Terrain-based Vehicle Localization to Obtain GPS-Equivalent Vehicle Position Accuracy

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Outline of Task 3

- Past work
  - Motivation for using terrain maps to localize a vehicle
  - Feasibility of location-based road “fingerprints”
  - Framing localization as a nonlinear particle-filter correlation problem
  - Attacking the nonlinear problem with a Kalman approach
  - Hybridizing the method to have the advantages of both the linear/nonlinear approaches
- Task 3 items
  - Vehicle integration, data collection
  - Accuracy reduction including vehicle and maps
  - Integration of terrain-based localization with existing vehicle localization architectures.
  - Large road network testing

Terrain-Based Localization

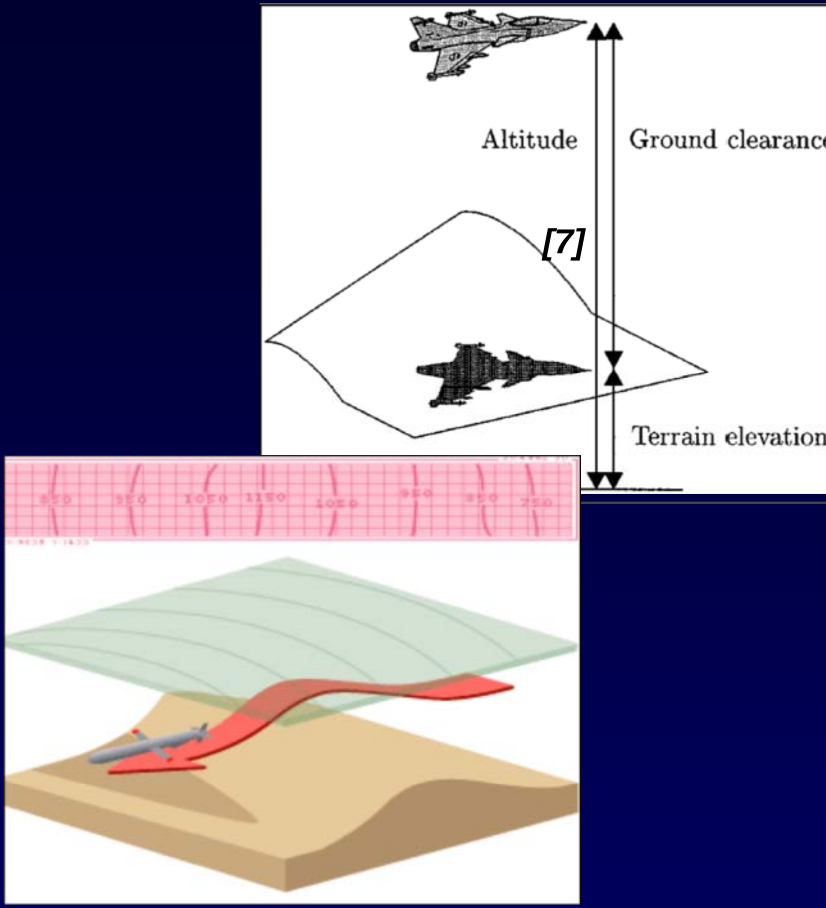
Terrain contour matching (TERCOM) was the pre-GPS guidance method for:

- Missiles
- Aircraft
- Underwater systems

J. P. Golden, “Terrain contour matching/TERCOM/- A cruise missile guidance aid,” *Image processing for missile guidance*, pp. 10–18, 1980.

F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P. J. Nordlund, “Particle filters for positioning, navigation, and tracking,” *Signal Processing, IEEE Transactions on*, vol. 50, no. 2, pp. 425–437, Feb. 2002.

A. Bachmann and S.B. Williams. Terrain aided underwater navigation–A deeper insight into generic Monte Carlo localization. In Australasian Conference on Robotics and Automation, pages 1–7, 2003.



http://www.bbc.co.uk/portuguese/especial/2001/eua_military_hardware/cruise_missile/3.shtml

Vehicle terrain-based localization

- Matching steering inputs to maps
  - M. E. E. Najjar and P. Bonnifait, “A road-matching method for precise vehicle localization using belief theory and kalman filtering,” Auton. Robots, vol. 19, no. 2, pp. 173–191, 2005.
- Matching pressure changes to maps (!)
  - W. Holzapfel, M. Sofsky, and U. Neuschaefer-Rube. Road profile recognition for autonomous car navigation and Navstar GPS support. Aerospace and Electronic Systems, IEEE Transactions on, 39(1):2–12, 2003.
- Both subject to HUGE errors (+/- 1 km!)

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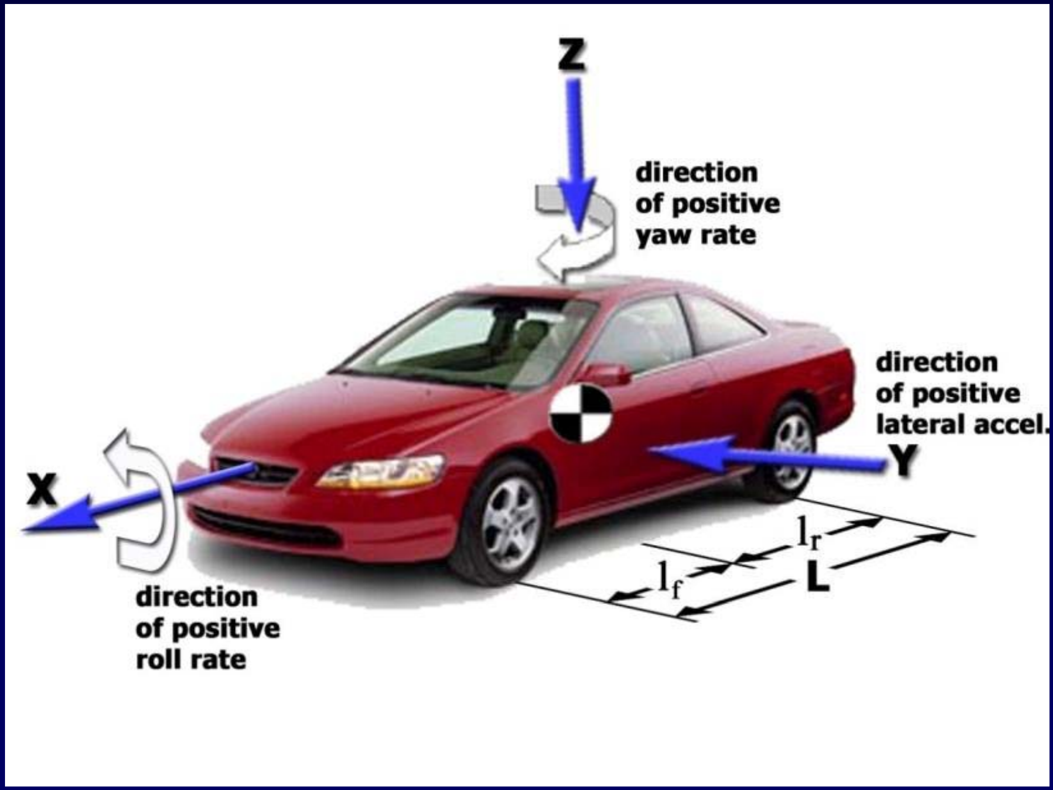
An accidental discovery while examining sideslip during previous work…

Some terminology to get started…

- Standard SAE sign convention



Analytical Vehicle Models

- Model 1 – 2DOF Bicycle Model $\quad q = \begin{bmatrix} y \\ \psi \\ \phi \end{bmatrix}$

$$\begin{bmatrix} -m & 0 & 0 \\ 0 & -I_{zz} & 0 \\ 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} \dot{V} \\ \dot{r} \\ \ddot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & -mU & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} V \\ r \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} y \\ \psi \\ \phi \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2l_f & -2l_r \\ 0 & 0 \end{bmatrix}\begin{bmatrix} F_f \\ F_r \end{bmatrix}$$

$$\begin{bmatrix} F_f \\ F_r \end{bmatrix} = \begin{bmatrix} -\frac{C_f}{U} & -\frac{l_f C_f}{U} & 0 \\ -\frac{C_r}{U} & \frac{l_r C_r}{U} & 0 \end{bmatrix}\begin{bmatrix} V \\ r \\ \phi \end{bmatrix} + \begin{bmatrix} C_f \\ 0 \end{bmatrix}\delta_f$$

Analytical Vehicle Models

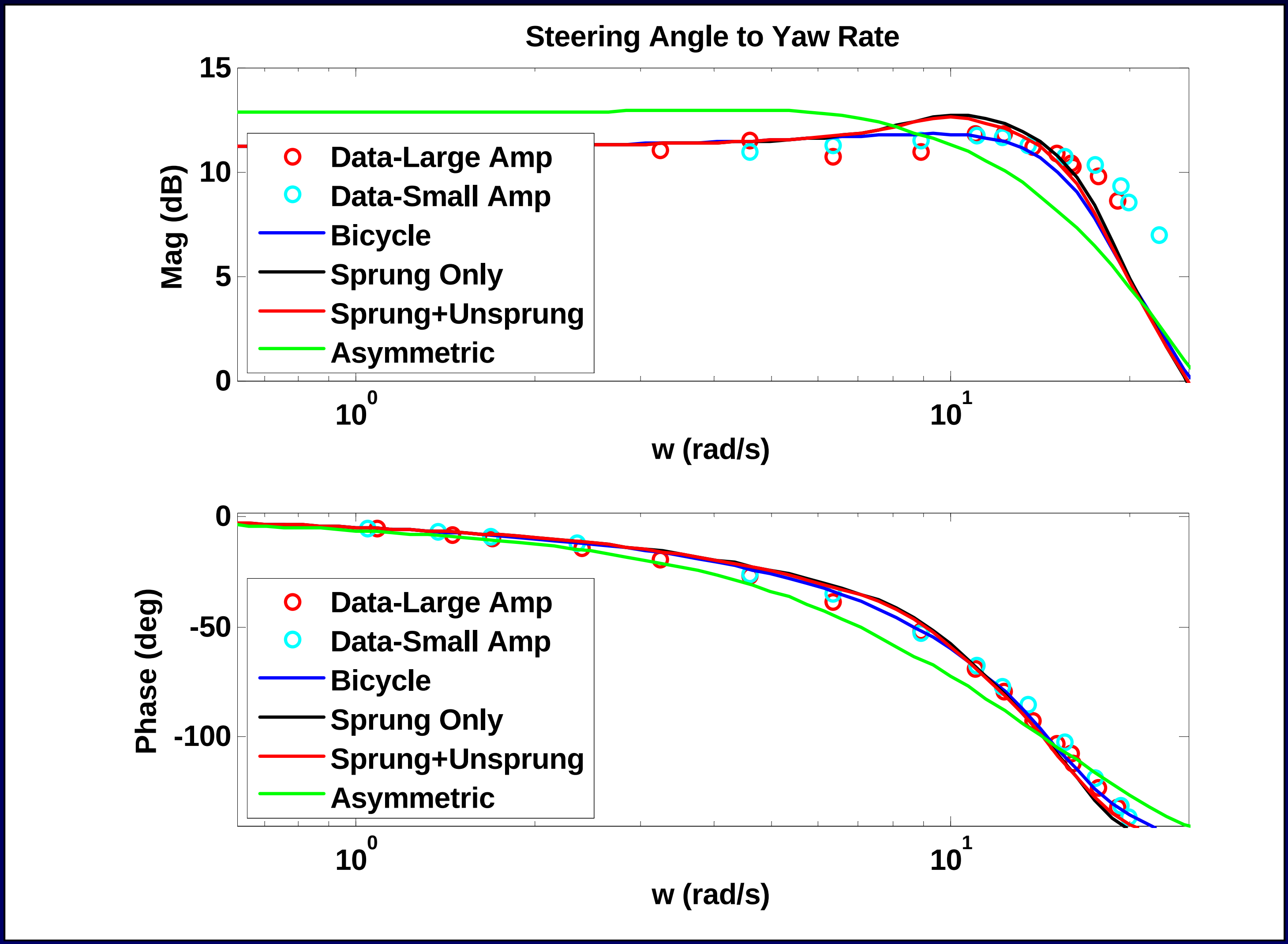
- Model 4 – 3DOF Roll Model
  - Assumes a sprung mass suspended upon a massless frame
  - x-z planar symmetry
  - No roll steer influence
  - Originally presented by Carlson and Gerdes, Stanford University, 2003

$$\begin{bmatrix} -m & 0 & 0 \\ 0 & -I_{zz} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{V} \\ \dot{r} \\ \ddot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & -mU & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} V \\ r \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ \psi \\ \phi \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2l_f & -2l_r \\ 0 & 0 \end{bmatrix} \begin{bmatrix} F_f \\ F_r \end{bmatrix}$$

$$\begin{bmatrix} -m & 0 & -mh \\ 0 & -I_{zz} & 0 \\ 0 & 0 & I_{xx} \end{bmatrix} \begin{bmatrix} \dot{V} \\ \dot{r} \\ \ddot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & -mU & 0 \\ 0 & 0 & 0 \\ 0 & 0 & D_\phi \end{bmatrix} \begin{bmatrix} V \\ r \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & K_\phi - mgh \end{bmatrix} \begin{bmatrix} y \\ \psi \\ \phi \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2l_f & -2l_r \\ 2h & 2h \end{bmatrix} \begin{bmatrix} F_f \\ F_r \end{bmatrix}$$

Model Fitting

Frequency Response – Yaw Rate



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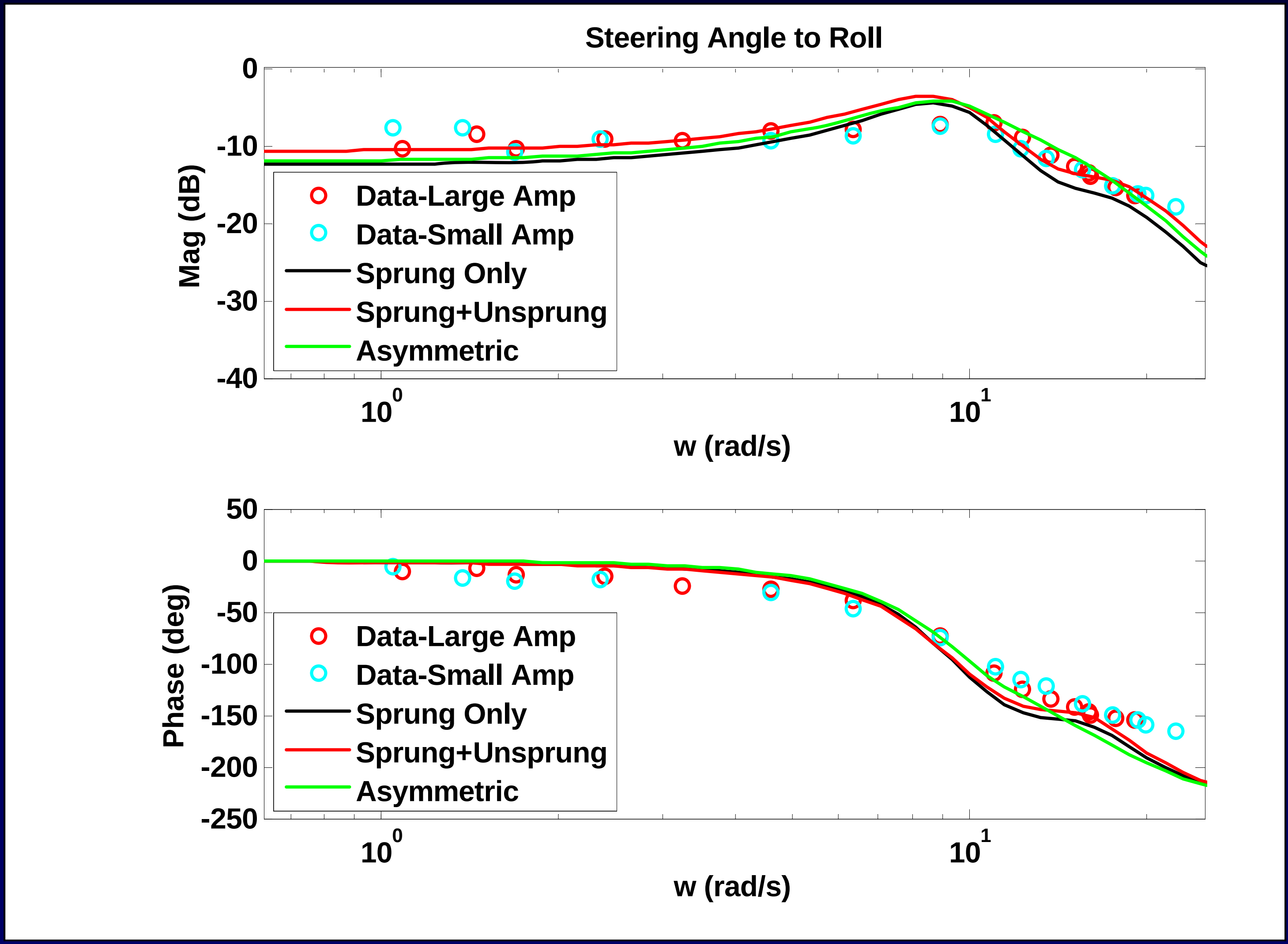
Model Fitting

Frequency Response – Roll Angle

Frequency responses show good fits!
How about roll responses? Time domain?



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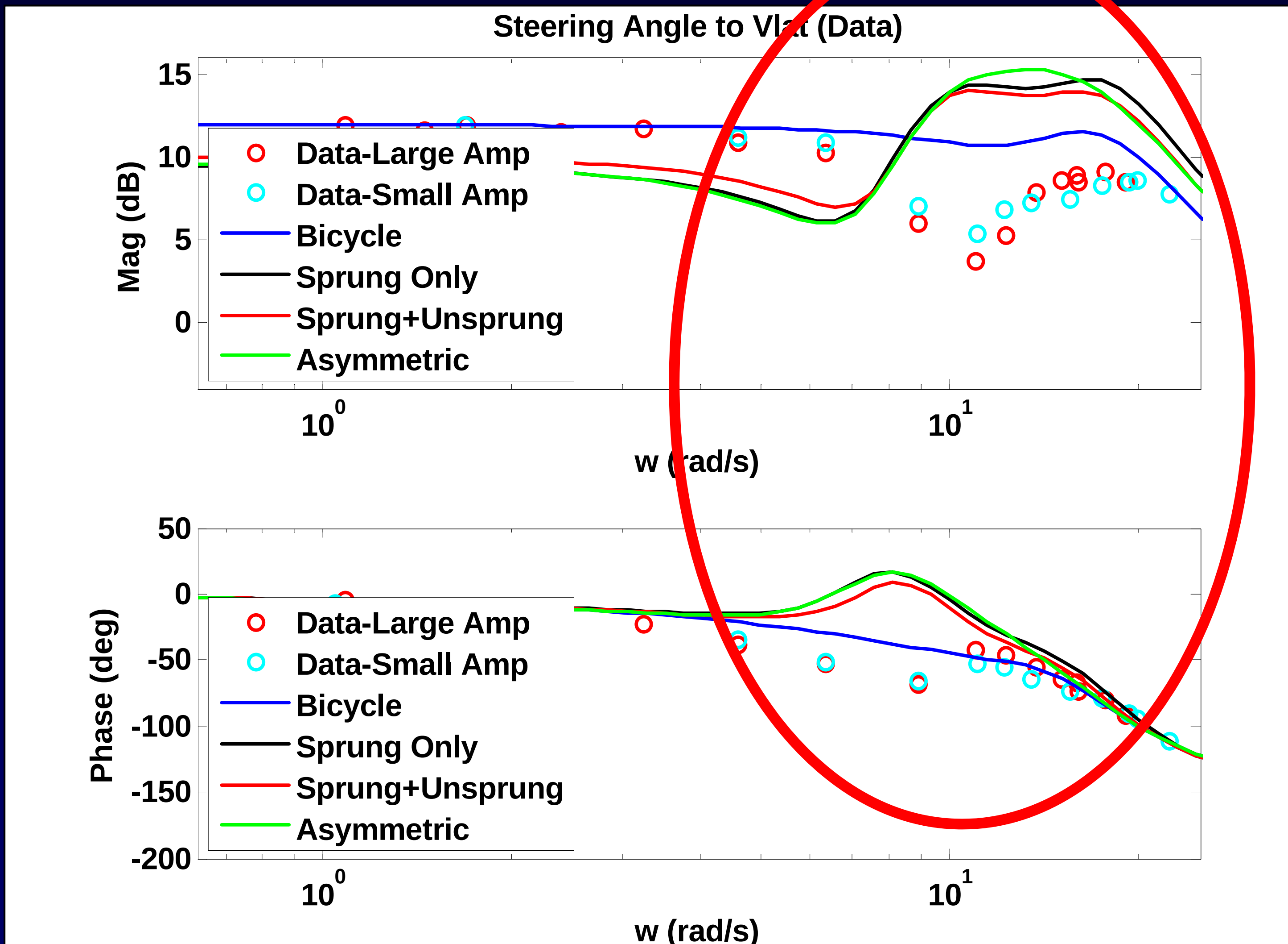
Model Fitting

Frequency Response – Lateral Velocity

AWFUL fit
Turns out have a poor SNR
EXACTLY in region of interest



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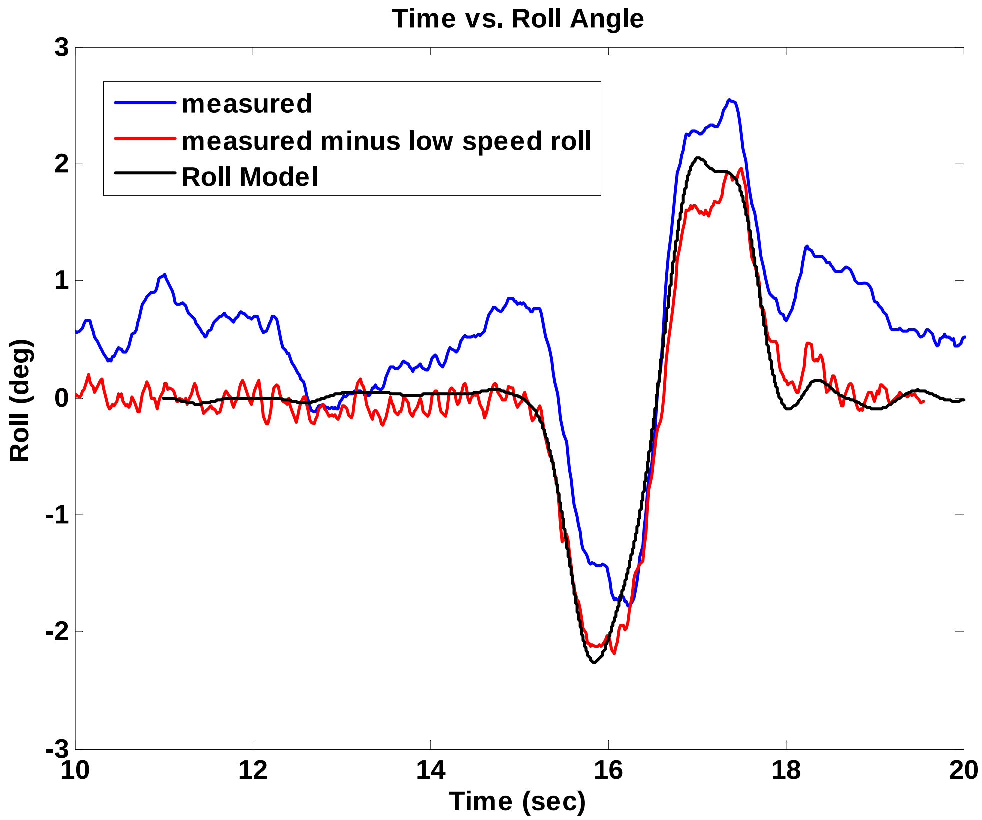
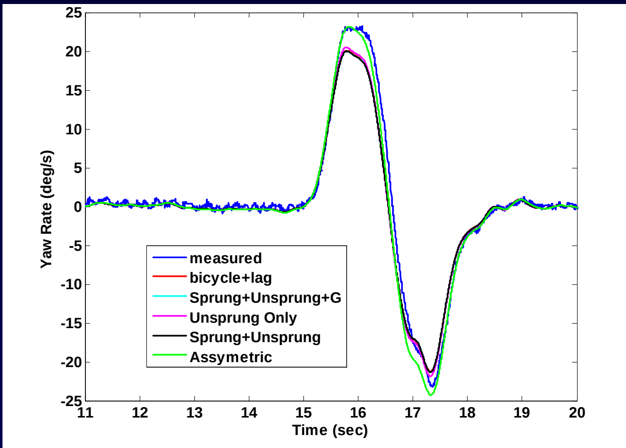
The influence of terrain

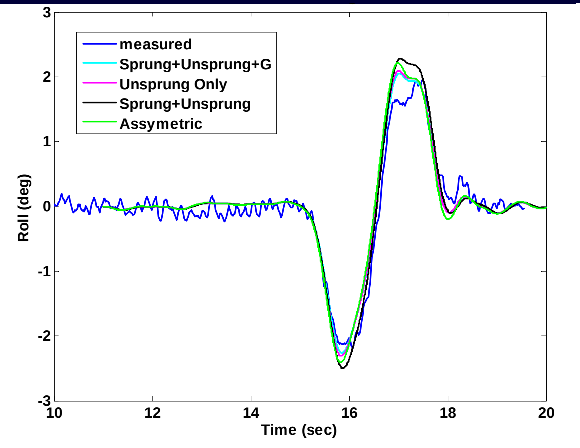
Step 1: Collect data set 1 along a path at high speed. Note tire marks
Step 2: Drive over tire marks at low speed, collect data set 2.
Step 3: Subtract data set 2 from data set 1. Plot results.

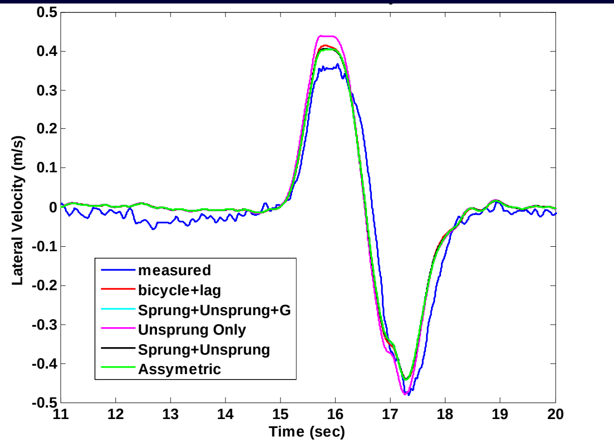


“Terrain Corrected” Model Fits – Time Domain
lane change

After terrain influence is removed…







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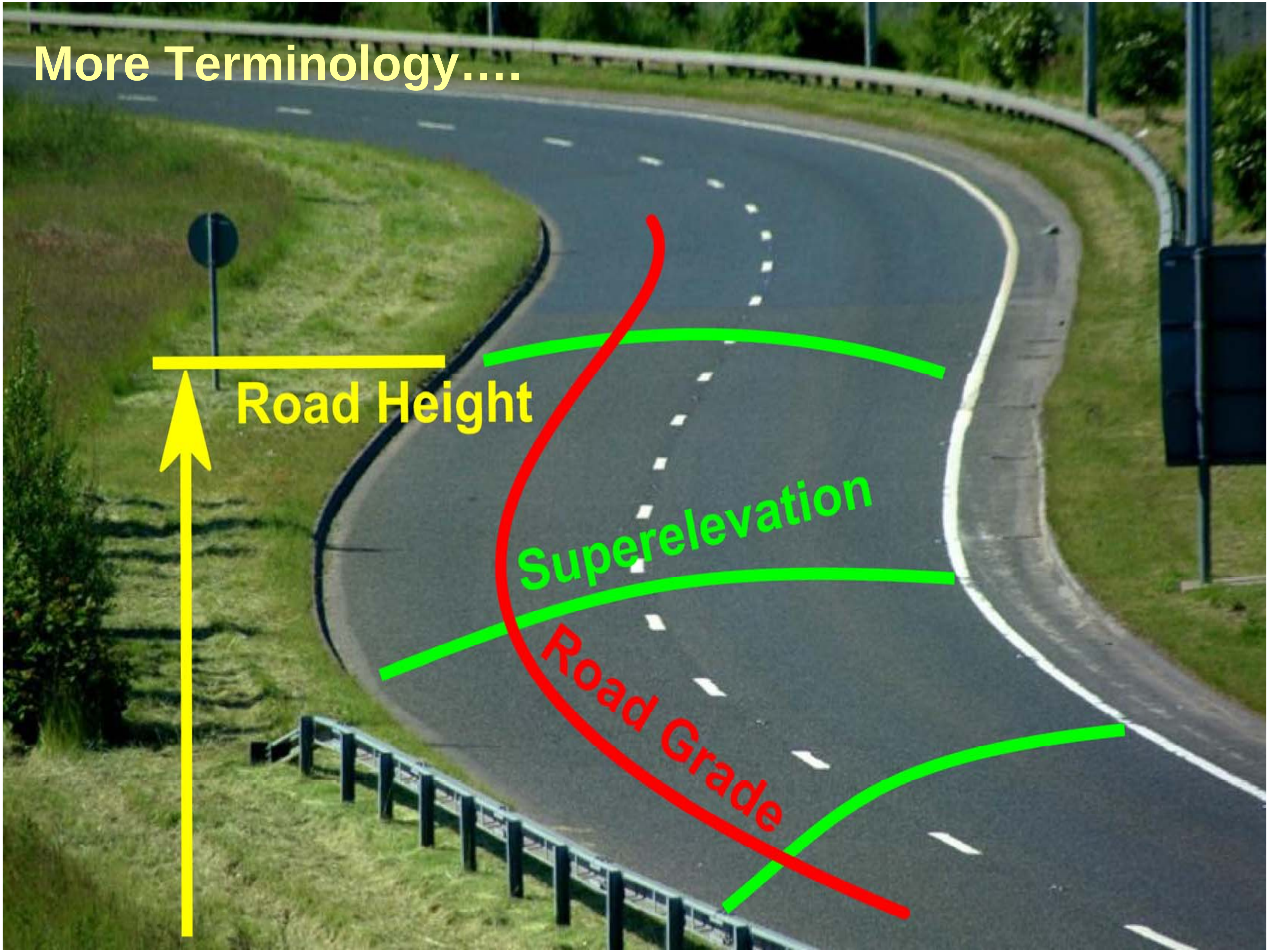
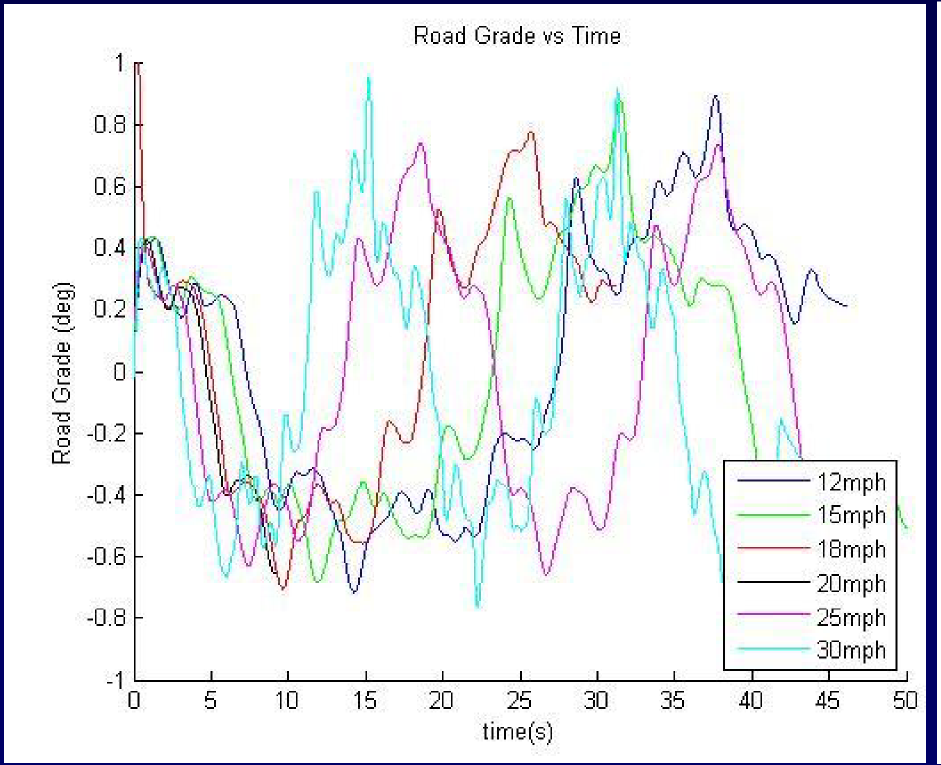
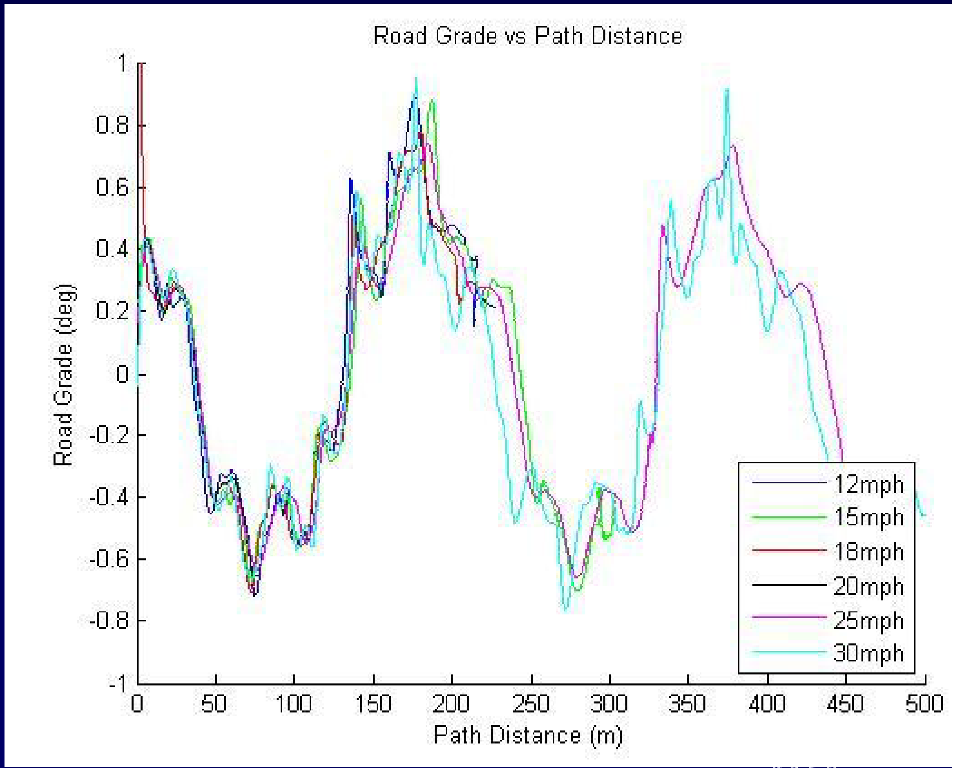

More Terminology….
Road Height
Superelevation
Road Grade

Further analysis of the influence of terrain

- Road grade (vehicle pitch) investigated for steady state circle at various speeds
- When aligned based on global yaw angle (path distance covered), the road grade measurement is very repeatable regardless of speed





Feasibility

- Past work
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Again… go back to the test track!

“Theory guides. Experiment decides." - Anonymous

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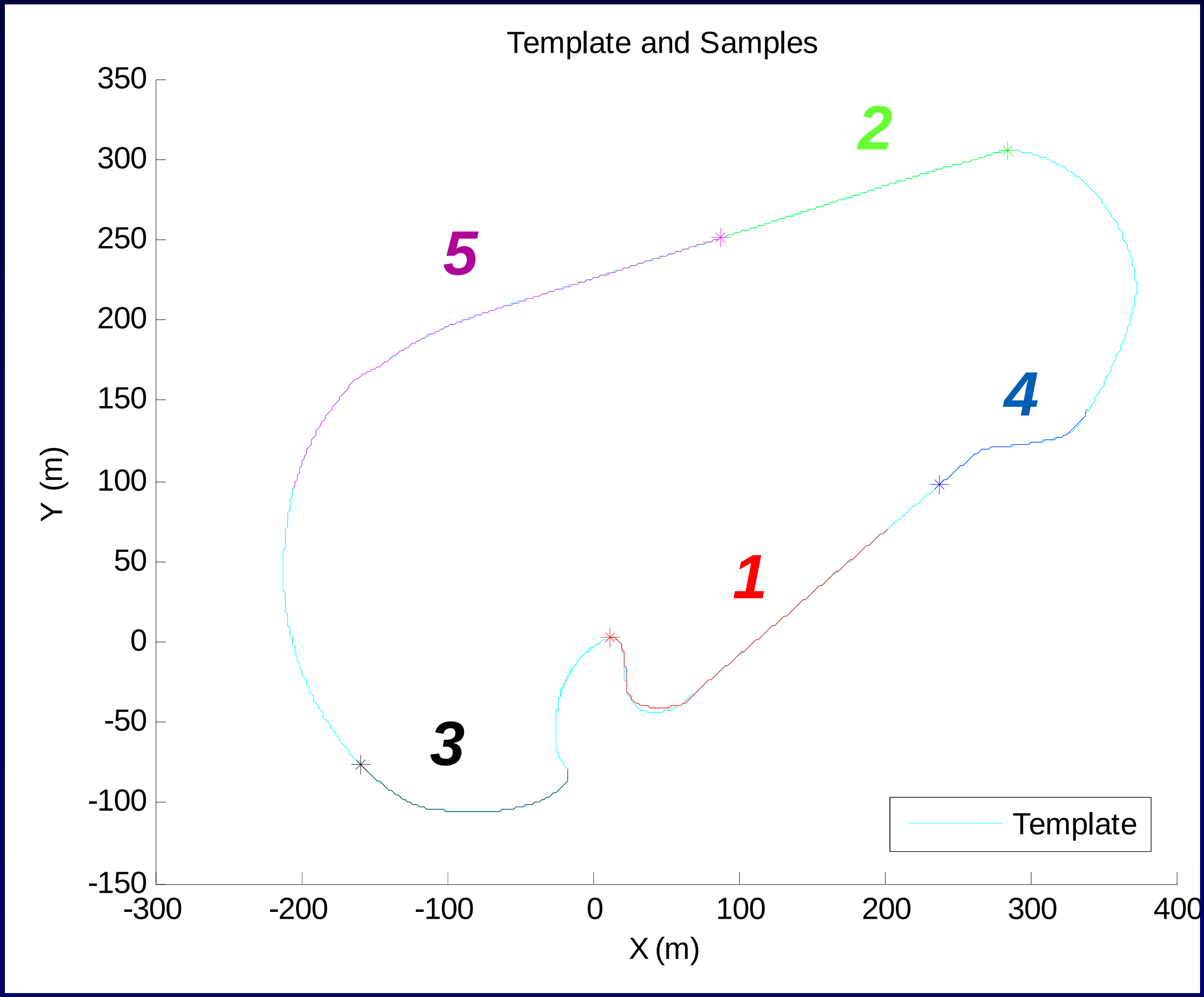
Road Grade Positioning

- 5 Trials



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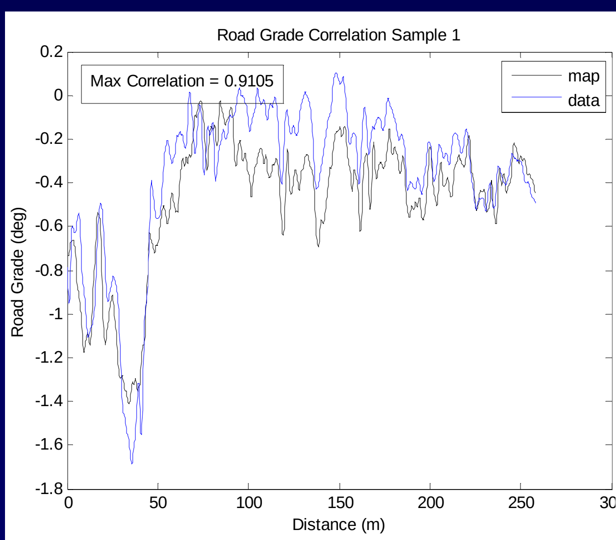
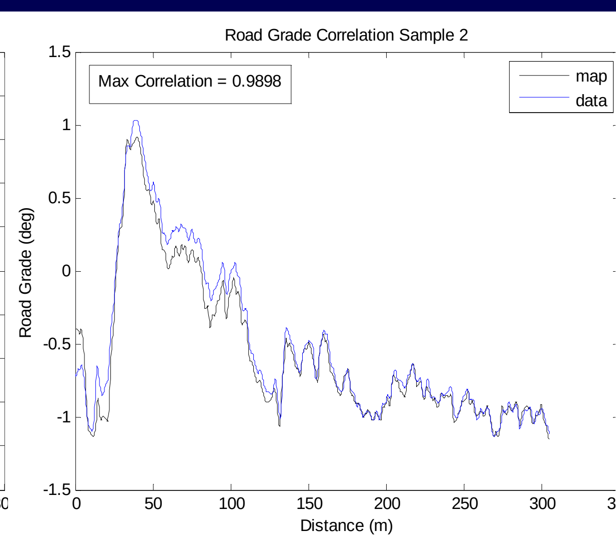
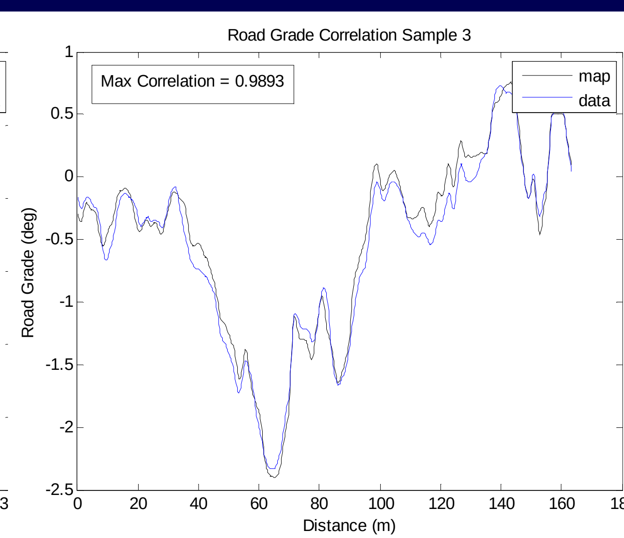
Road Grade Positioning

Sample	Average |Path Error|	Standard Deviation	Average |Lane Keeping Error|	Correlation
1	134 cm	27 cm	48.6 cm	0.9105
2	15 cm	12 cm	11.5 cm	0.9898
3	9 cm	5 cm	9.7 cm	0.9893
4	66 cm	14 cm	16.7 cm	0.961
5	13 cm	14 cm	9.1 cm	0.9889







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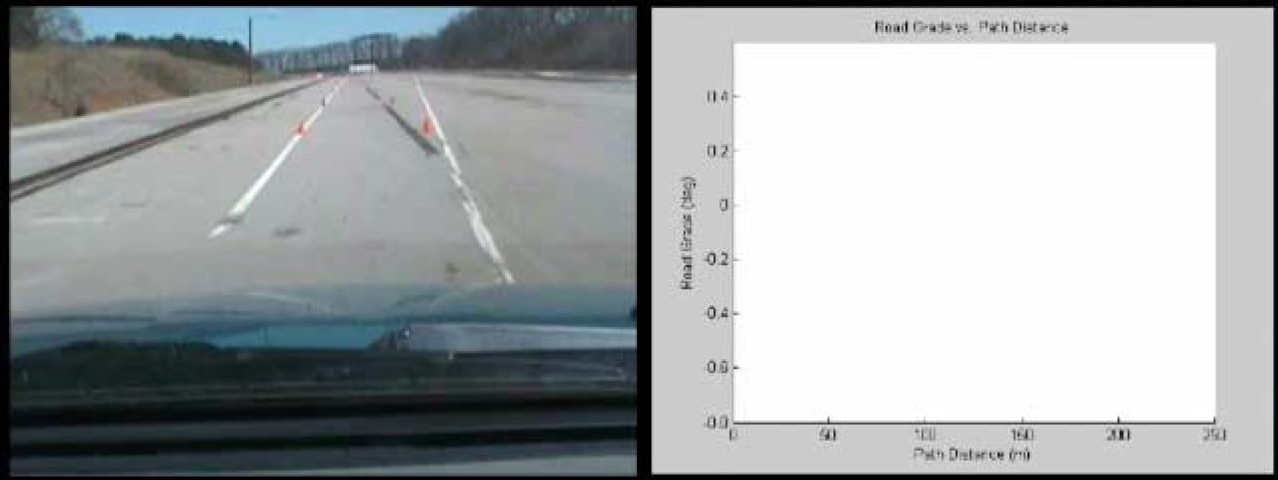
Are we matching BIG bumps in the road? No…



What is being correlated?

Roadway surface texture ~ 0.01 meters

Potholes ~ 0.1 meters

Step changes in surface elevation ~ 1 meter

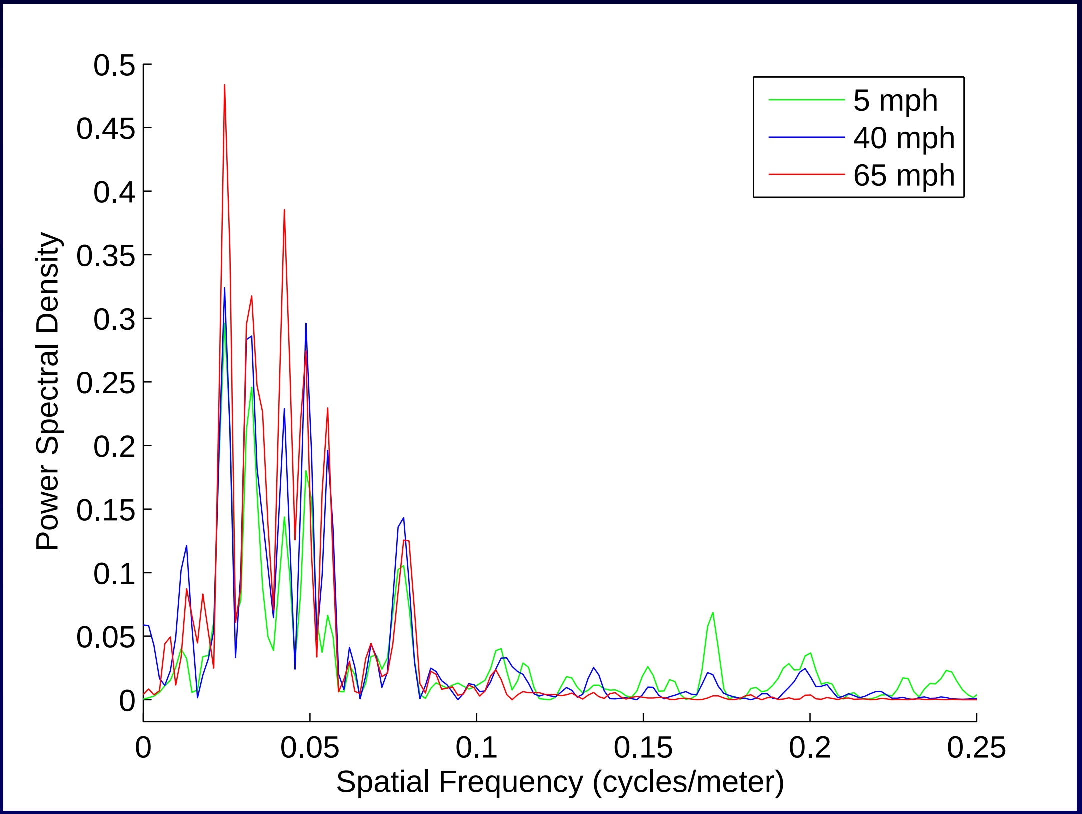
Surface leveling undulations ~ 10 – 100 meters

Road elevation ~ 1000 meters

Speed Invariance Test

The Power Spectral Density of the vehicle response at various speeds shows:

- The low-speed data has a higher power density at high frequencies
- The correlation between signals matches quite well for frequencies < 0.1
- Use a low-pass filter at 0.1 cycles/meter for speed invariant correlation



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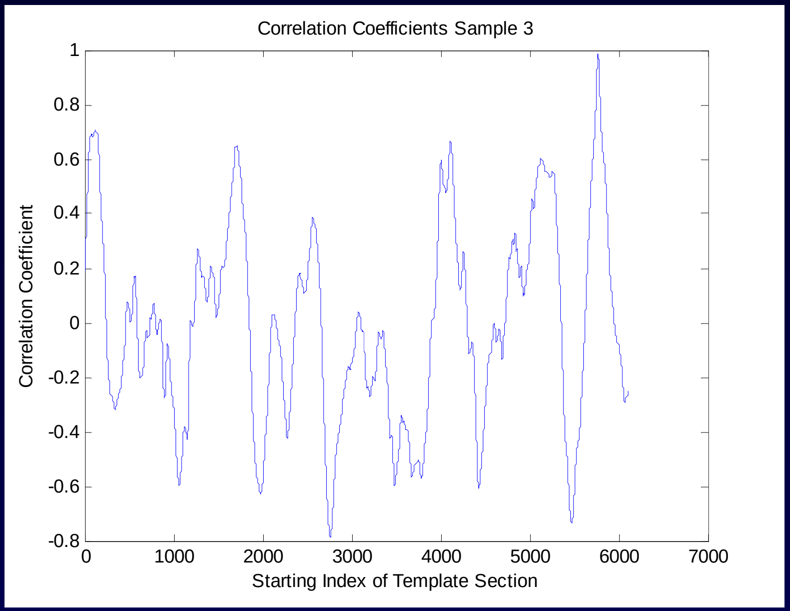
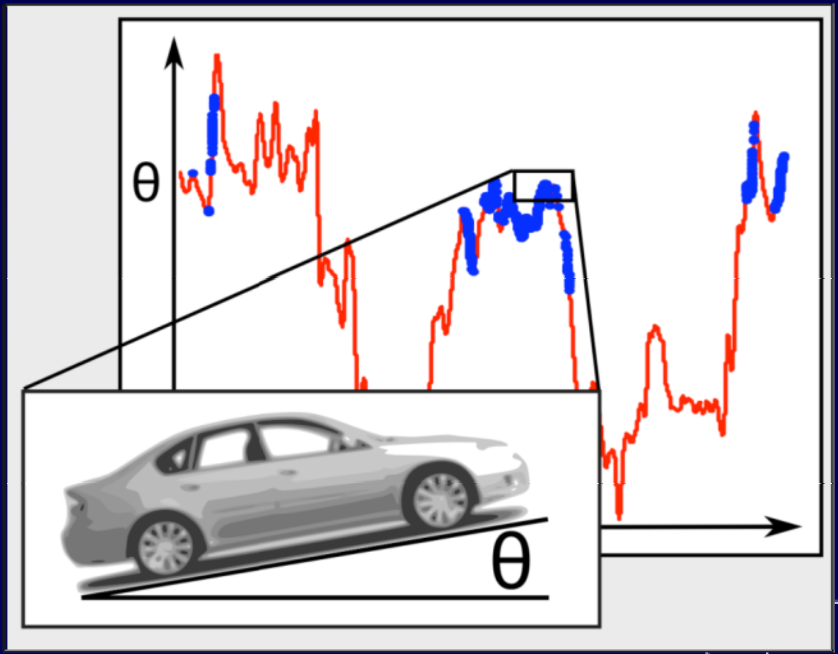
Terrain-Based Approach

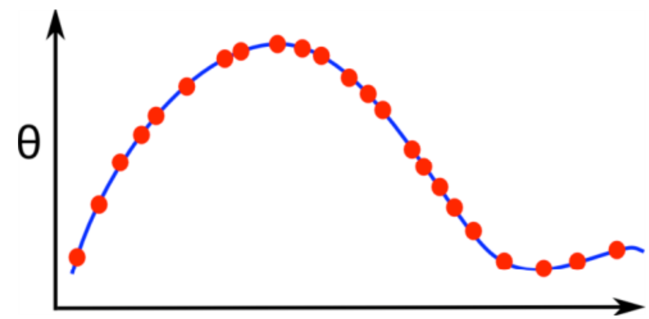
- Goal: use a terrain map for road vehicle localization using attitude measurements, assuming:
  - The lane of travel has been previously mapped
  - The map is available on-board the vehicle
- Problem: multiple local solutions
- First approach: use a Particle Filter



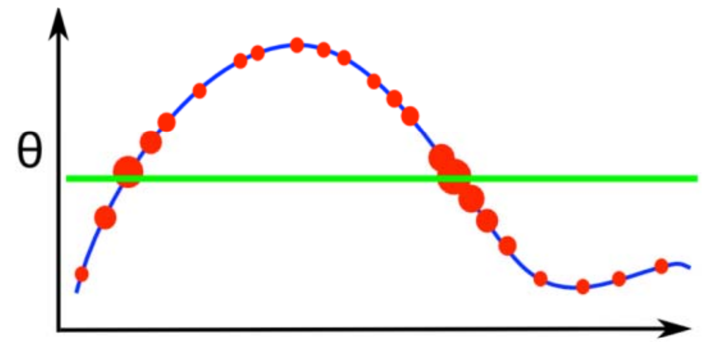


Particle Filtering Using Road Data

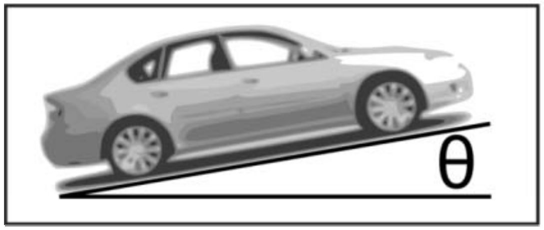
1. Populate a road grade or pitch response map with N particles



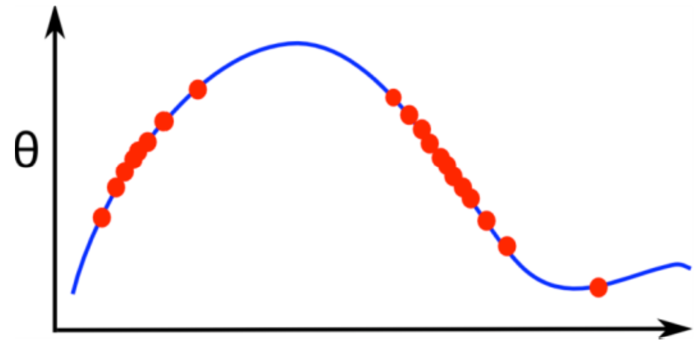
2. Weight the particles according to their pitch using the true pitch measurement and:



$$q_i^k = \frac{exp\left(-\frac{1}{2\cdot R}\cdot(\theta_a - \theta_{p,i})^2\right)}{\sum_{i=1}^{N}\left(exp\left(-\frac{1}{2\cdot R}\cdot(\theta_a - \theta_{p,i})^2\right)\right)}$$

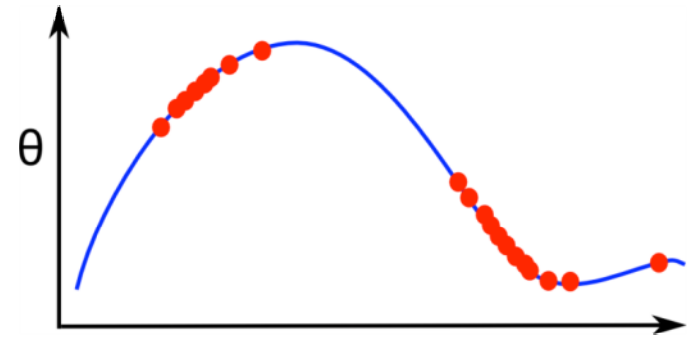


3. Resample the particles according to their weight. High weights get more particles nearby.

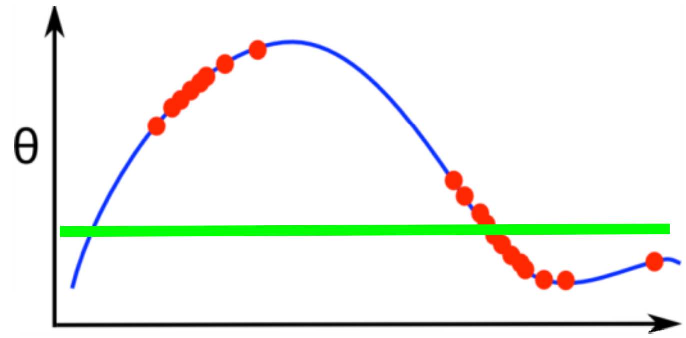


4. Shift the particles using the measured odometry and added variance:

$$P_X^k = P_X^{k-1} + dX + Qx$$

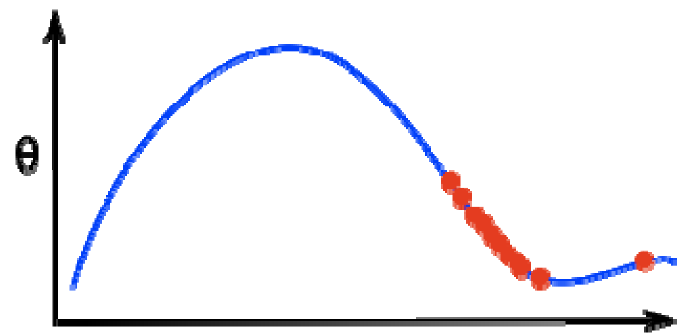


Repeat using a new pitch measurement

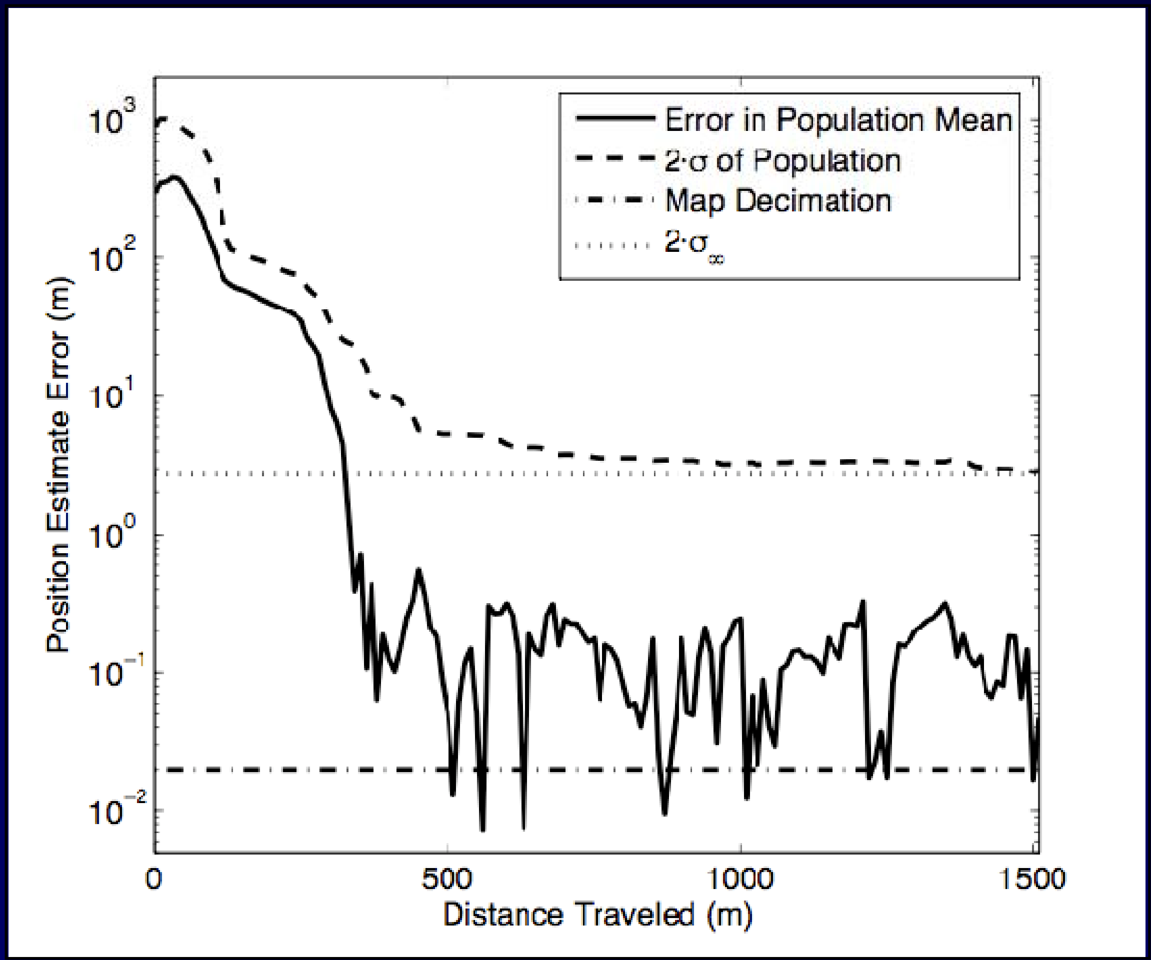


$$q_i^k = \frac{exp\left(-\frac{1}{2\cdot R}\cdot(\theta_a-\theta_{p,i})^2\right)}{\sum_{i=1}^{N}\left(exp\left(-\frac{1}{2\cdot R}\cdot(\theta_a-\theta_{p,i})^2\right)\right)}$$

And resample the weighted particles



Longitudinal Positioning:
LTI Results



Kalman Filtering

- Past work
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System Model

- Assuming the state model to be:

$$\begin{aligned} x_k &= A \cdot x_{k-1} + B_u \cdot u_{k-1} + B_w \cdot w_{k-1} \\ y_k &= C \cdot x_k + D_u \cdot u_{k-1} + D_v \cdot v_{k-1} \end{aligned}$$

- Can approximate the particle filter using a single-step Kalman filter

$$\begin{aligned} x_{k+1} &= A \cdot (I - K_k C) \cdot x_k + A K_k y_k + B_u u_k \\ K_k &= P_k C^T \cdot (C P_k C^T + R)^{-1} \end{aligned}$$

$$\begin{aligned} P_{k+1} &= Q + A P_k A^T - \\ &\quad A P_k C^T \left(C P_k C^T + R\right)^{-1} C P_k A^T \end{aligned}$$

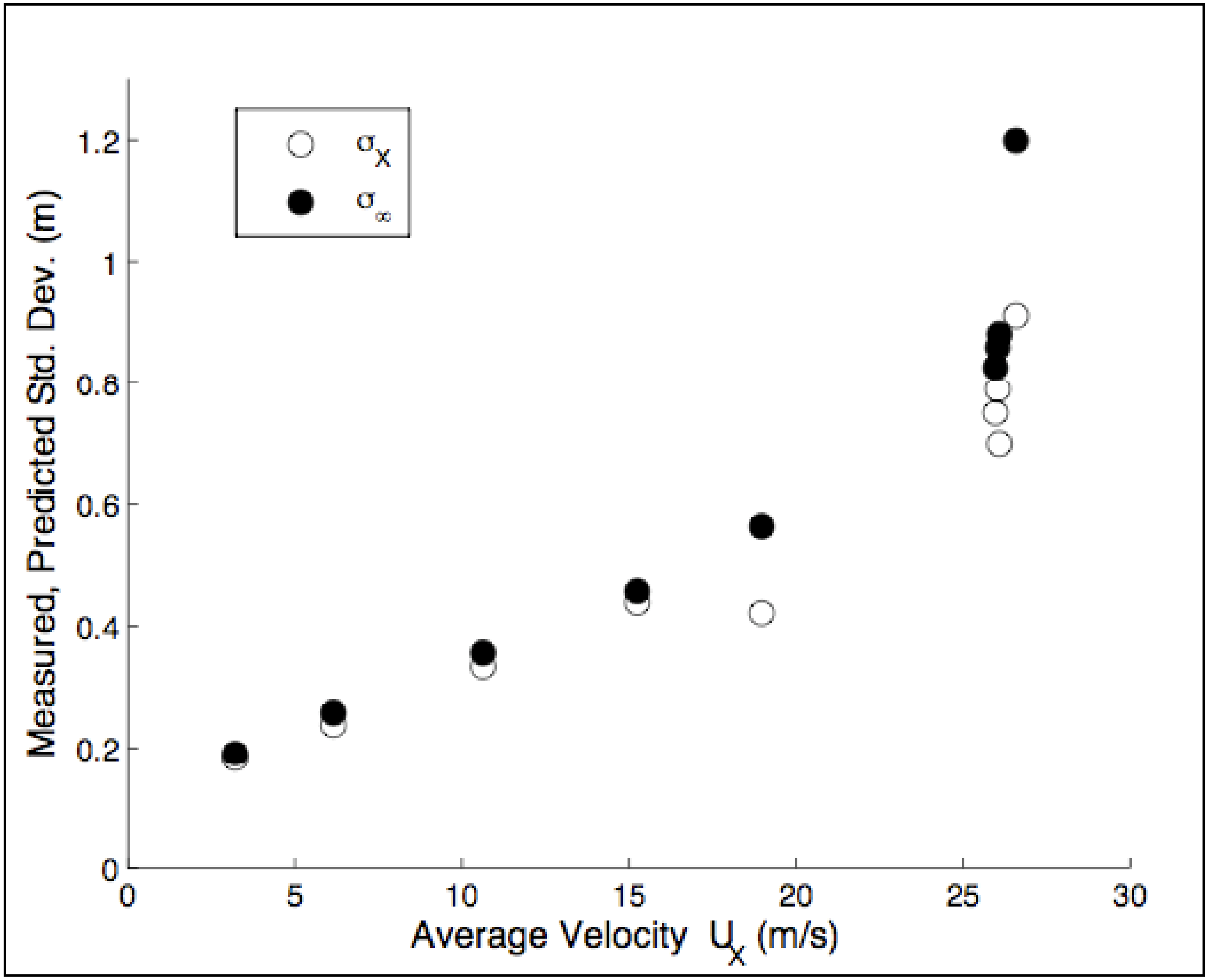
- Under conditions of controllability and observability, the covariance will converge to:

$$\begin{aligned} P_\infty &= Q + AP_\infty A^T - \\ &\quad AP_\infty C^T \left(CP_\infty C^T + R\right)^{-1} CP_\infty A^T \end{aligned}$$

- Because it is independent of any measurements, let A = 1 and simplify to get

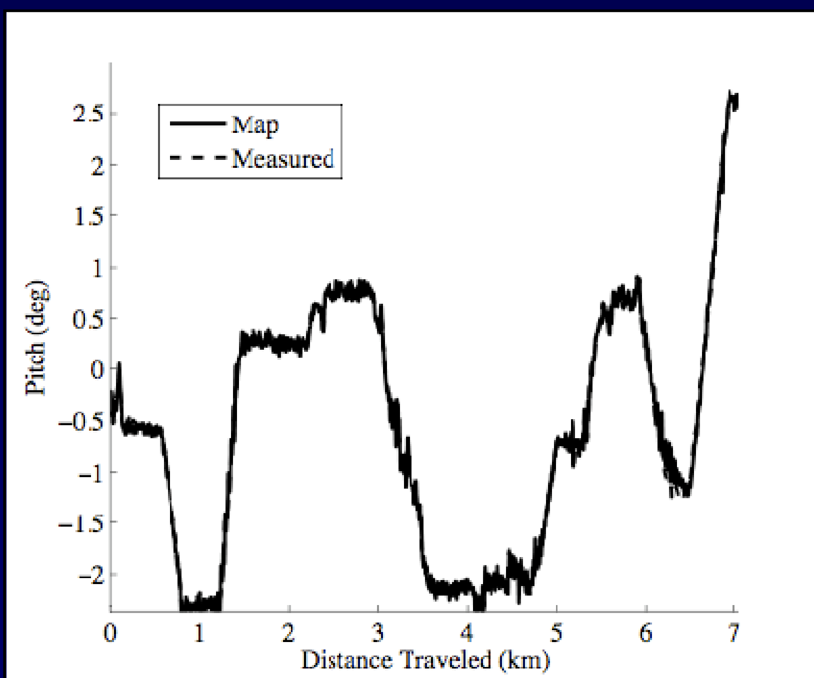
$$\boxed{\mathrm{P}_\infty = \frac{Q}{2} \cdot \left(1 + \sqrt{1 + \frac{4 \cdot R}{C^2 \cdot Q}}\right)}$$

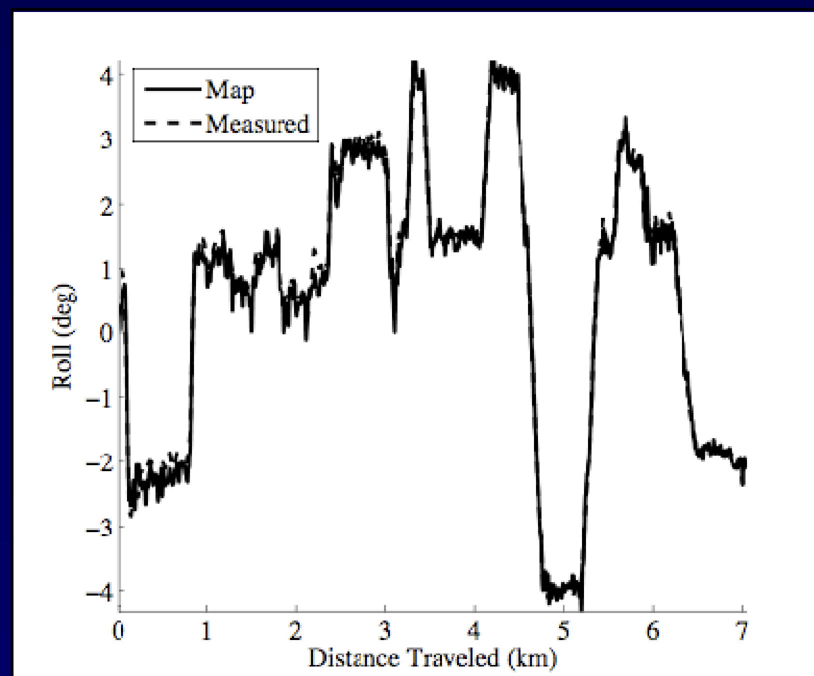
Predicted vs. Measured: Great Agreement!



Longitudinal Positioning: Highway Results (Time)

- Highway implementation more realistic and difficult
  - Smoothest roads available, reduced variations in pitch
  - High traveling speeds, increased wheelbase filtering

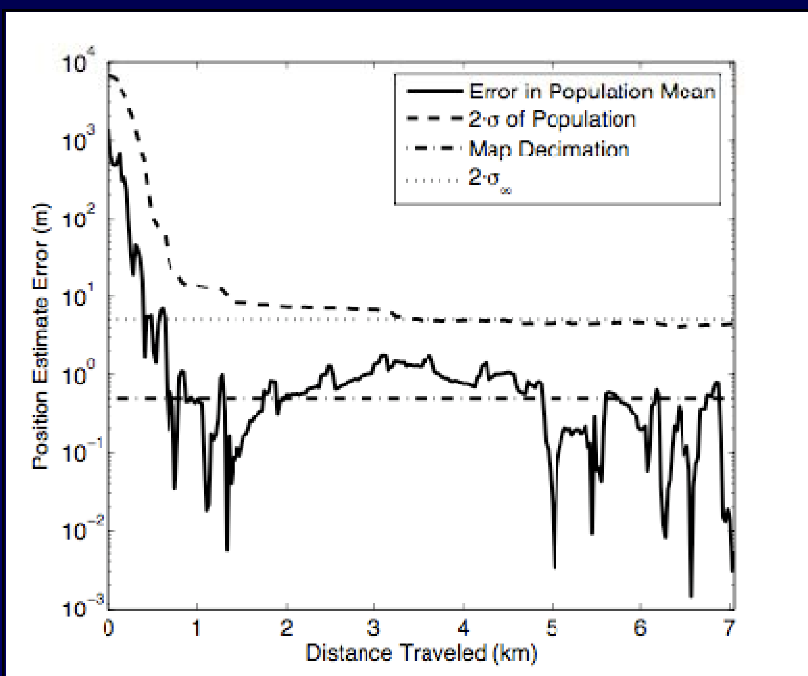




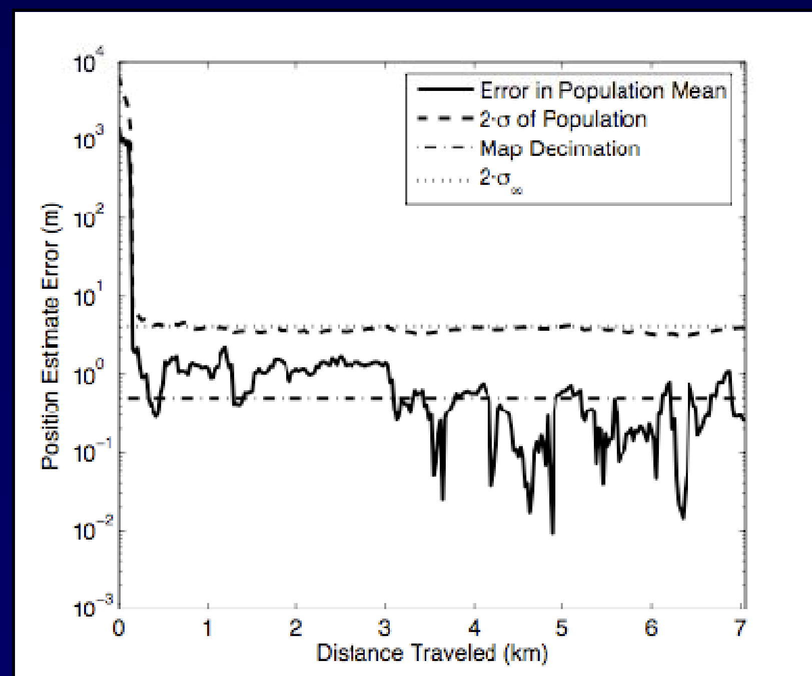
Longitudinal Positioning: Highway Results (Error)

- Estimated vehicle position with meter-level accuracy
- Using roll resulted in a faster convergence

Using Pitch Measurements

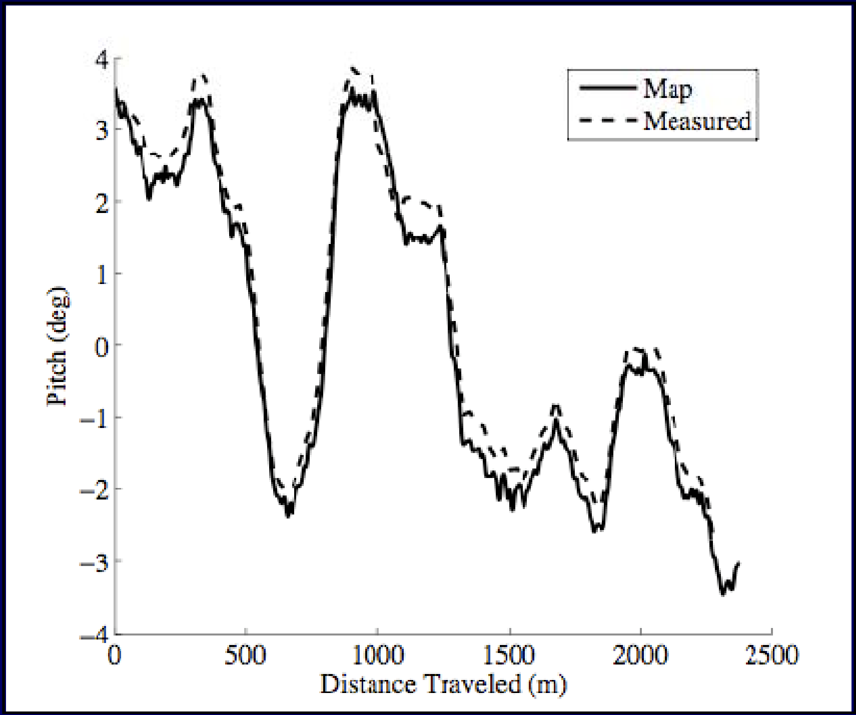


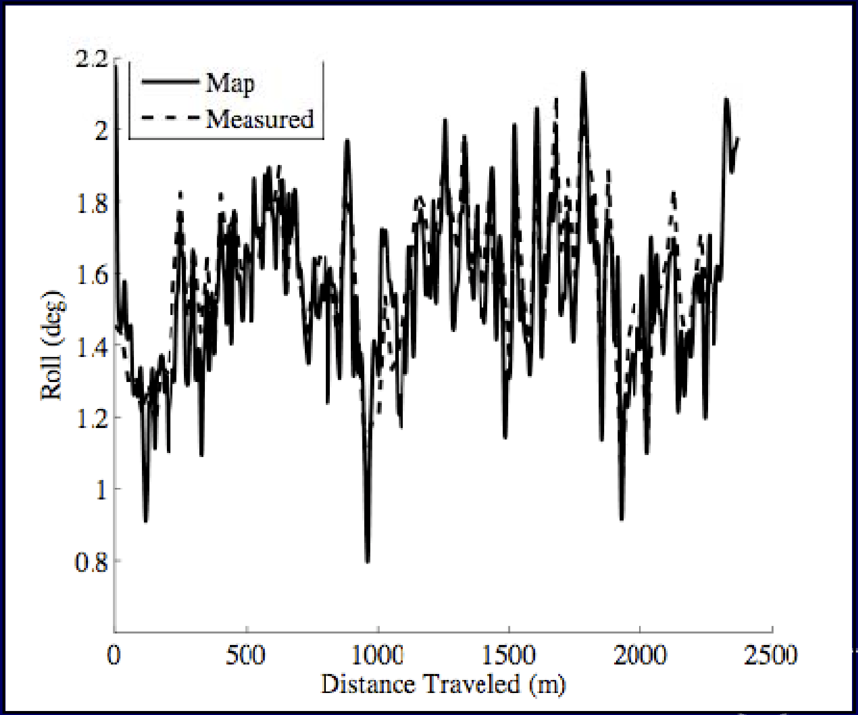
Using Roll Measurements



Longitudinal Positioning: City Results

- Localizing along secondary roadways can be:
  - More accurate due to large signal-to-noise ratio in pitch
  - Less accurate due to lane-keeping errors with uneven superelevation profiles

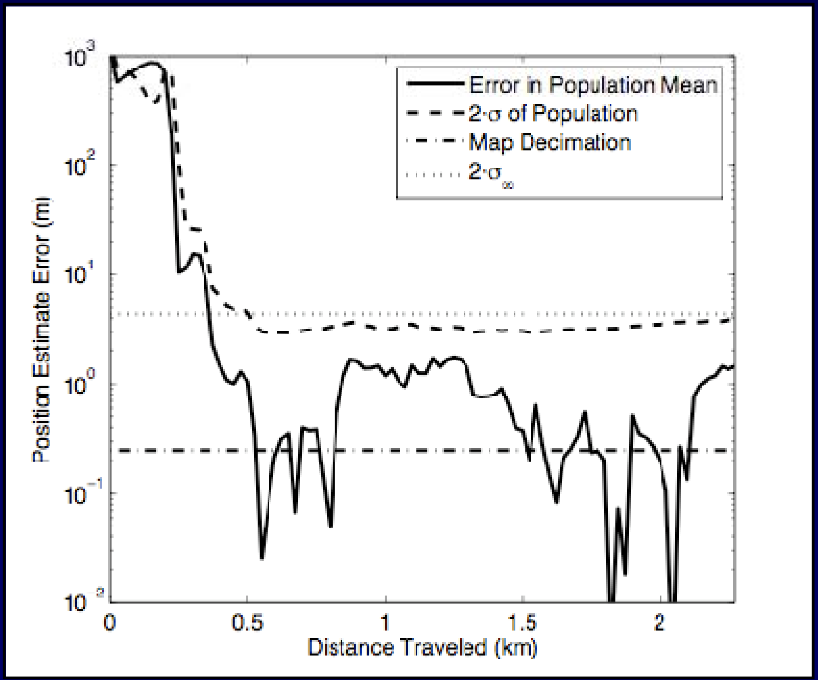




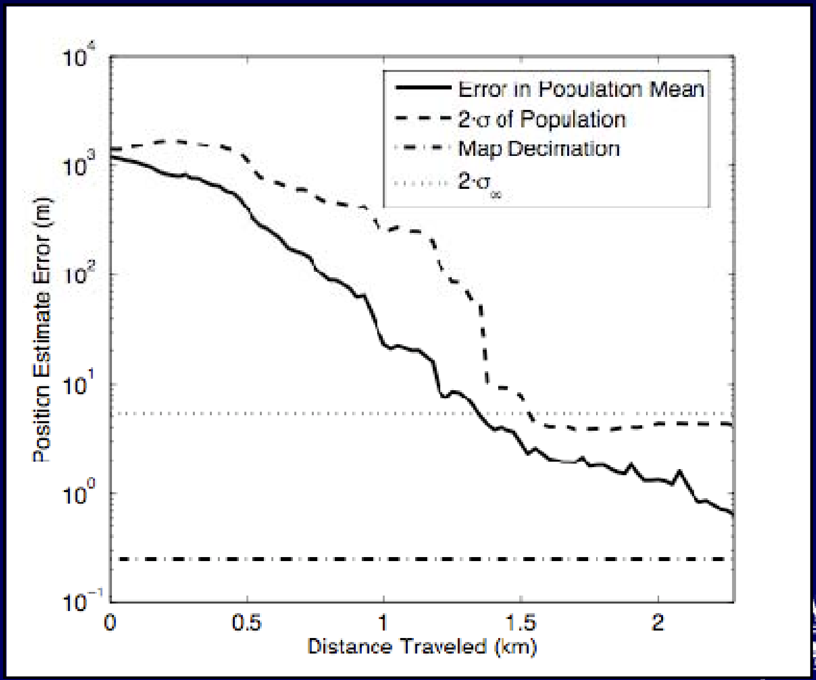
Longitudinal Positioning: City Results

- Using the pitch measurements resulted in meter-level accuracy
- The low signal-to-noise ratio of the roll measurements resulted in a slow convergence

Using Pitch Measurements



Using Roll Measurements



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Why a Hybrid approach?

	Particle Filter	UKF
Computational Complexity	High	Low
Initialization Complexity	Low	High

- Unscented Kalman Filters:
  - Are computationally cheaper than Particle Filters, actually a special case of a Particle Filter where you have 2n+1 particles instead of thousands
  - Need to be initialized with a Gaussian Probability Distribution

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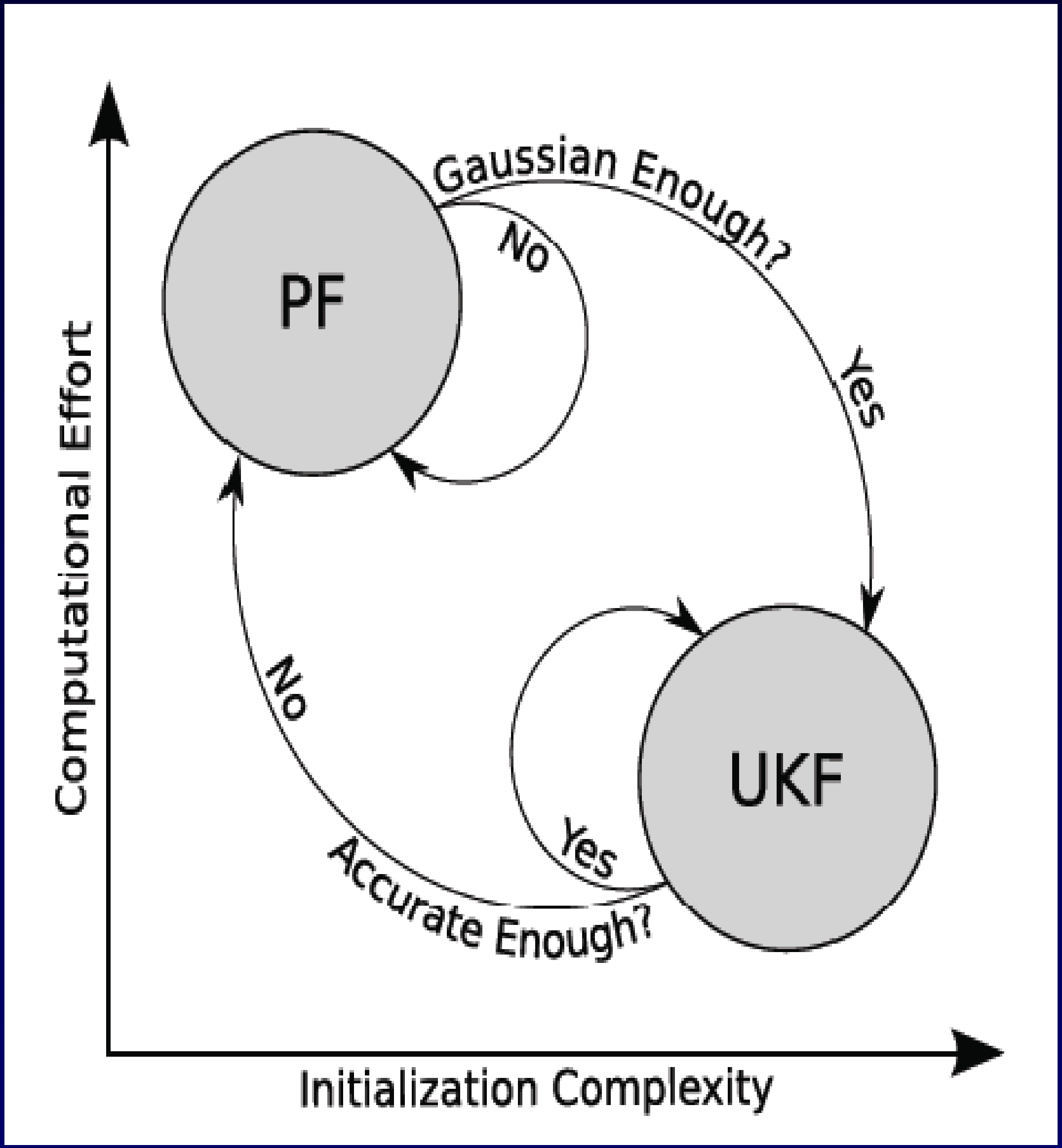
Using an Unscented Kalman Filter



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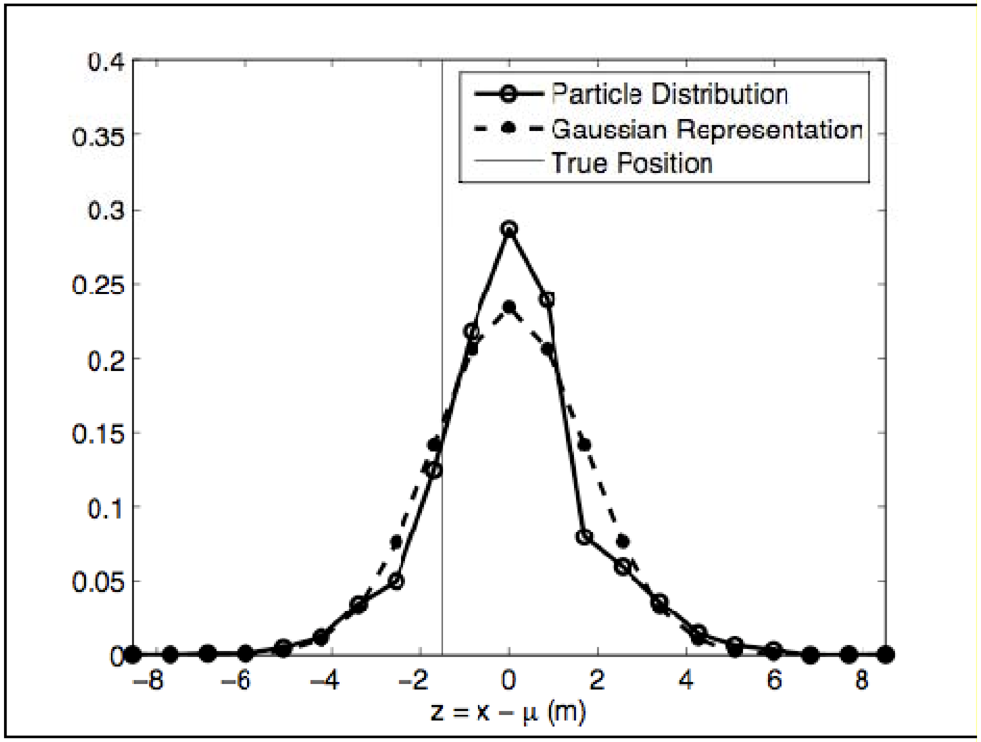
Initialization

- Use a Chi-squared test to detect a Gaussian distribution:

$$\chi^2 = \sum_{i=1}^{N_b} \frac{(h_i - G_i)^2}{G_i}$$

$$G_i = \frac{1}{\sigma_x \cdot \sqrt{2\pi}} \cdot exp\left(-\frac{b_i - \mu_x}{2 \cdot \sigma_x^2}\right)$$

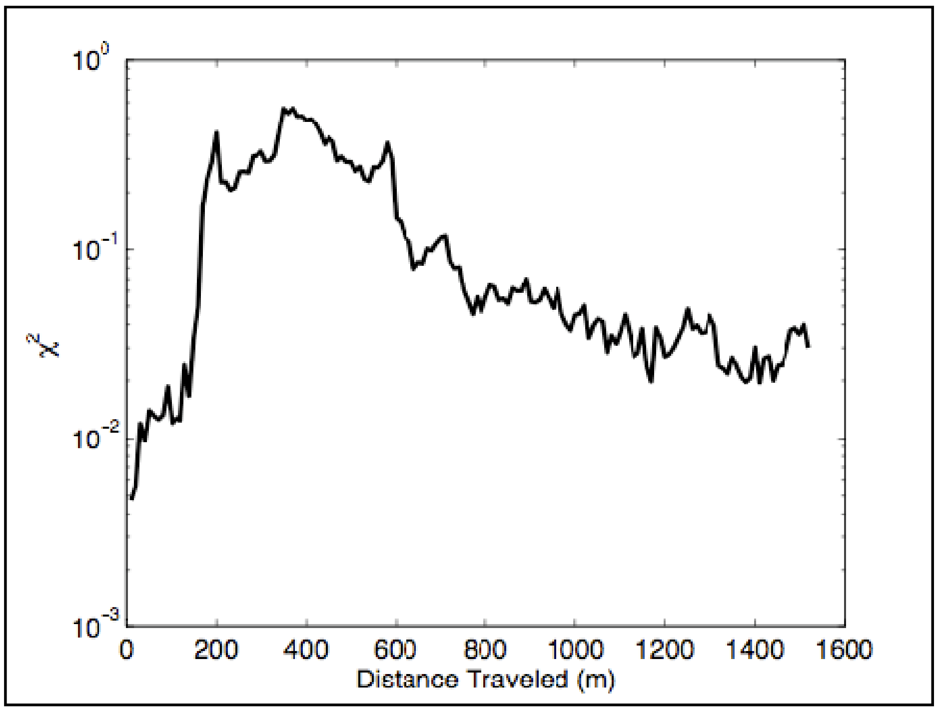


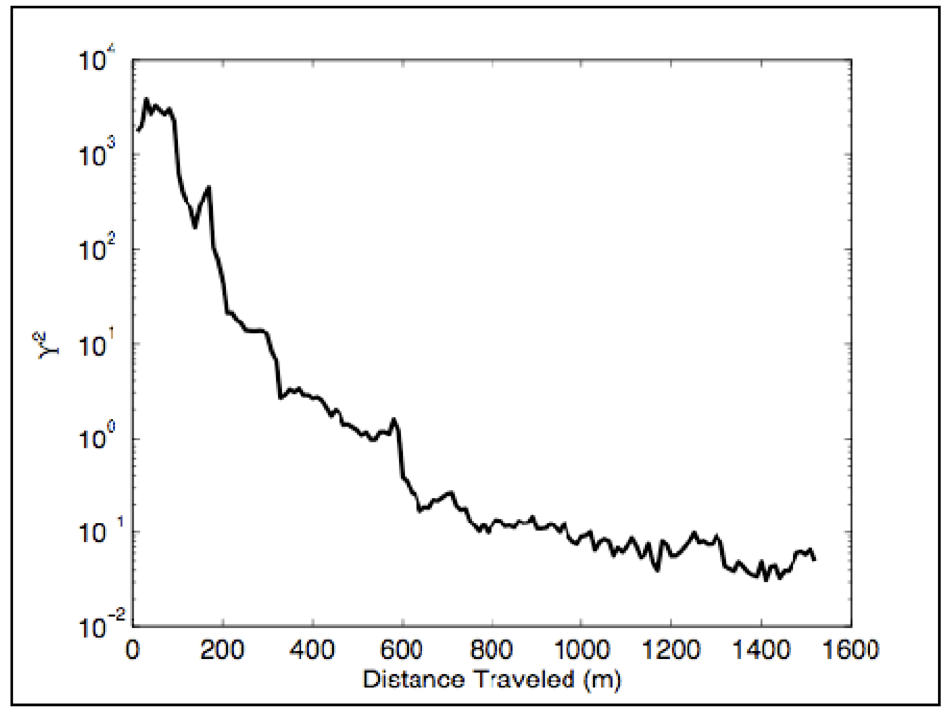
- where h_i is the histogram of the population at bins b_i and using the standard deviation of the population
- Switch to a UKF when reduced to a desired threshold σ_x

Modified Test

$$\chi^2 = \sum_{i=1}^{N_b} \frac{(h_i - G_i)^2}{G_i}$$

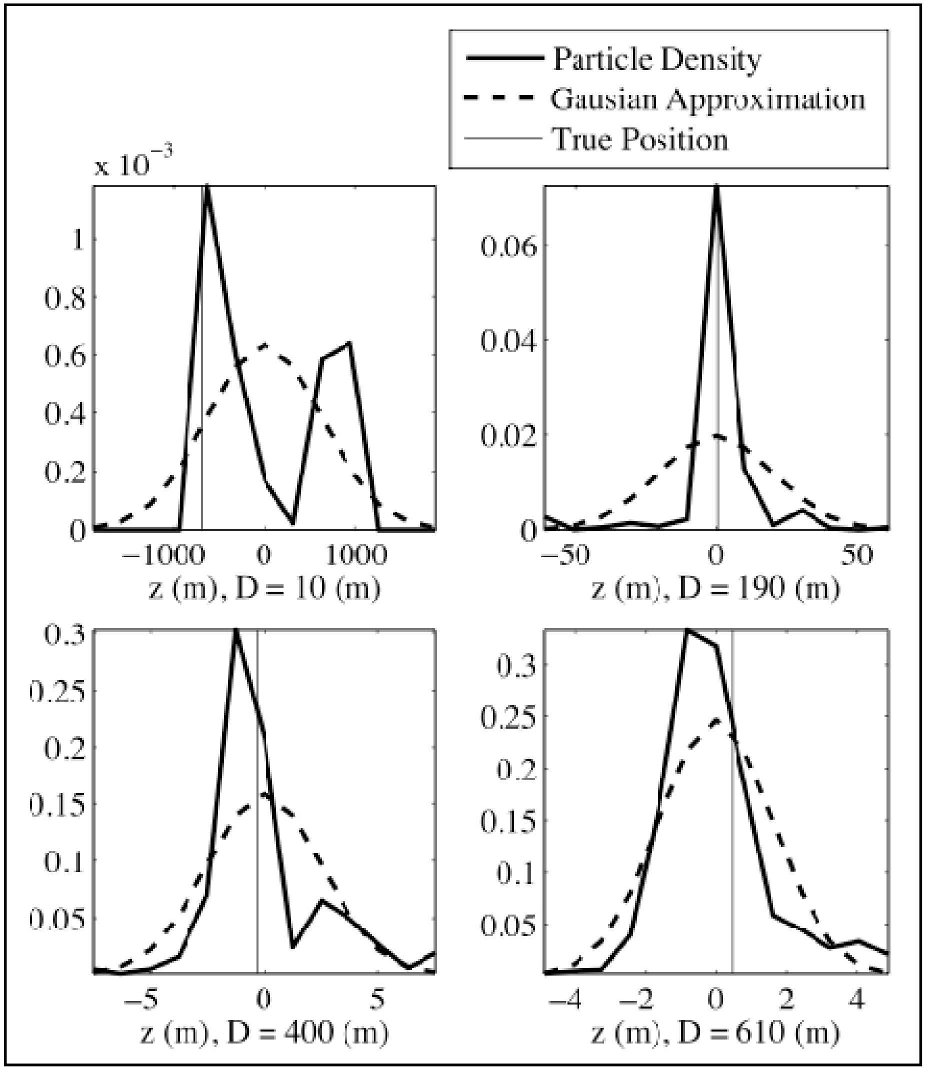
$$\Upsilon^2 = \chi^2 \cdot \sigma_x^2 = \sum_{i=1}^{N_b} \sigma_x^2 \cdot \frac{(h_i - G_i)^2}{G_i}$$

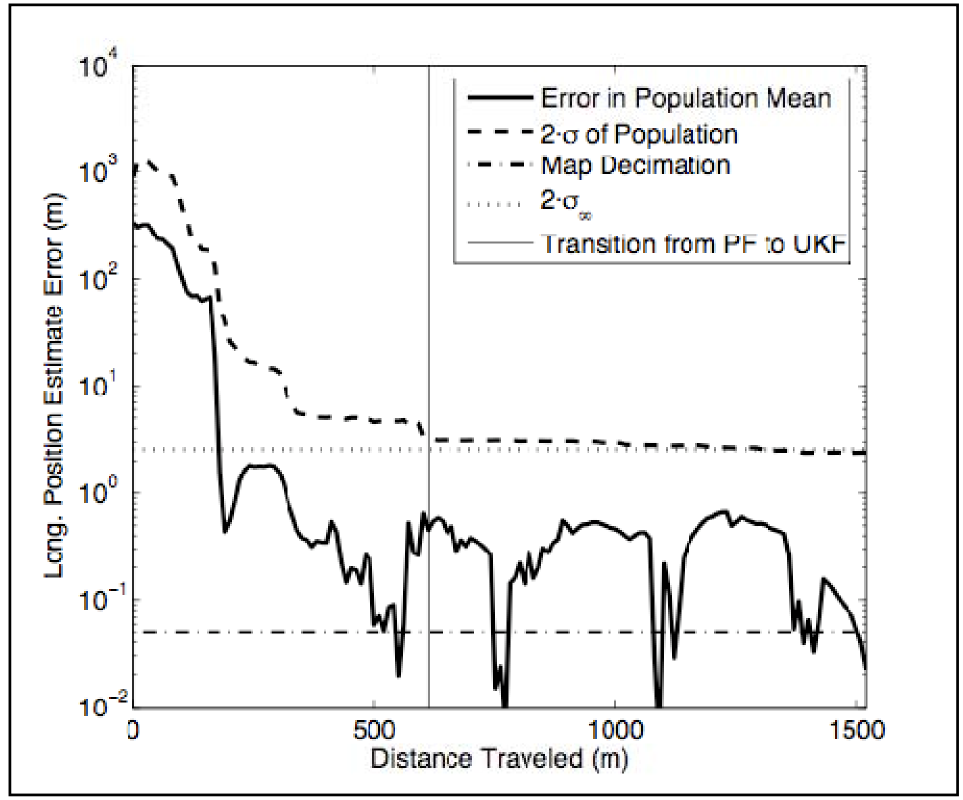




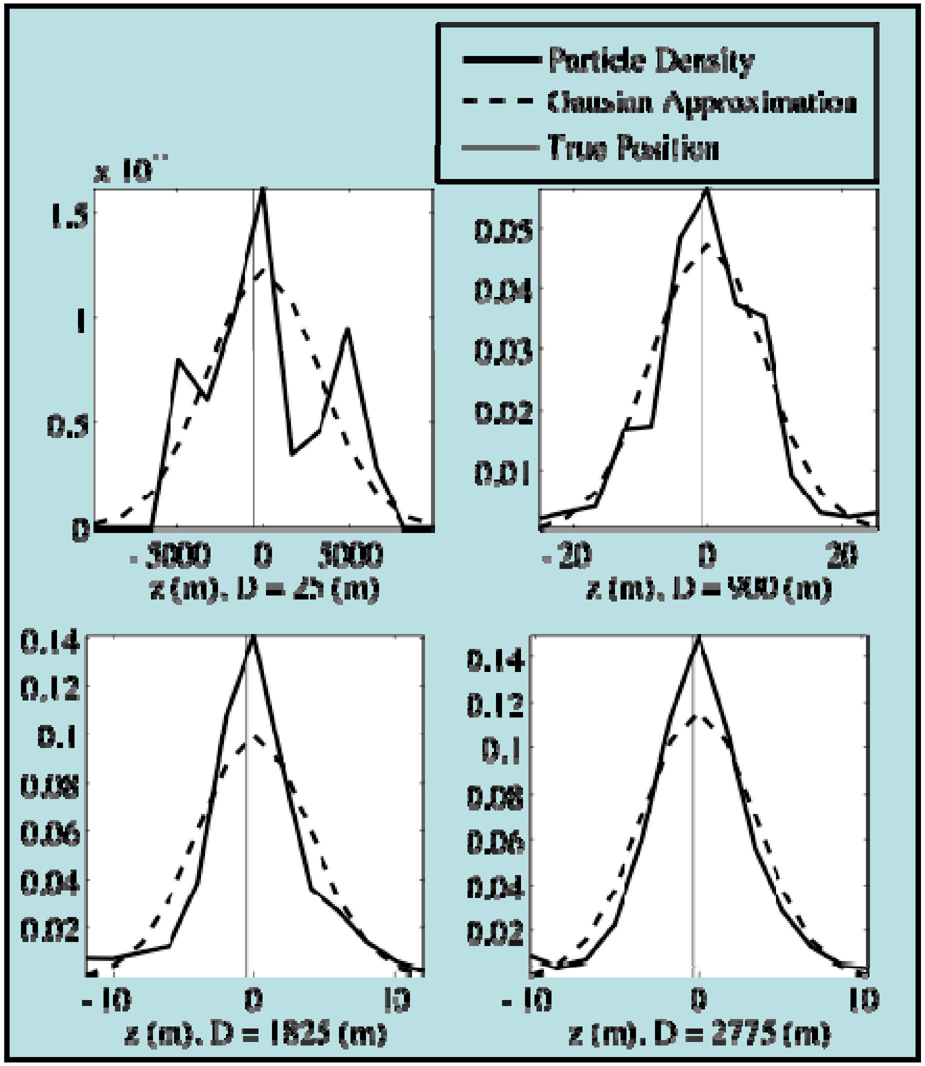
Threshold is more obvious using the modified test

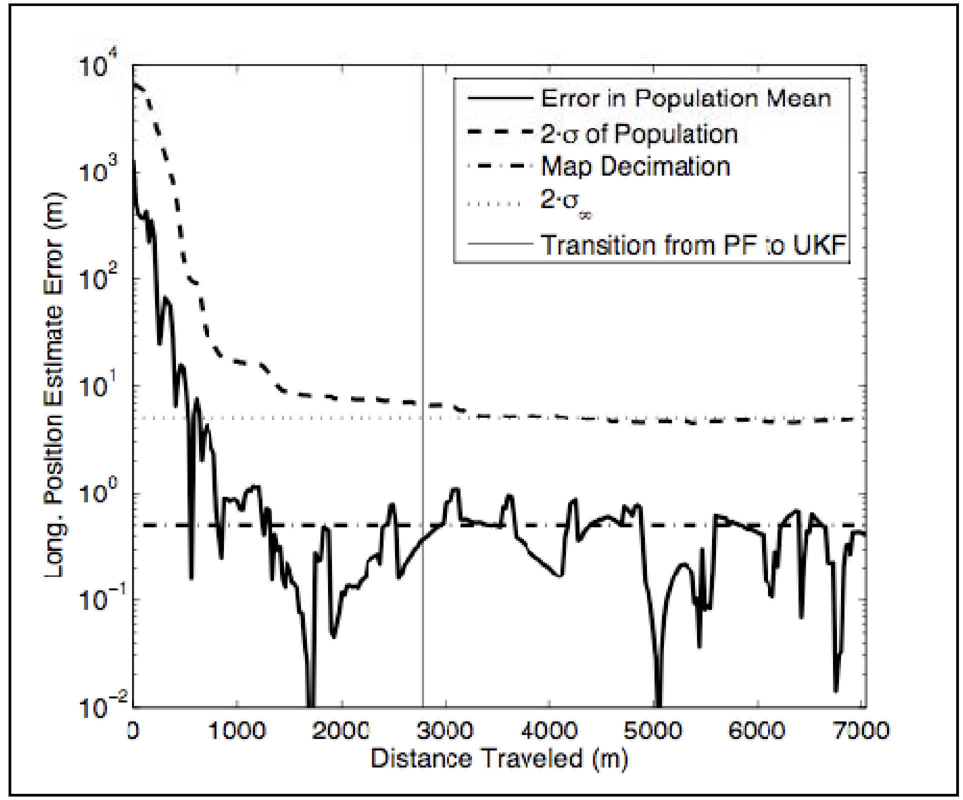
Localization Results: LTI





Vertical line transition shows point of from PF to UKF





- Resulted in a 99.7% decrease in FLOPS per iteration

Ongoing Work

- Past work
  - Motivation for using terrain maps to localize a vehicle
  - Feasibility of location-based road “fingerprints”
  - Framing localization as a nonlinear particle-filter correlation problem
  - Attacking the nonlinear problem with a Kalman approach
  - Hybridizing the method to have the advantages of both the linear/nonlinear approaches
- Task 3 items
  - Vehicle integration, data collection
  - Accuracy reduction including vehicle and maps
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  - Large road network testing

Data Acquisition

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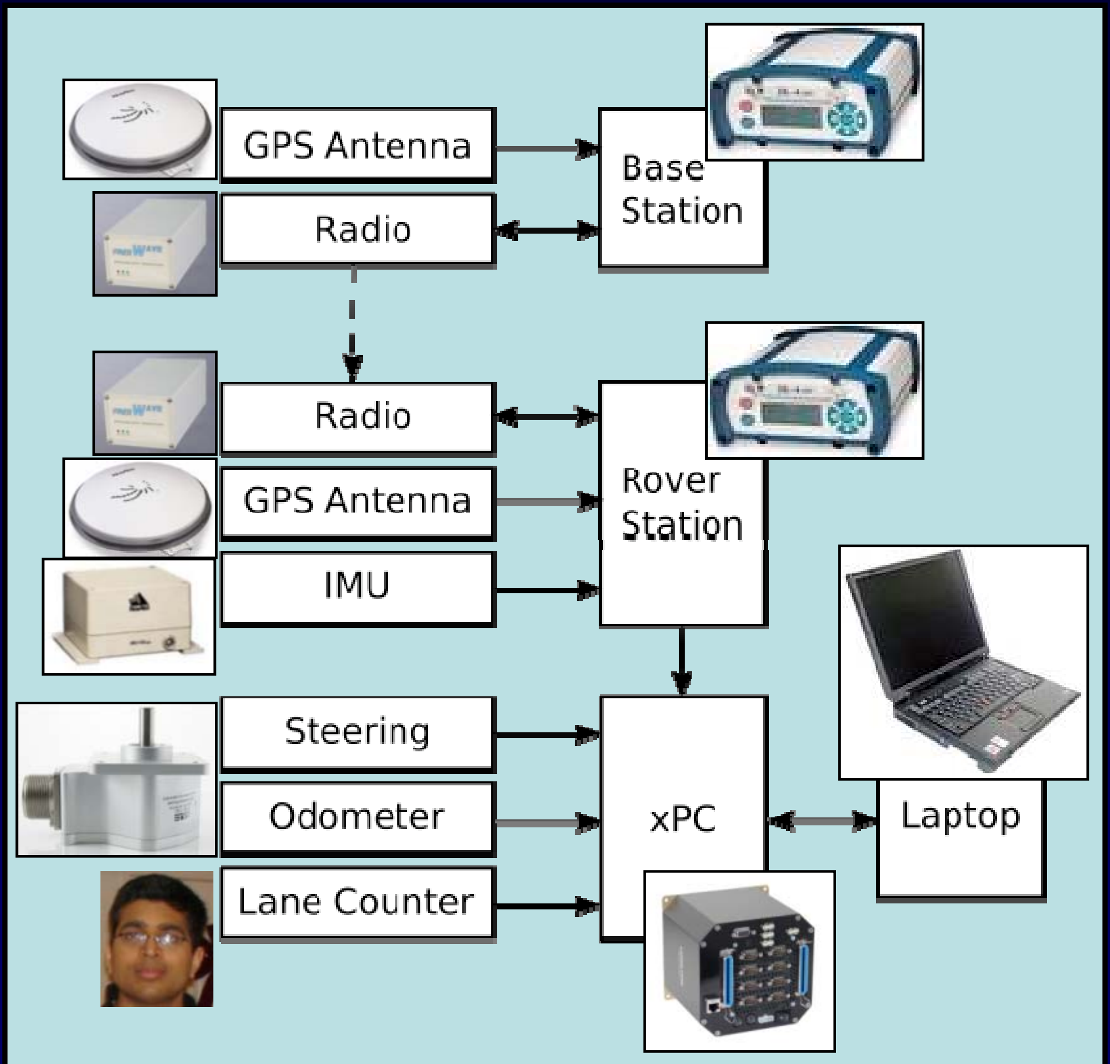
Data Acquisition

- Using:
  - NovAtel SPAN GPS/IMU system
  - US Digital Optical Encoders
  - Diamond PC104
  - IBM laptop
- Logging:
  - Vehicle Position
  - Vehicle Attitude
  - Steering Input
  - Wheel Odometry
  - Lane Index



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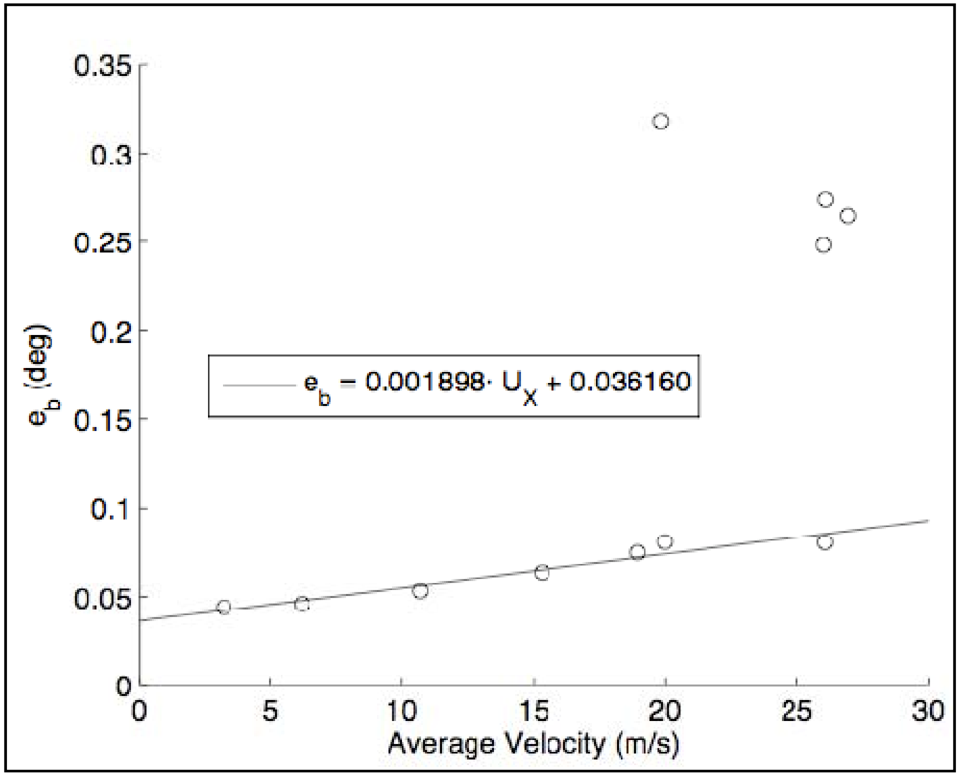
Accuracy reduction of vehicle data

- Accuracy of vehicle data needs to be determined, particularly on test vehicle.
- We have started this on our own vehicle, and found that sensor fidelity depends on
  - Speed
  - Roadway type (highway versus secondary)
  - Sensor specs
- We have functions that describe this behavior for our vehicle, but need to know if this holds on other vehicles

Sensor bias error versus speed

- We calculated the average bias of several data sets at various speeds
- Plotted as a function of traveling velocity and linearized
- Use to estimate the minimum variance:



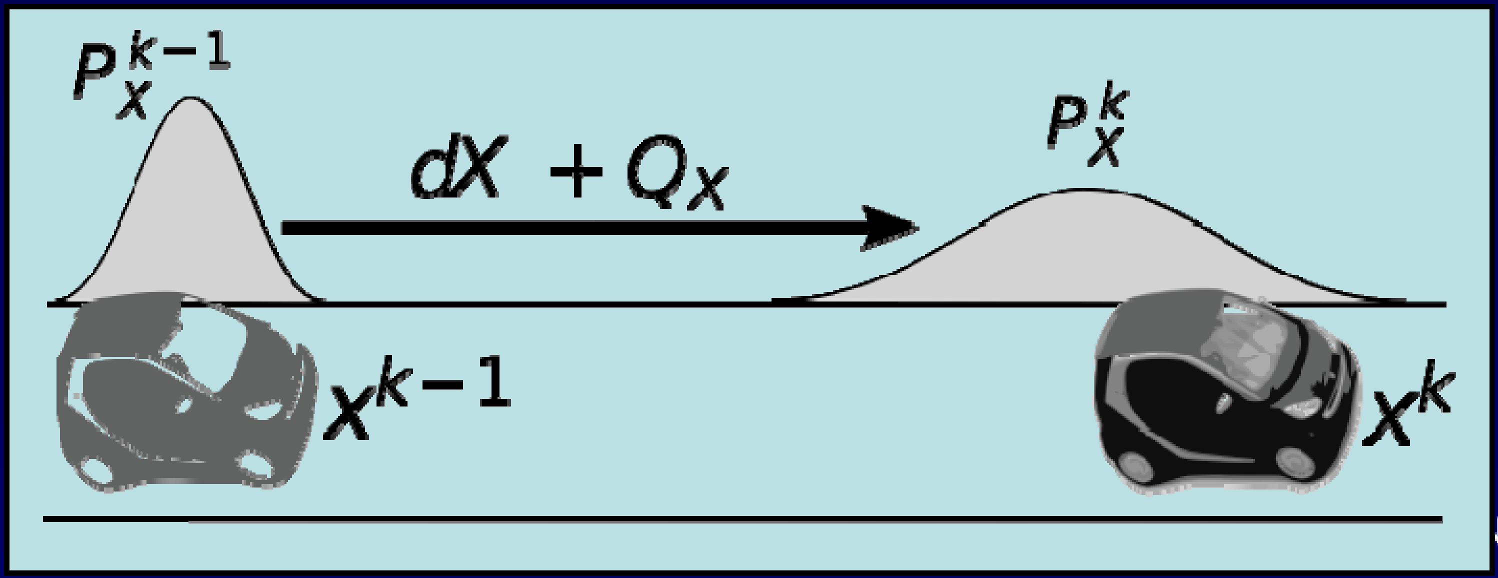
$$R_p = \sigma_p^2 = \left(\frac{e_b}{3}\right)^2 = (0.00063 \cdot u_x + 0.012)^2$$

- Use R_p to get:

$$P_\infty = \frac{Q}{2} \cdot \left(1 + \sqrt{1 + \frac{4 \cdot R}{C^2 \cdot Q}}\right)$$

Encoder-Induced Motion Variance

- The particle's longitudinal position are updated using the motion model: $P_X^k = P_X^{k-1} + dX + Q_X$
- The variance Q is used to model the variance in the odometry measurement dX



Encoder Motion Variance: the Q parameter in a Kalman filter

- Estimate variance Q using:
  - We used aUS Digital optical encoder with N_c = 8192 counts/revolution, sampled at 100 Hz
  - Distance between DGPS points as true travel distance
  - We need to collect similar data for test vehicle, using in-vehicle sensors!

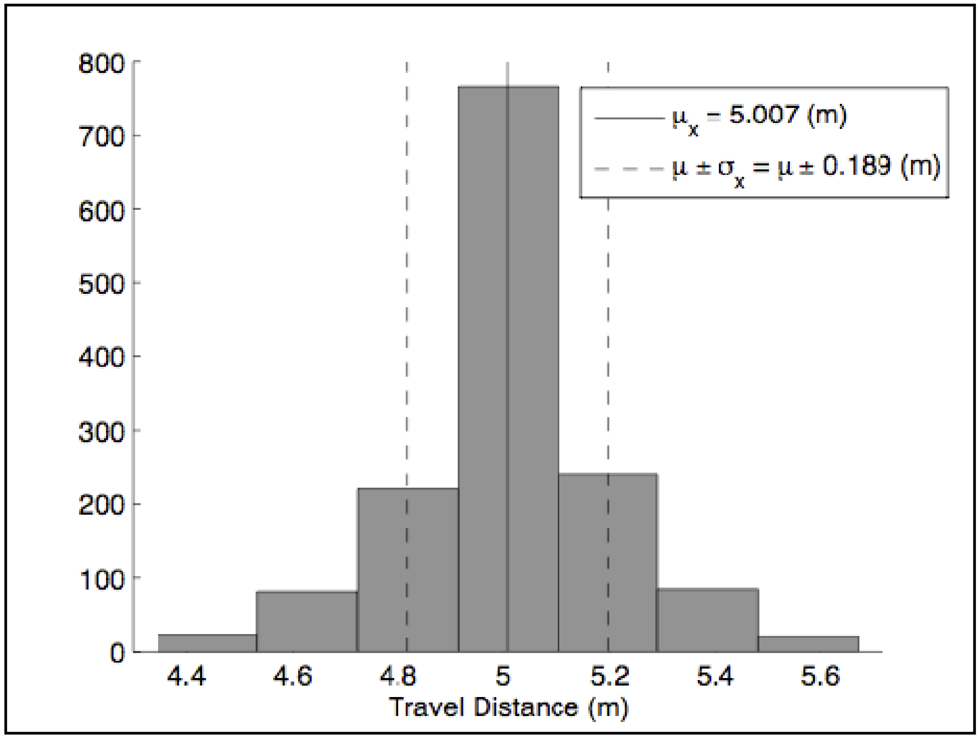
Motion Variance: Q

- Calculate the number of counts to travel 5 meters
- Convert counts to measured distance error:

$$z_{m,i} = \frac{2\pi R_w}{N_c} \cdot (n_{c,i} - \mu_c)$$

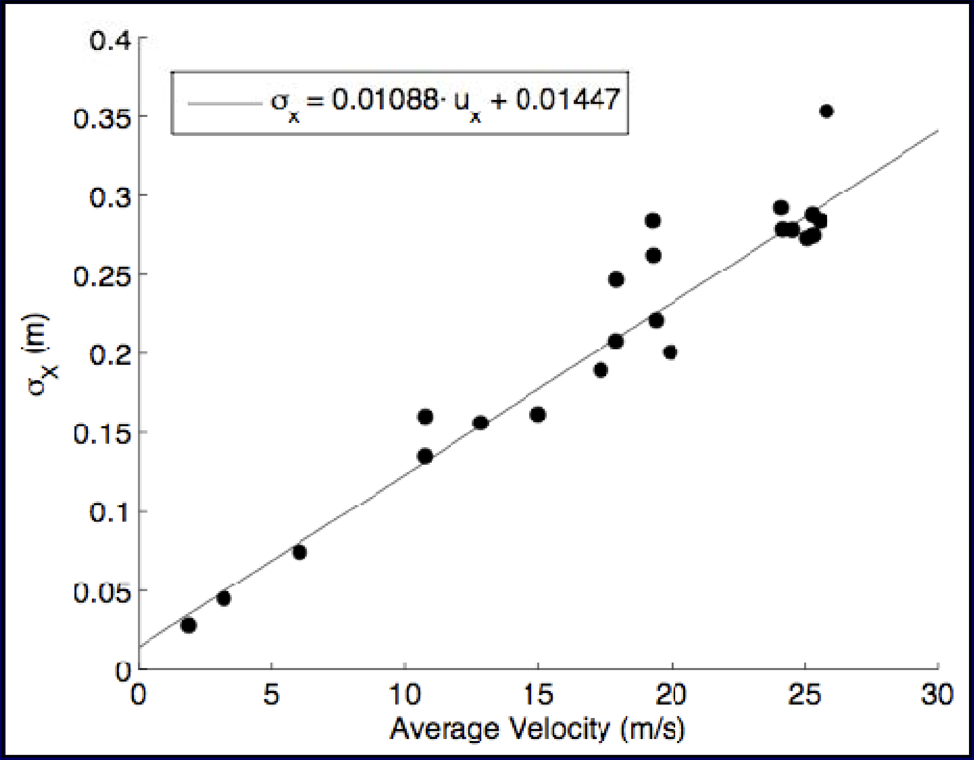
- Calculate the standard deviation of the errors:

$$\sigma_x = \sqrt{\frac{1}{n}\Sigma\left(z_{m,i}\right)^2}$$



Variance: Motion Model

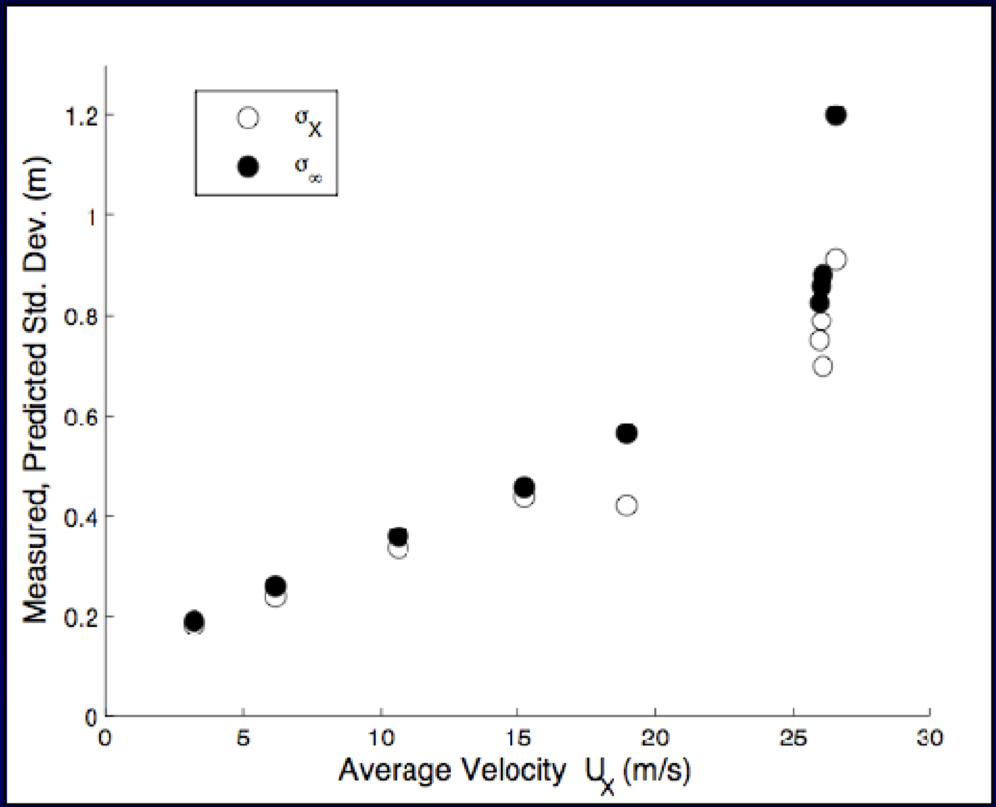
- Using several data sets from the LTI test track, city driving, and interstate highway:
  - Plot the standard deviation as a function of traveling speed
  - Use a linear fit to estimate variance in the motion model:



$$Q = \sigma_x^2 = (0.01 \cdot u_x + 0.015)^2$$

What are sensor models good for? They predict the accuracy of position information!

- Predicted versus measured variance in PF versus KF (KF is used to predict PF)



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Accuracy reduction of maps

- Currently are saving location histories every 10 cm on highway, 2 cm on arterial and secondary roads. Results show this is clearly “overkill”
- Currently working on several ideas to reduce data storage for maps.

1. Downsampling
   – Using polynomials or interpolation to save fewer points
2. Feature methods
   – Use wavelet representations of road features to reduce point-by-point representation
   – The same techniques allow a feature-space representation, and thus enable a “search tree” approach.

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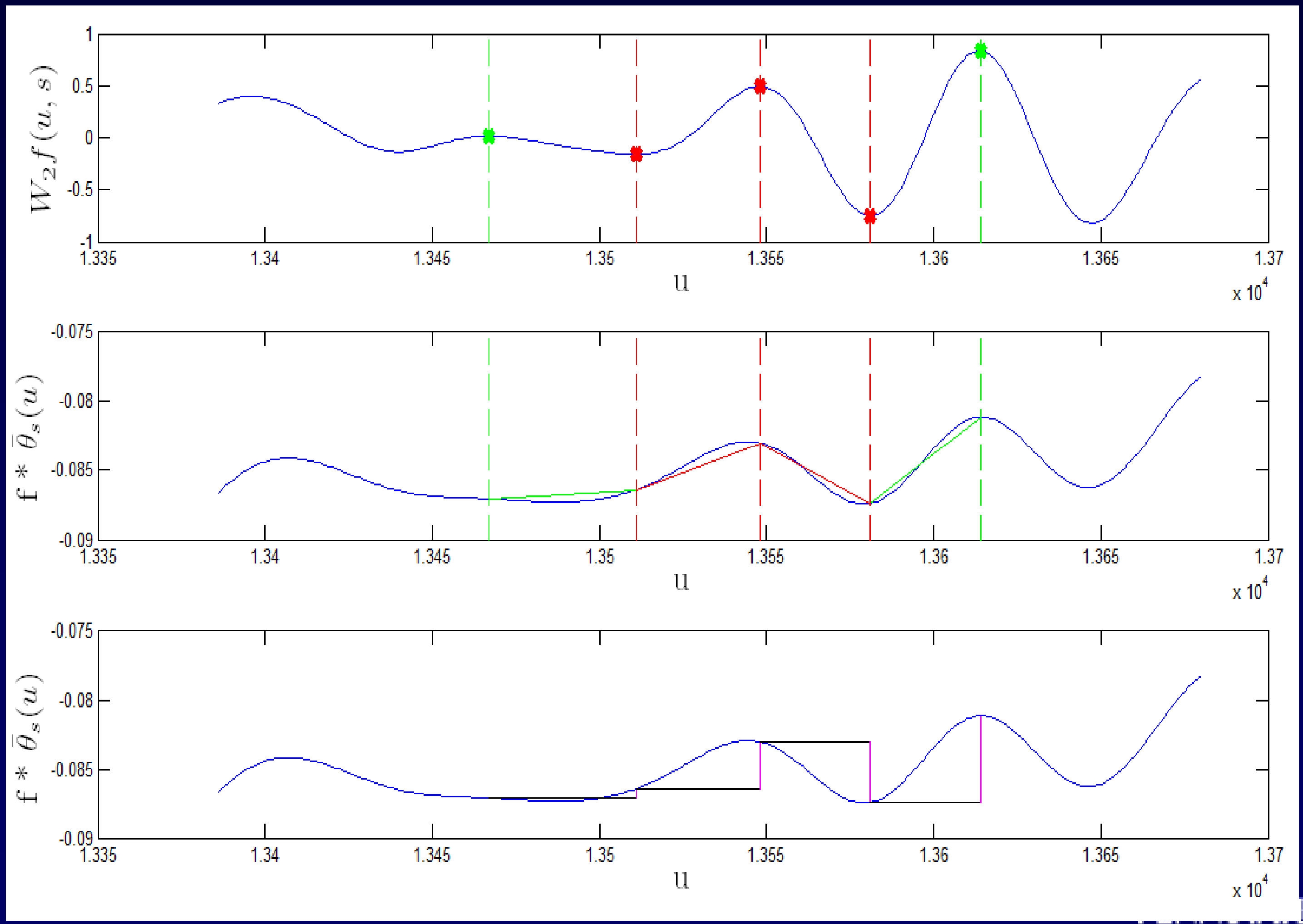
Example of feature-points method

Maxima / Minima

Linearization

Feature vectors



Ongoing Work

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Example of fused sensor inputs

In the past, we've looked at combining camera data with terrain maps to create augmented reality match

- **Real and virtual scenes are compared.**
- **Preliminary results show orientation accuracies of 0.1 deg**

Wonderful potential in this project for similar work!

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Multi-dimensional System Model

- Assuming the state model to be:

$$
\begin{aligned}
x_k &= A \cdot x_{k-1} + B_u \cdot u_{k-1} + B_w \cdot w_{k-1} \\
y_k &= C \cdot x_k + D_u \cdot u_{k-1} + D_v \cdot v_{k-1}
\end{aligned}
$$

- The previous equations still apply, but instead have higher dimension!

$$
\begin{aligned}
x_{k+1} &= A \cdot (I - K_k C) \cdot x_k + A K_k y_k + B_u u_k \\
K_k &= P_k C^T \cdot (C P_k C^T + R)^{-1}
\end{aligned}
$$

$$
\begin{aligned}
P_{k+1} &= Q + A P_k A^T - \\
& A P_k C^T \left(C P_k C^T + R\right)^{-1} C P_k A^T
\end{aligned}
$$

To integrate terrain-localization sensor with other measurements, what is needed?

1. Dynamics of the terrain "sensor"
   a) How fast does it converge
   b) Does convergence rate change as a function of road position?
2. Internal calculation of the estimate "health"
   a) Obtained by RMS error between predicted/measured values at each location
   b) If disagreement is large, need to indicate this somehow with a voting algorithm or median filter
3. Estimates of variance of the terrain-based sensor
   a) For PF's, can use particle population variance – useful to discern multi-modal estimates
   b) For KF, can use covariance

Ongoing Work

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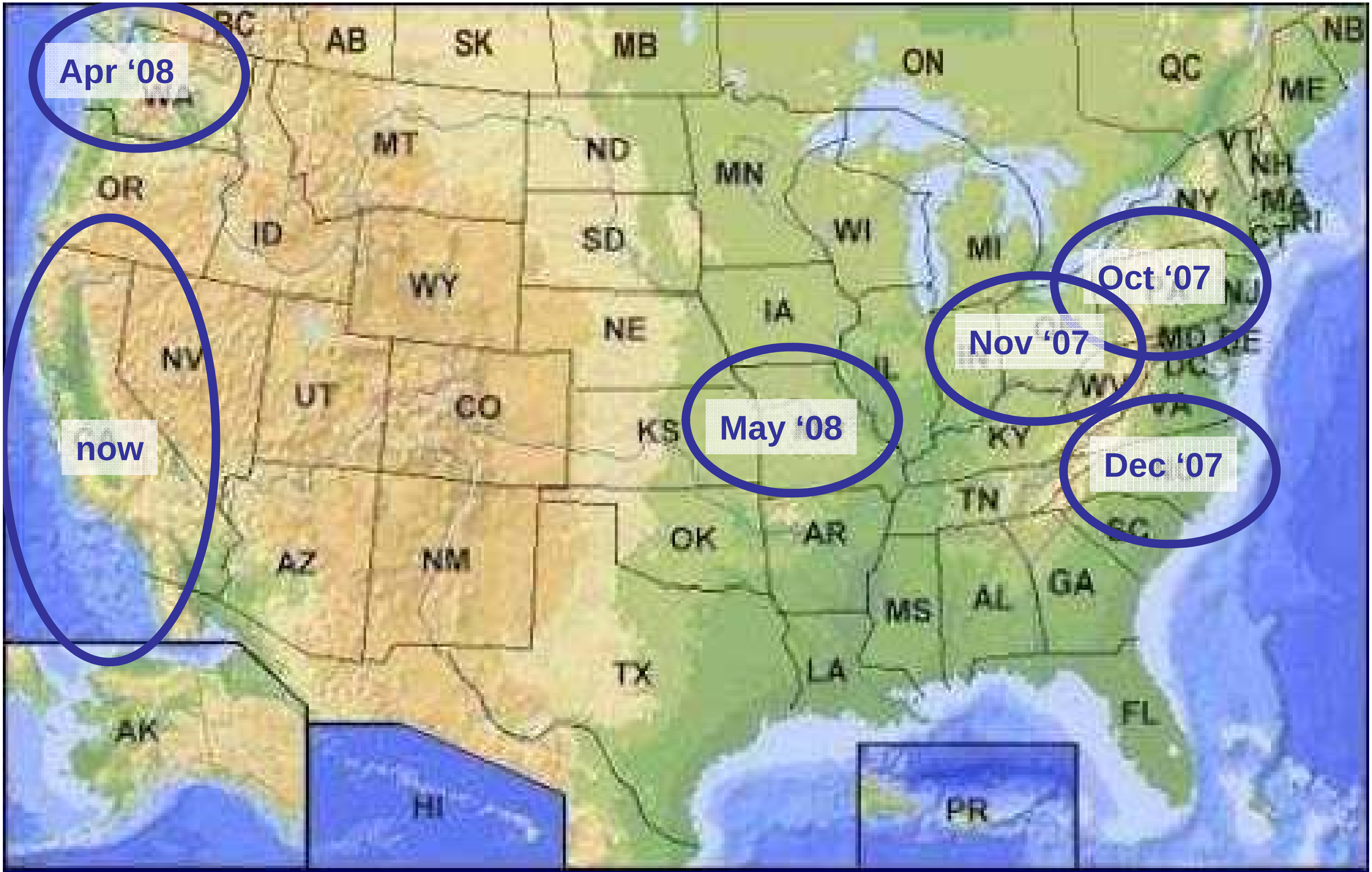

See http://controlfreaks.mne.psu.edu for more info

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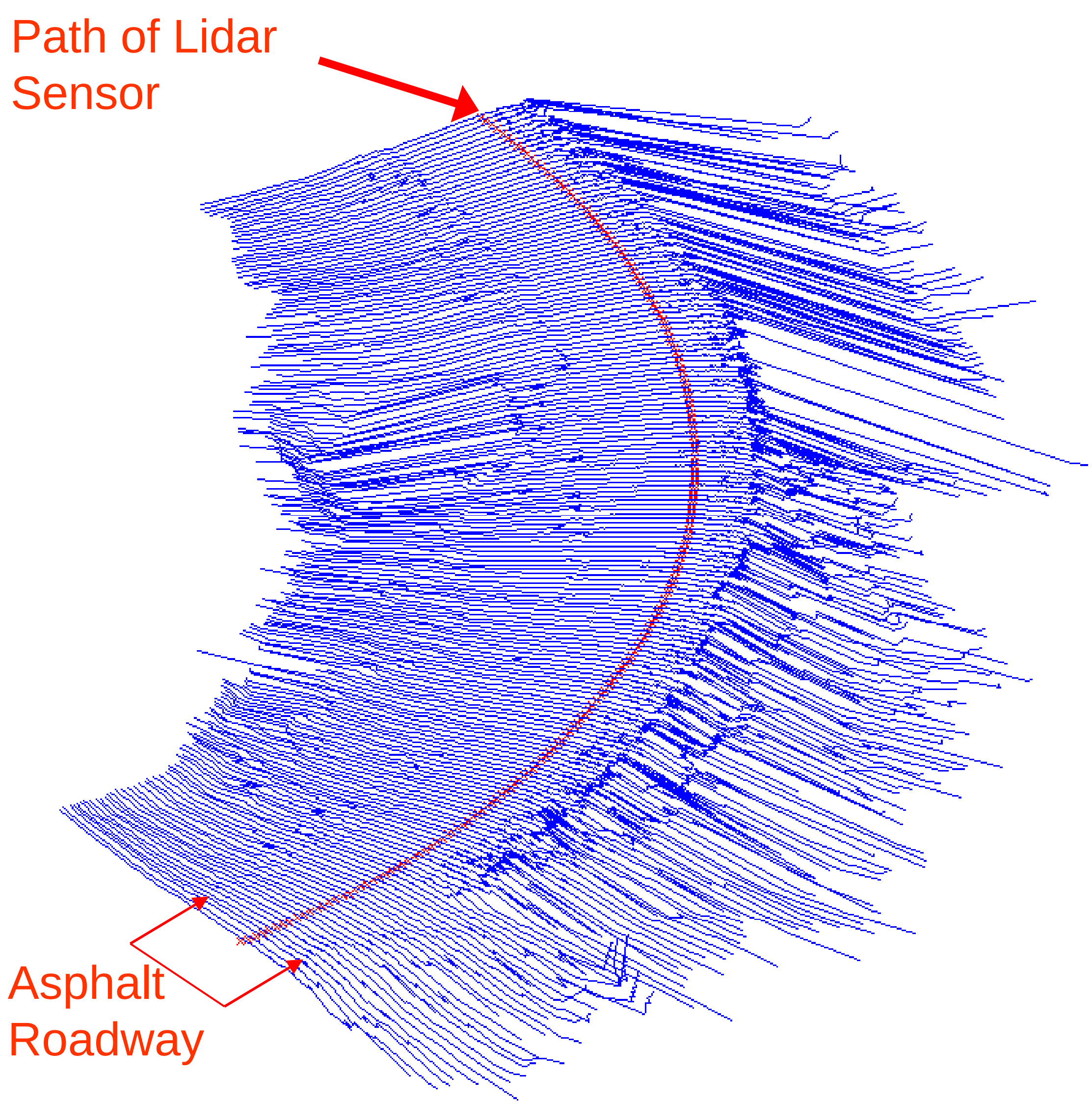
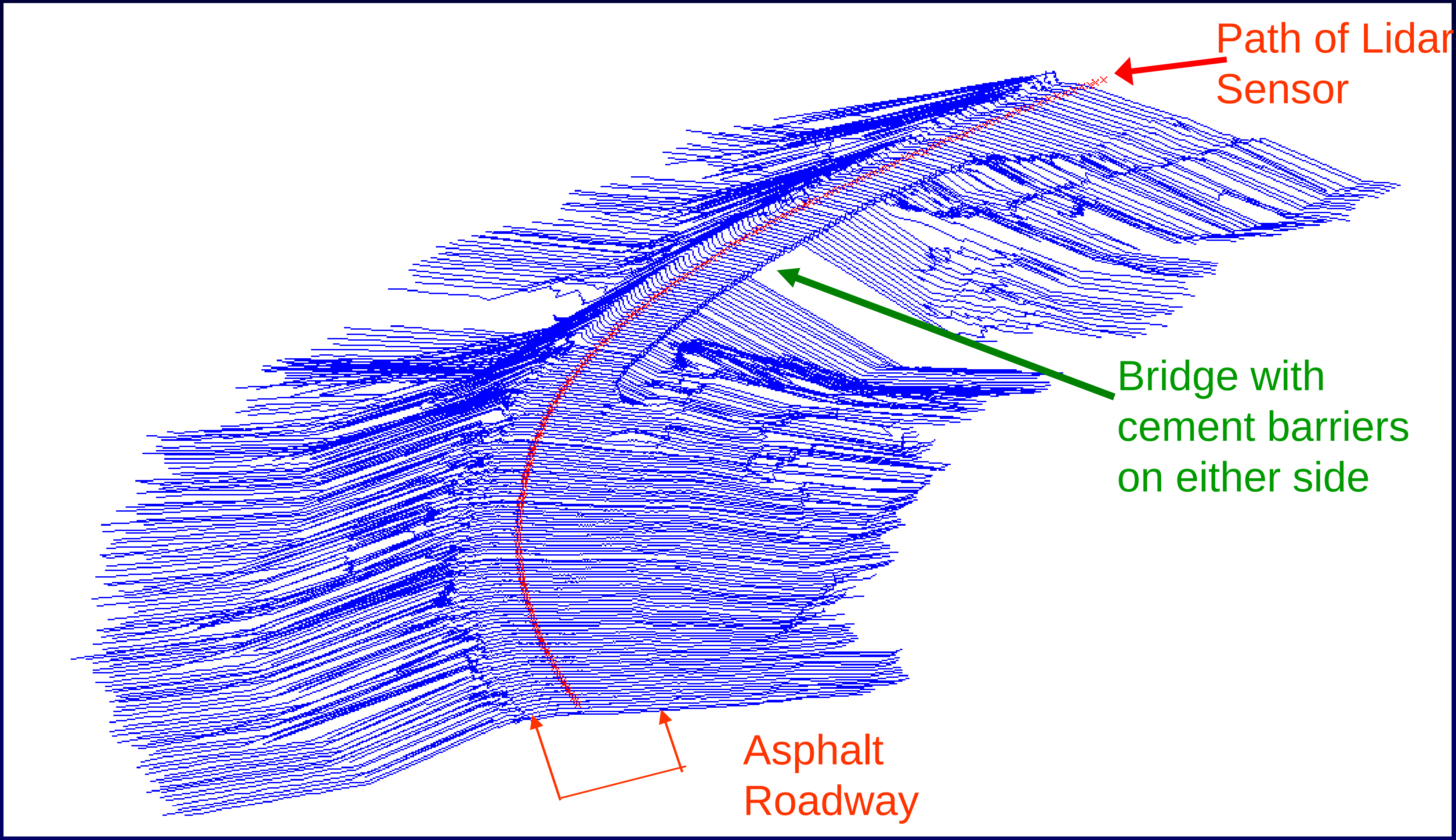
Mapping terrain

- Shown at right is a banked curve from the test track
- Getting 10 to 30 scans per second out to 80 meters of range.
- Accuracy on the order of 6 cm at best case (perfect GPS).
- Actual error is on the order of a meter or less.



Example bridge section



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INTELLIGENT VEHICLES AND SYSTEMS GROUP, PENN STATE .

Remaining field mapping

We propose to include terrain-based localization methods over a large area network. Steps:

1) **Collect data over a large network locally (so it can be re-mapped)**

   Starting in Jan 2010, we will be mapping (LIDAR) entire region around Penn State area (Pennsylvania and sections of NY)

   - **Sponsored by SHRP2, so can leverage same effort for this project**
   - **Database will be public in 3-6 years**

2) **Collect data over a large network remotely**

   Use portable data-collection system to map

   - **Auburn area**
   - **New York City (ITS)**
   - **Other sites?**

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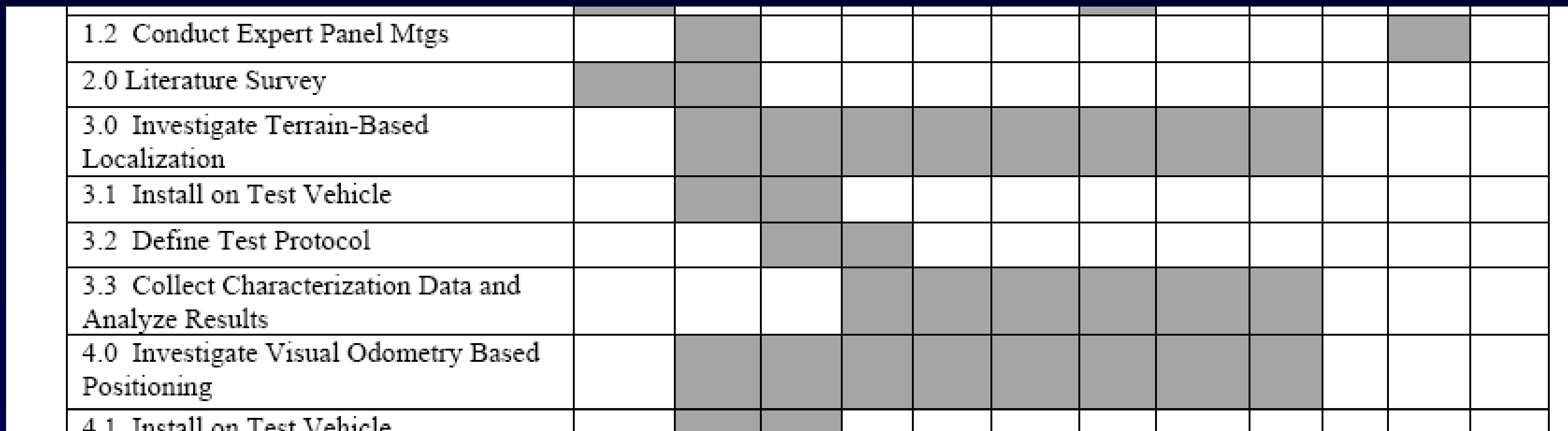
Task 3 estimated timeline



- Milestones?
  - 3.1: Test data
    - Vehicle characterization data transferred to PSU
    - Characterization of sensor bias / error for Kalman filter
  - 3.2: Protocol
    - Regions for testing and test routes identified
  - 3.3: Data collection
    - Field data collected for at least one “prime” region
    - Error analysis for test routes

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Past and other ongoing supporters

The National Science Foundation – funded research into fundamentals of dynamic behavior through several student fellowships. (~$200k)

The National Academy of Science, The Transportation Research Board – funded roadway scanning and terrain modeling (~$300k)

Army TACOM – currently funding HIL work (~$1M) and vehicle platooning work

The Federal Transit Agency – funded test track and vehicle systems used on the track such as the DGPS/IMU system (track ~$14M, current project ~$300k)

Naval Explosive Ordinance Disposal – currently funding robotics work that uses terrain models (~$600k)

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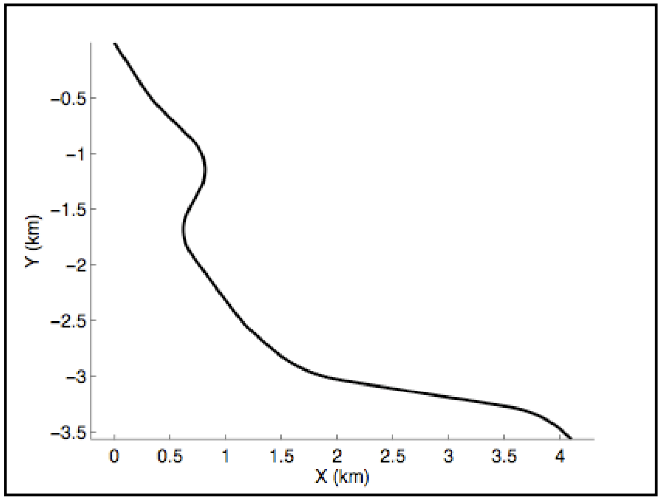
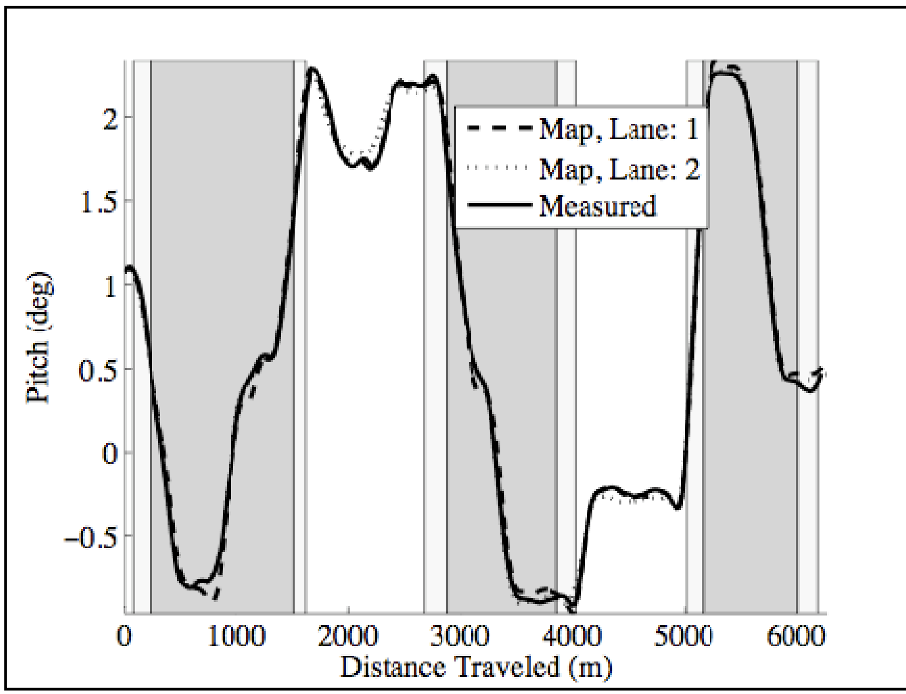
Questions?

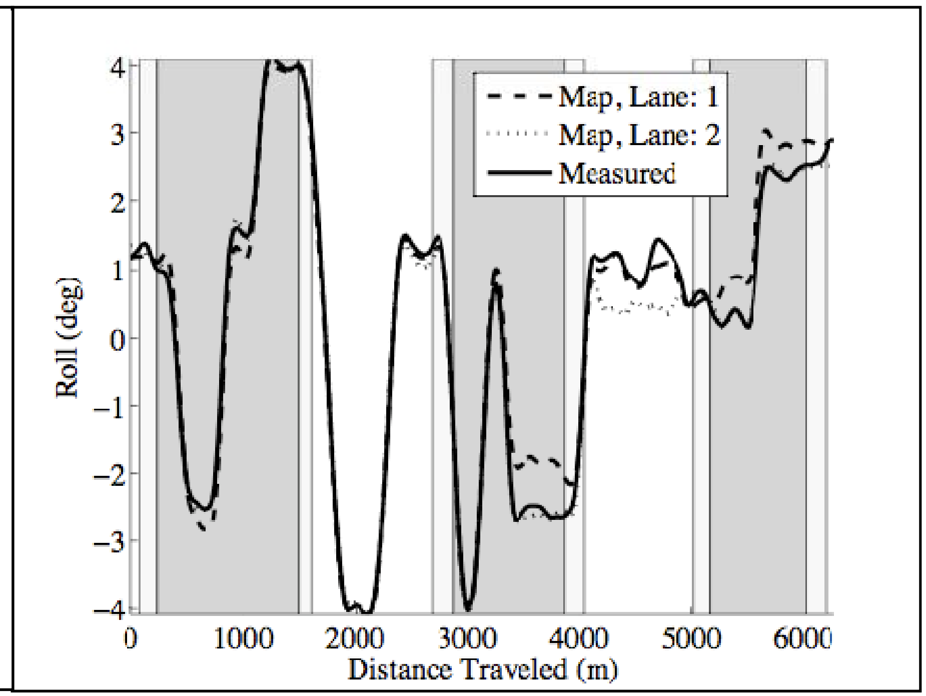
Extra slides follow

Multi-Lane Terrain Maps



- ***White:*** ***Right lane***
- ***Light gray:*** ***Lane change***
- ***Dark gray:*** ***Left lane***



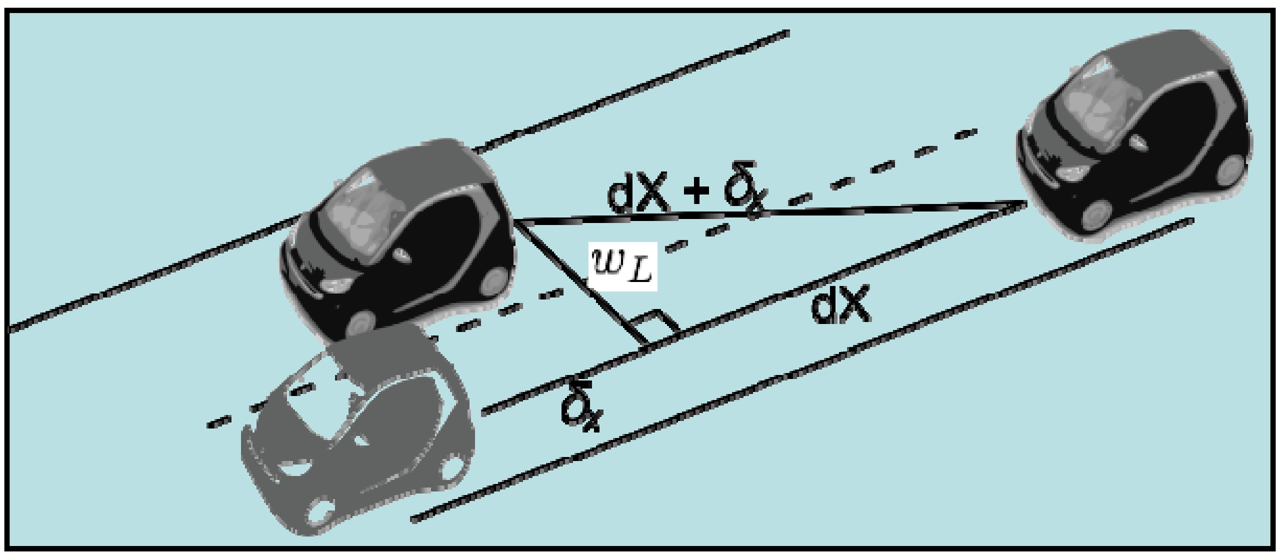


Lateral Positioning: PF

- Decouple the longitudinal and lateral positioning estimates
- Modify the motion model to account for odometry errors due to lateral motion

$$\delta_x = \sqrt{dX^2 + w_L^2} - dX$$

$$P_X^k = P_X^{k-1} + dX - \frac{\delta_x}{w_L} \cdot \left| P_Y^k - P_Y^{k-1} \right| + Q_x$$

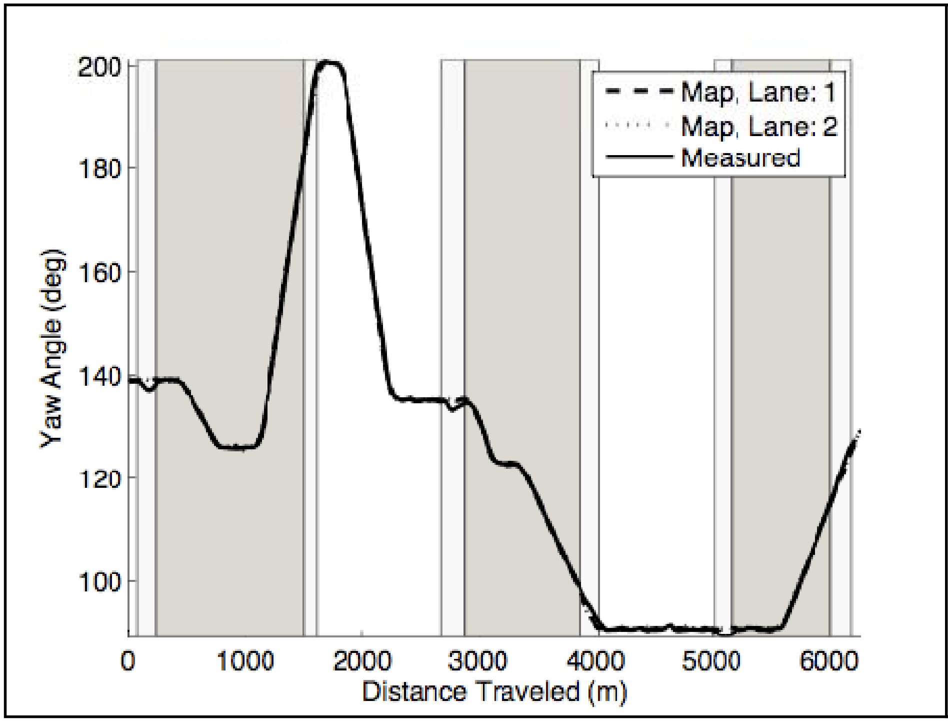


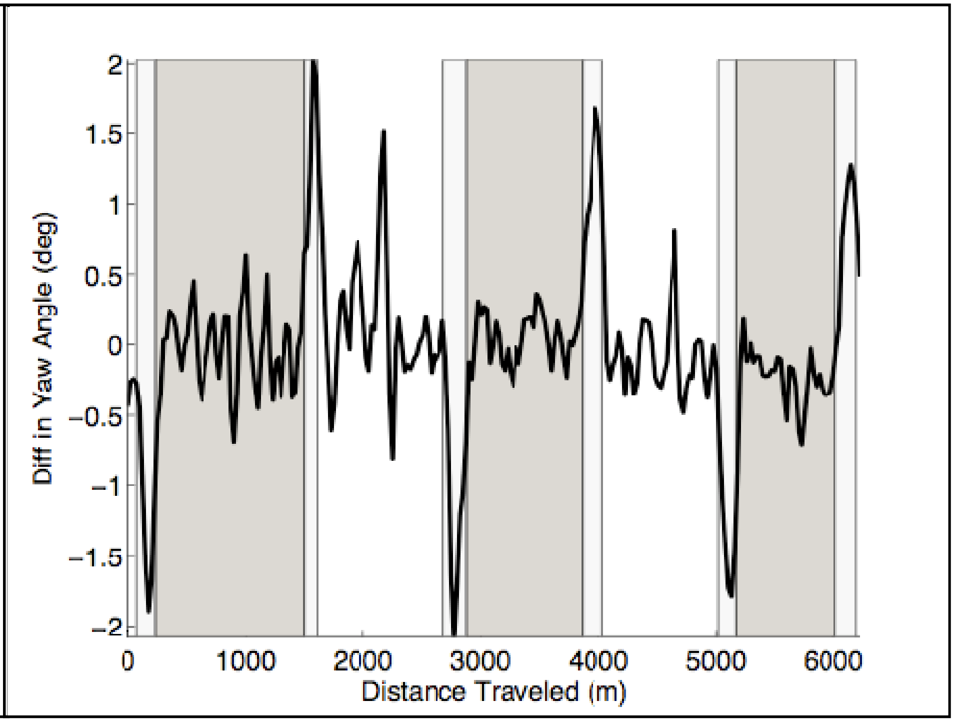
Measuring Lane Maneuvers

- Add the lateral position estimate to the motion model using:

$$P_Y^k = P_Y^{k-1} + K \cdot (\psi_a - \psi_p) + Q_y$$

- Use difference in yaw measurements to shift particles laterally

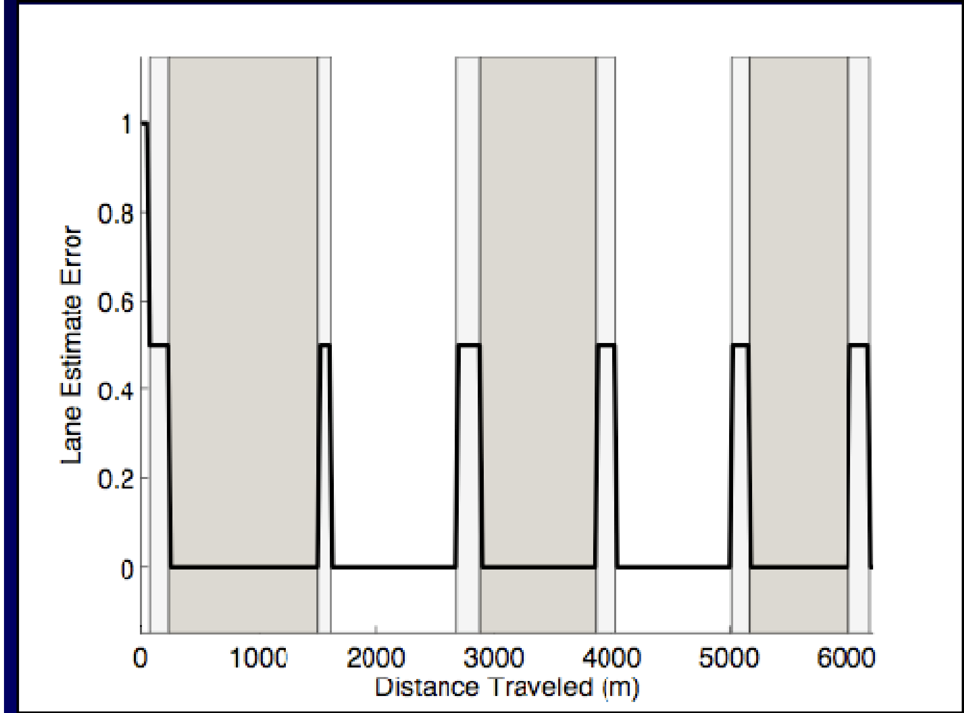




Lane Indexing

- Round the particles lateral position to the nearest lane

Using Pitch Measurements



Using Roll Measurements