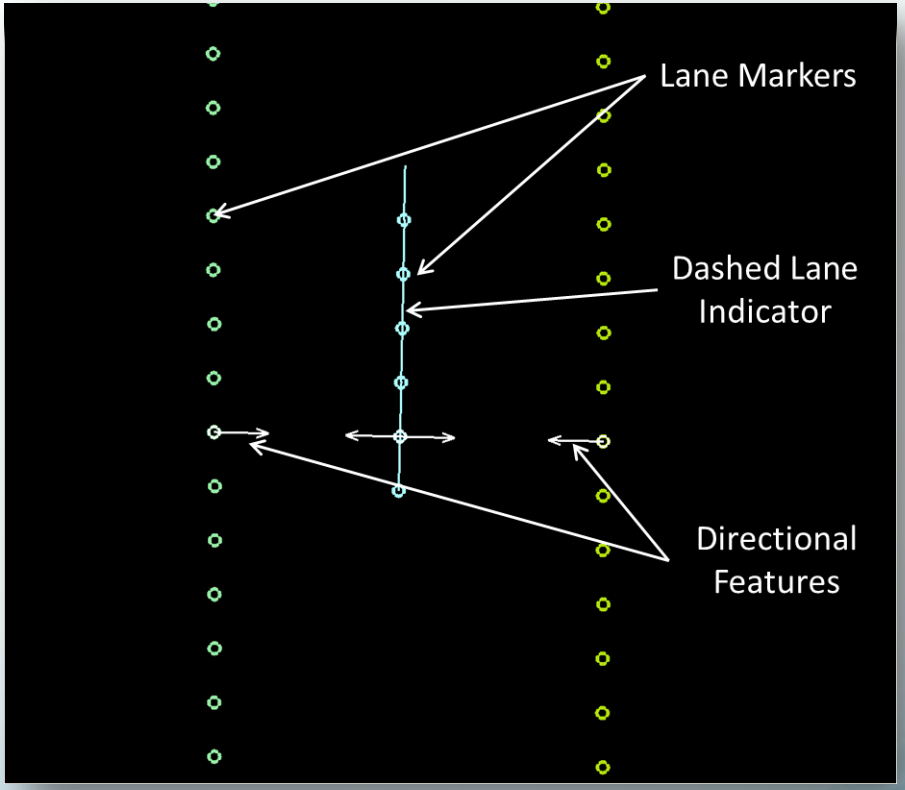
Feature Extraction

- OSM Ways are up-sampled so that each node is placed a 1m distance
- Group line markers together using greedy flood fill algorithm in longitudinal direction
- Associated these grouped line Markers with corresponding nearest OSM Node
- Compute Offset Distance
- Lane Markers: Projected points on Line Markers from OSM Node computed during offset calculation



Semantic Information

- Check for Dashed lanes
- Compute Directions



Particle Filter

Approximation of Bayes Filter:

$$Bel(x_n) \mu\ p(z_n \mid x_n) \grave{O} p(x_n \mid x_{n-1}) Bel(x_{n-1}) dx_{n-1}$$

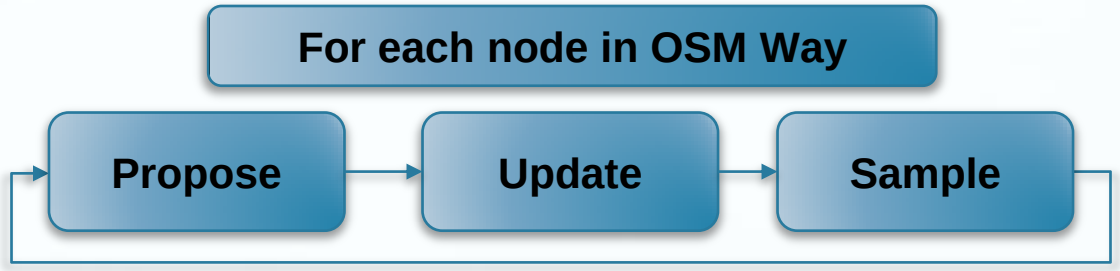
Represented by set of ‘m’ weighted particles

$$Bel(x) \approx \{x^{(i)}, f^{(i)}\}_{i=1\ldots m}$$

where: ‘x’ is the state of lane estimate, ‘z’ is observations, ‘Φ’ is the weight of the particle

State of Lane Estimate(x) is offset (o) and width (*w*)

Conventional Particle Filter



- Sampling: Sample ‘m’ particles from *Bel*(x_{n-1}):
  - Sample from the previous weighted distribution
  - Introduce few new particles distributed normally around OSM Node and expected standard lane width (~3.5m)
- Proposal Distribution: Gaussian noise is added to sampled particles to account for noise and inaccuracies in OSM

$$x_n^{(i)} : \{o_{n-1}^{(i)} + N(0, s_o), w_{n-1}^{(i)} + N(0, s_w)\}$$

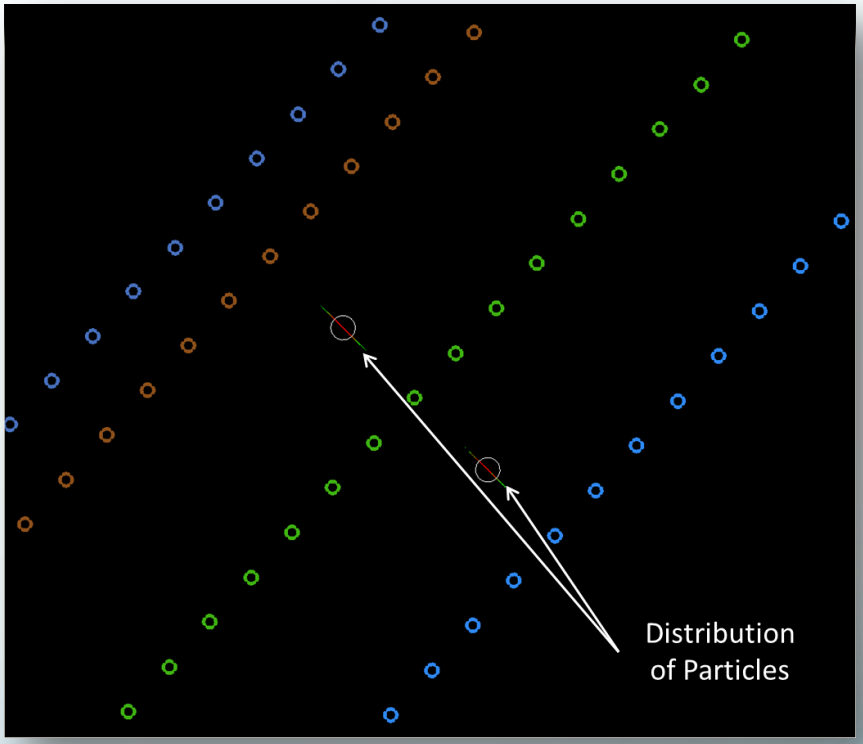
Conventional Particle Filter

- Update Function: Weight update for each particle is done according to following scheme:
  - For each particle, we perform data association with the lane observation
  - Compute new lane offset and widths from the observations
  - Update the weight according to Gaussian weighting scheme given in the following equation:

$$\phi_n^{(i)} = \frac{1}{2\pi\sigma_o} e^{\frac{-(\tilde{o}_n^{(i)} - o_n^{(i)})^2}{2\sigma_o^2}} \frac{1}{2\pi\sigma_w} e^{\frac{-(\tilde{w}_n^{(i)} - w_n^{(i)})^2}{2\sigma_w^2}}$$

Conventional Particle Filter

- Disadvantages:
  - Different type of lane configurations
  - More particles to cover the entire state space



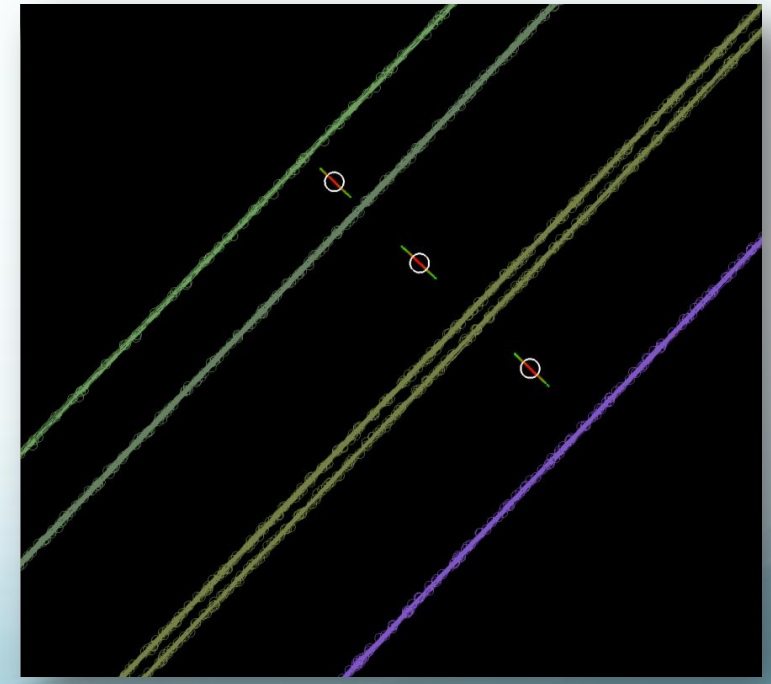
Dual Particle Filter

Switch the role of proposal and update functions

Proposal Distribution: New particles are proposed in the system based on the observations

$$x_n^{(i)} : \{\frac{l_j + l_{j+1}}{2} + N(0, s_o); (l_{j+1} - l_j) + N(0, s_w)\}$$

where $l_i : \{l_1..l_k\}$ are k lane markers observed at current node and j is uniformly selected



Dual Particle Filter

- Update Function: Importance factor for each particle is corrected using prior belief *Bel*(x_n).
- Generate ‘m’ samples using proposal distribution in a conventional particle filter

$$x_n^{(i)} \sim p(x_n \mid x_{n-1}) Bel(x_{n-1})$$

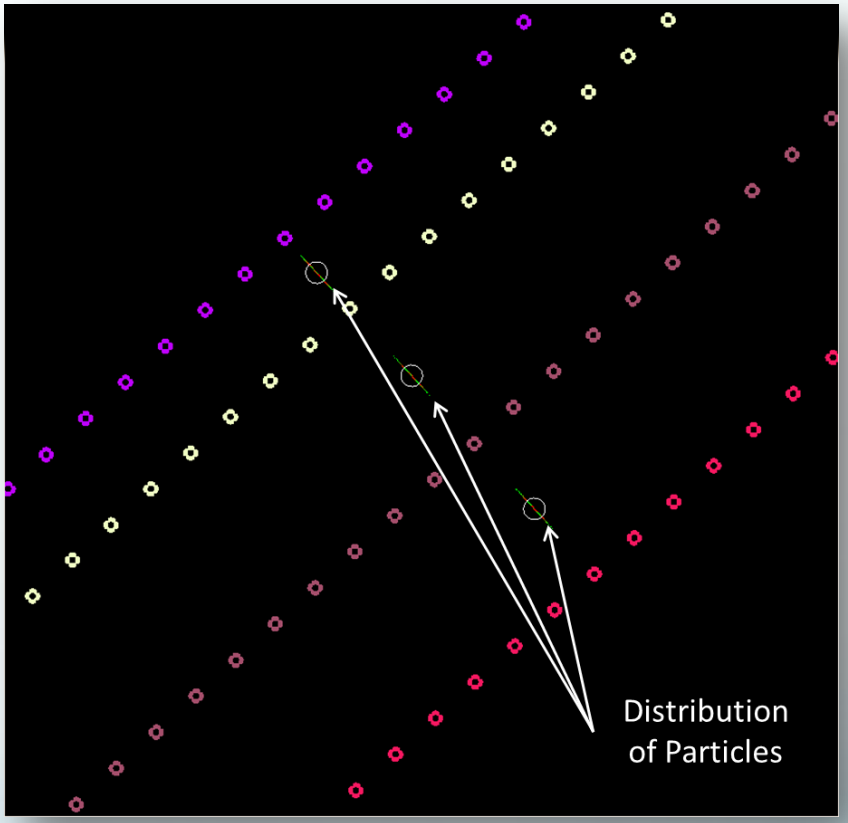
Using a Kernel Density approach, importance factor is given by

$$\phi_n^{(i)} = h(\{\tilde{x}_n\}; x_n^{(i)})$$

where, *h* is the parameterized kernel density function

Dual Particle Filter

- This approach is able to estimate non-standard lane configurations
- Disadvantages:
  - Failure to identify lane additions
  - Failure to identify lanes at intersections

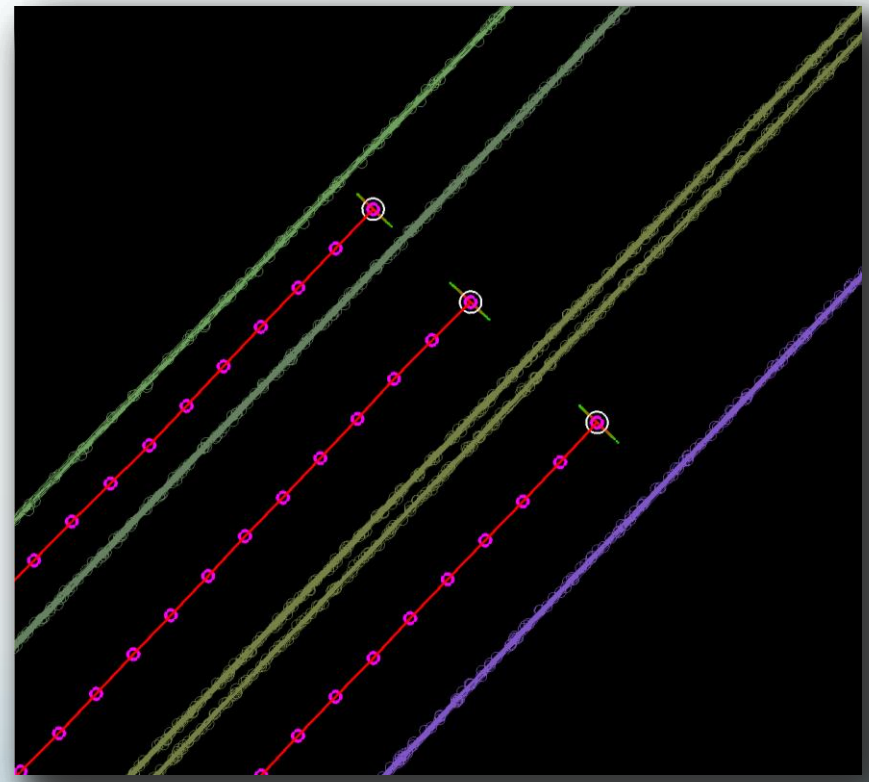


Mixture Particle Filter

- Combination of both regular and dual particle filter
- Variable mixture ratio θ: Ratio of particles sampled from conventional particle filter as compared to Dual Particle particle filter.
- Variable mixture ratio allows for more flexible modeling based on situations
  - θ can be dialed down near intersections where dual will perform poorly

Lane Indexing

- Number of lanes are unknown a-priori
- Modes are found using EM-based weighted clustering algorithm
- Clusters are indexed and particles associated with the index are assigned same index
- Modes with same index are connected across Filter Iterations



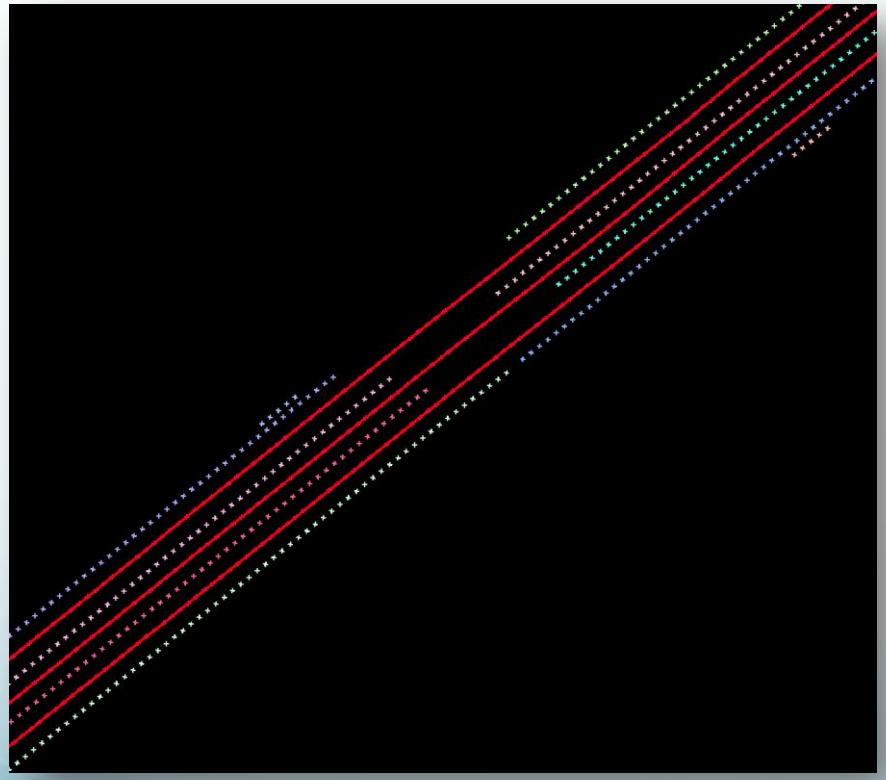
Results

We compare our approach with hand labeled road network data consisting of urban roads, country roads and freeways

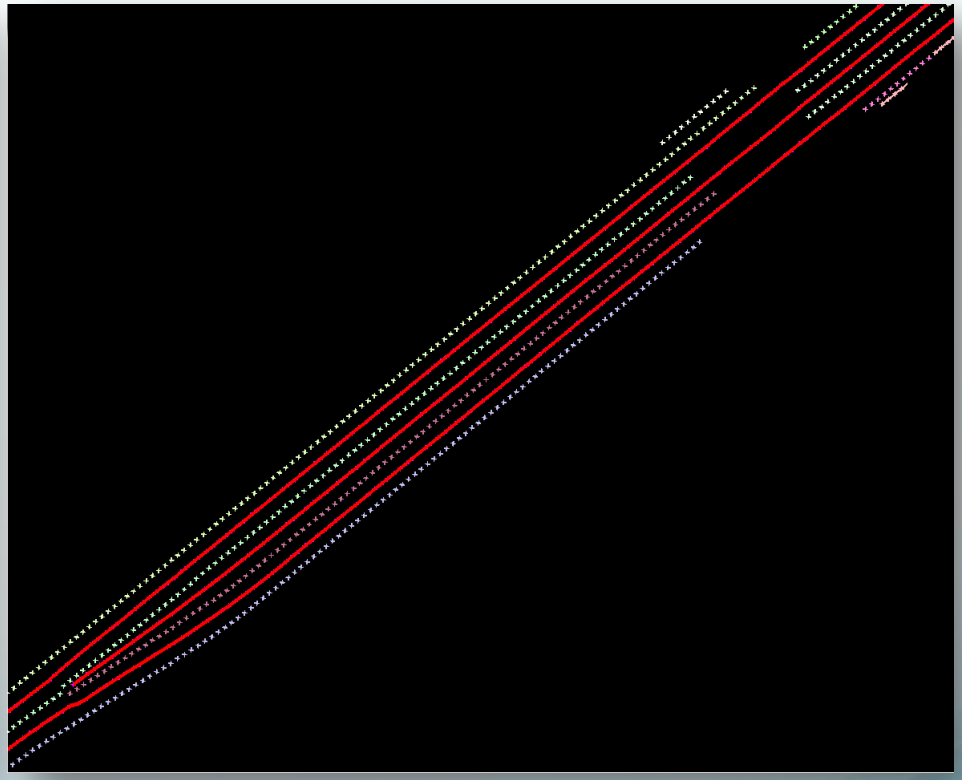
Method	Mean Error(m)	Max Error(m)
Regular PF – Urban	0.06	0.38
Regular PF – highway	0.05	0.13
Regular PF – all data	0.06	0.38
Mix PF – urban	0.06	0.22
Mix PF – highway	0.04	0.08
Mix PF – all data	0.05	0.22

Mixture PF is able to recover most of the bike lanes and highway ramps missed by Regular PF

Results

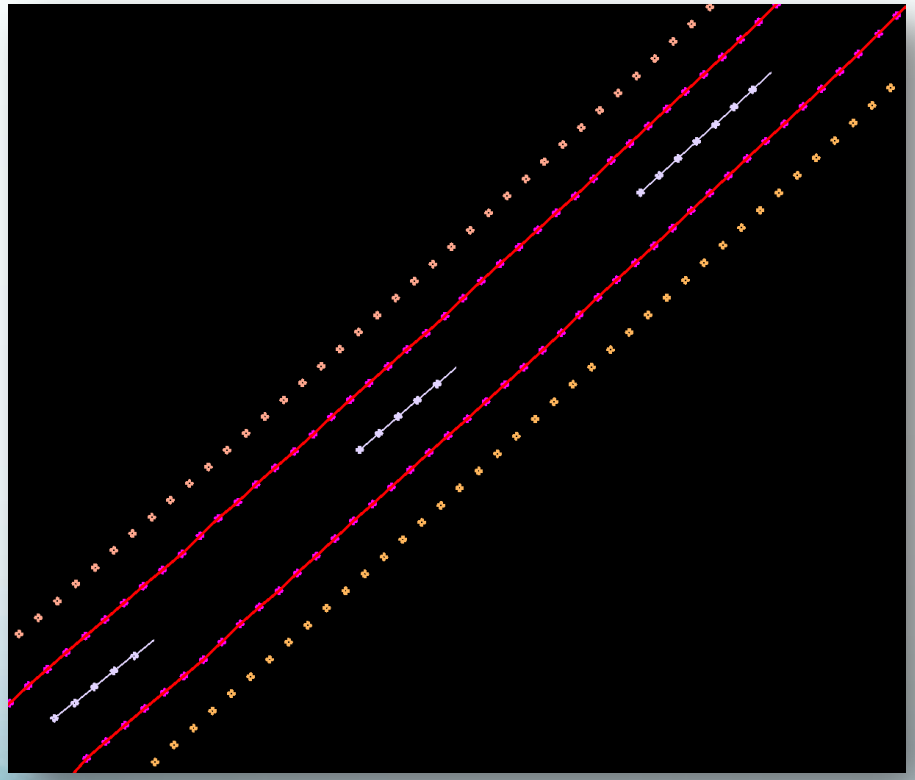


Accurate lane estimates even when data is missing

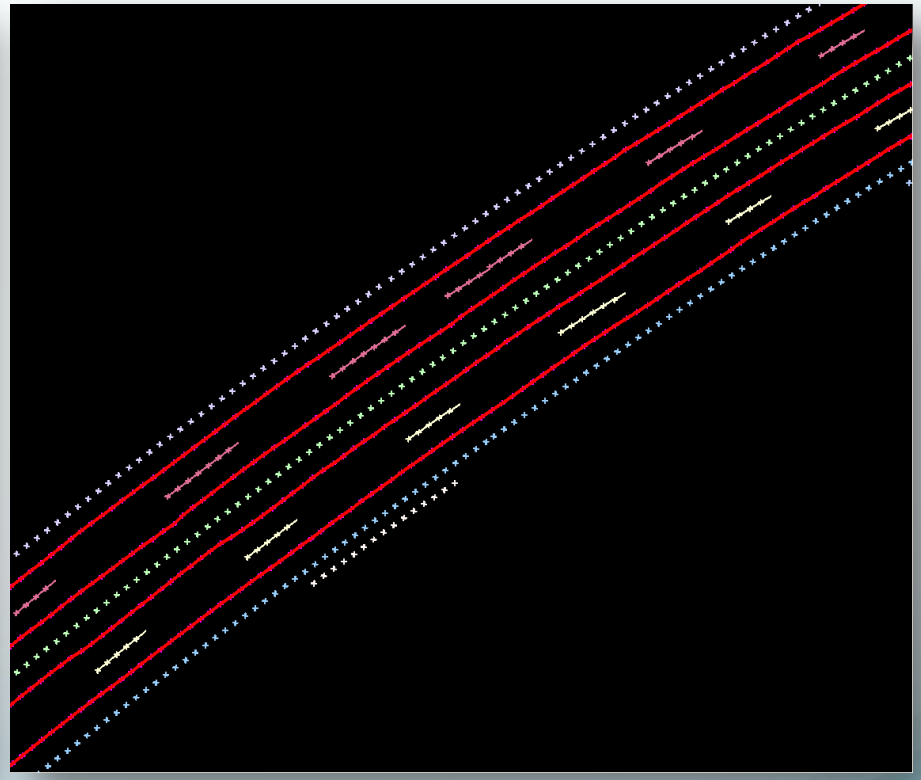


Handling Lane Additions

Results



Highway data with dashed lanes

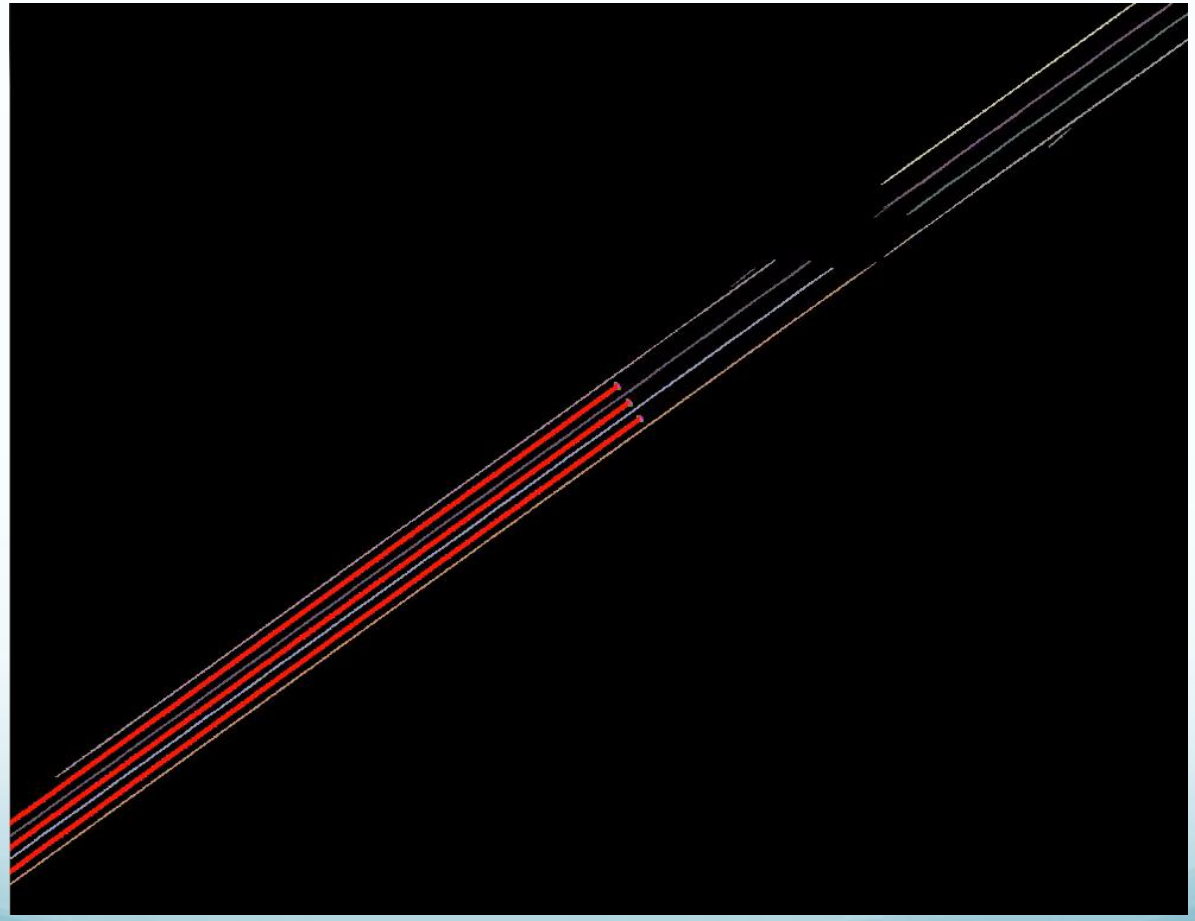


Wide city roads with multiple lanes processed simultaneously

Conclusions

- Structural priors can be leveraged in real world outdoor mapping task
- Future work include:
  - Using prior information to handle intersections
  - Learning the model of how and when to modify the inference based on situations
  - Develop a method of detecting and correcting maps when world changes

Thank You!



Lane Indexing

- Number of lanes are unknown a-priori
- Lane estimates at each node need to be linked with previous and future nodes to get a continuous lanes.
- Final Lane Estimates: Modes found using EM-based weighted clustering algorithm on the discreet distribution obtained from the particle filter
- Clusters are indexed and particles associated with the clusters are assigned the same index.

Lane Indexing

- Number of lanes are unknown a-priori
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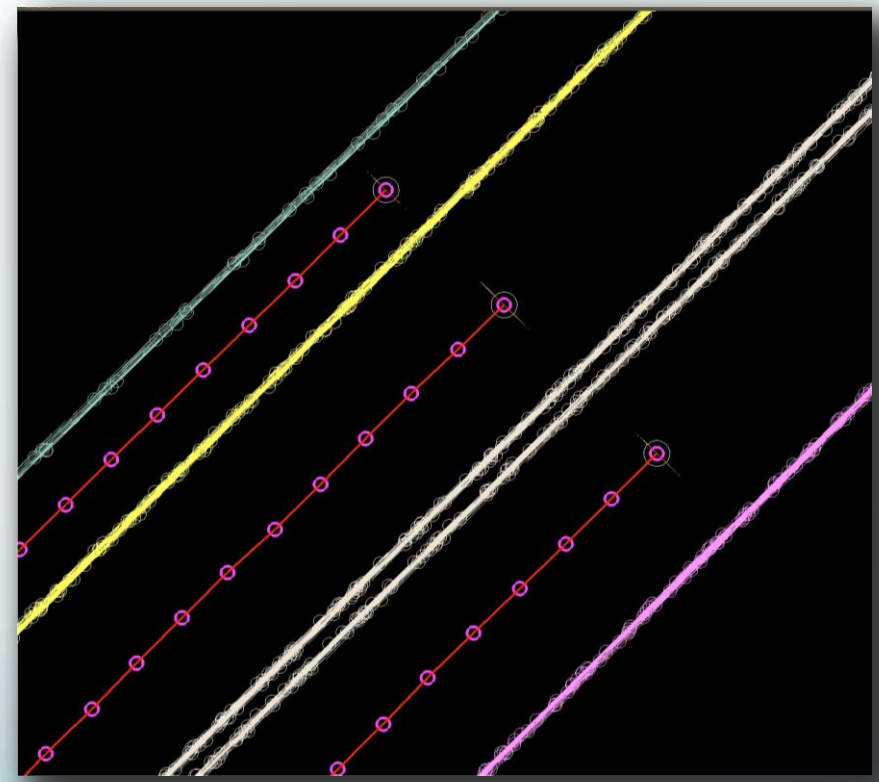
- Modes with same index are connected across Filter Iterations



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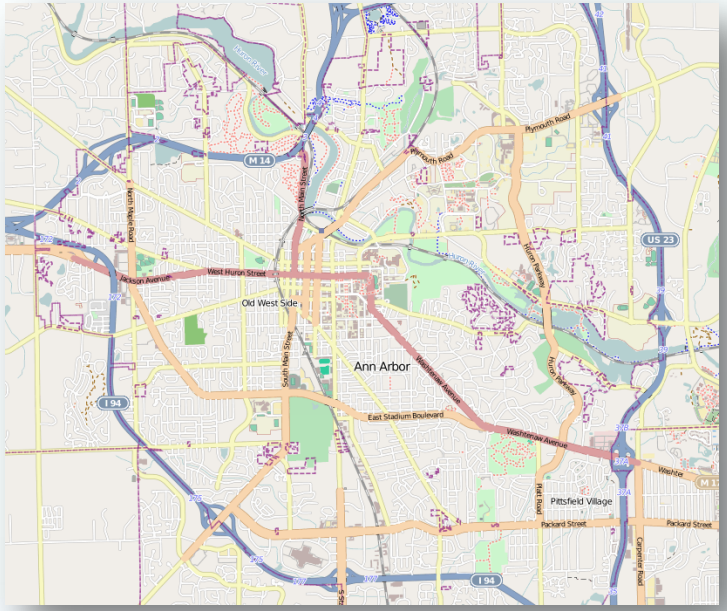

Goal: Leverage this data with high precision data from the sensors to create accurate lane maps

Dual Particle Filter

Switch the role of proposal and update functions

Proposal Distribution: New particles are proposed in the system based on the observations

$x_n^{(i)}$; $w)\}$

w s

o s