Auburn University GAVLAB

GNC & UGV Research

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GPS and Vehicle Dynamics Lab

Currently 20 Students (8 PhD, 8 MS, 4 BS) at $500K/year

- Vehicle modeling
- Vehicle parameter estimation
- Determination of rollover propensity
- Vehicle sensor fusion/integration
- GPS/INS navigation
  - Using various grade IMUs and receivers
  - Analysis of different aiding techniques
  - Loosely, Tightly, and Ultra-Tightly Coupled Algorithms
- IMU & laser scanner fusion
- Sensor characterization and modeling
- Development of a software GPS receiver
- High speed control of ground vehicles

GAVLAB Resources

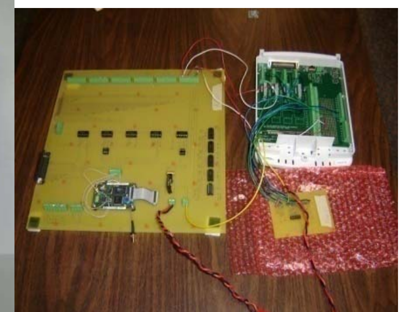
Instrumented and Automated Vehicles







Various Grade GPS Receivers Lidars, Cameras. etc



Various Grade IMUs



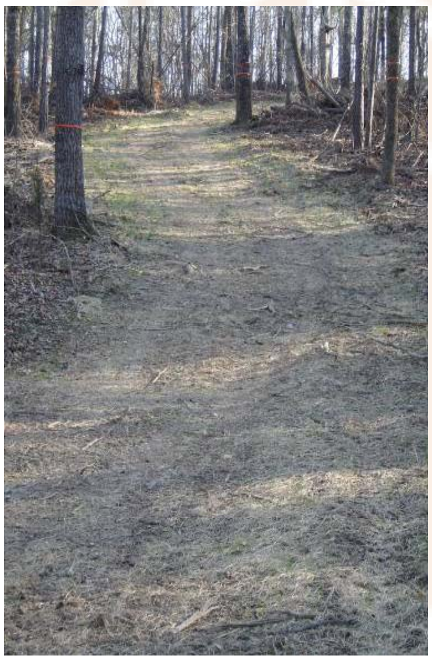
NCAT Test Track

- Two Lane Track
- 1.7 Mile Oval
- Asphalt Instrumentation
- Well Surveyed
  - Level
  - 2° Crowns
  - 8° Banked Turns
- 802.11 and wireless serial communication around entire facility
- RTK system setup with corrections available in all paved areas

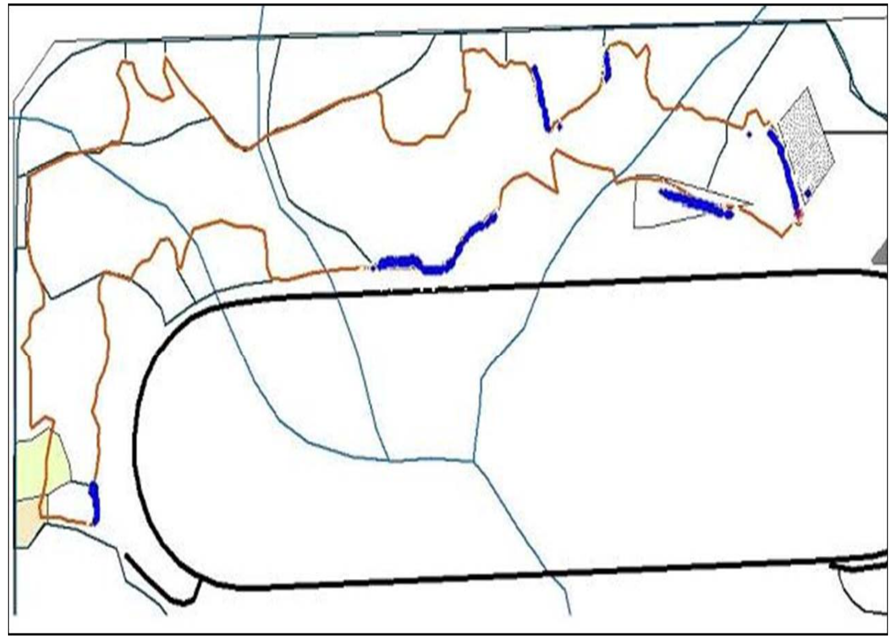
Test facility is available for validating vehicle modeling and estimation algorithms using instrumented vehicle test-beds

Auburn's Mini Baja Track

- Approximately 2.08 miles long, 20 ft wide, and 90 ft of elevation change with various types of terrain
- Average Speed in a Mini Baja car is 15 mph (top speed of 35+ mph)
- UGV proving ground



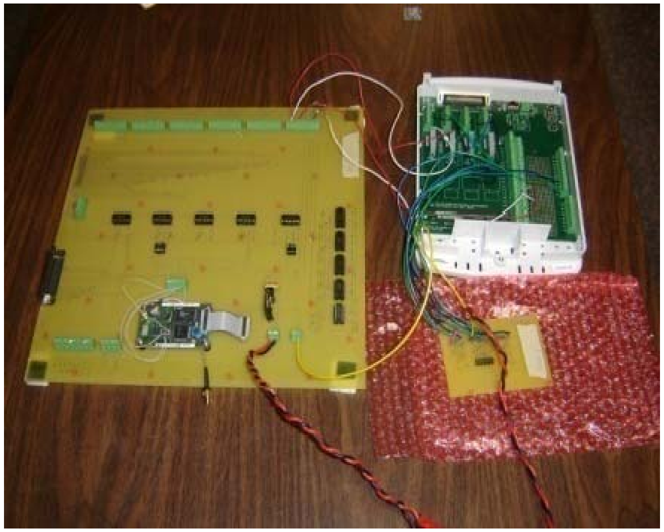
Located adjacent to the 1.7 mile NCAT paved test track



Red—Baja Course
Blue – Navcom Starfire GPS Coverage
Black—NCAT Track

Real-Time L1 GPS Software Receiver

- NordNav R30:
  - Can record raw IF samples and replay the data through the receiver multiple times
  - Built-in tracking loops are reconfigurable
  - Can open up the tracking loops to provide >50 Hz GPS data
  - Ability to simulate various scenarios (signal loss, multi-path, loss of specific satellites, etc.)
- GAVLAB DIv1
  - All of the above features
  - User-definable tracking loop framework allows use of external inputs (INS) for real-time use



Lab Research

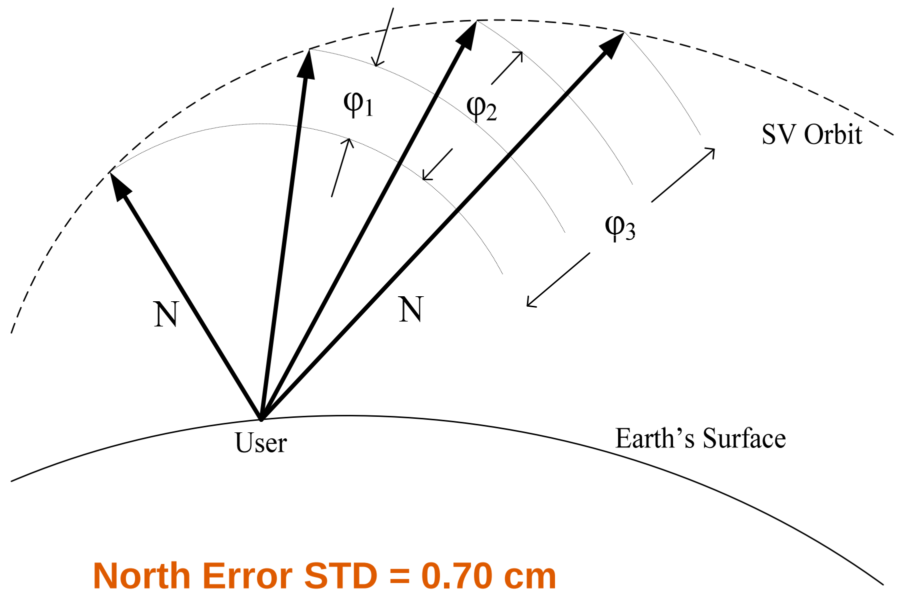
- DRTK
  - Performing accurate relative position
  - Integrating DRTK with INS (align leader/follower IMU)
- GPS Error Compensation
  - Remove erroneous errors caused by multi-path or foliage
- GPS Simulator
- Terrain Characterization
  - Generate simulated terrain
  - Characterize real terrain for simulation
- Vehicle Modeling
  - Estimate friction to predict stopping distance
  - Estimate rollover prediction
- IMU integration with Object Registration
  - Develop object registration based navigation
  - Align leader/follower IMU using object registration
- Experimental Studies
  - Setting up UGV for experimental validation

Recent Technology Integration

- DRTK integrated into ANS with GDRS
  - Evaluated L1 only DRTK performance to fit existing ANS capabilities
- DRTK integrated into War Fighter with Lockheed Martin (i.e. CAST) in January
- Terrain characterization and vehicle modeling are being integrated into the ANS simulation environment
- Object registration work is being incorporated into a SLAM algorithm for GDRS work funded by the ARL

DRTK Overview

- Code based range measurements have meter level accuracy
- Phase based range measurements are near millimeter level accurate, but are ambiguous
- Relative position measurements are formed by differencing range measurements between two receivers



Carrier Phase Signal Model

$$\phi_A^j(t) = \phi_A - \phi^j + N_A^j + f\delta^j + f\delta_A - \gamma_I + \tau_T + Q_A^j$$

$$\phi_B^j(t) = \phi_B - \phi^j + N_B^j + f\delta^j + f\delta_B - \gamma_I + \tau_T + Q_B^j$$

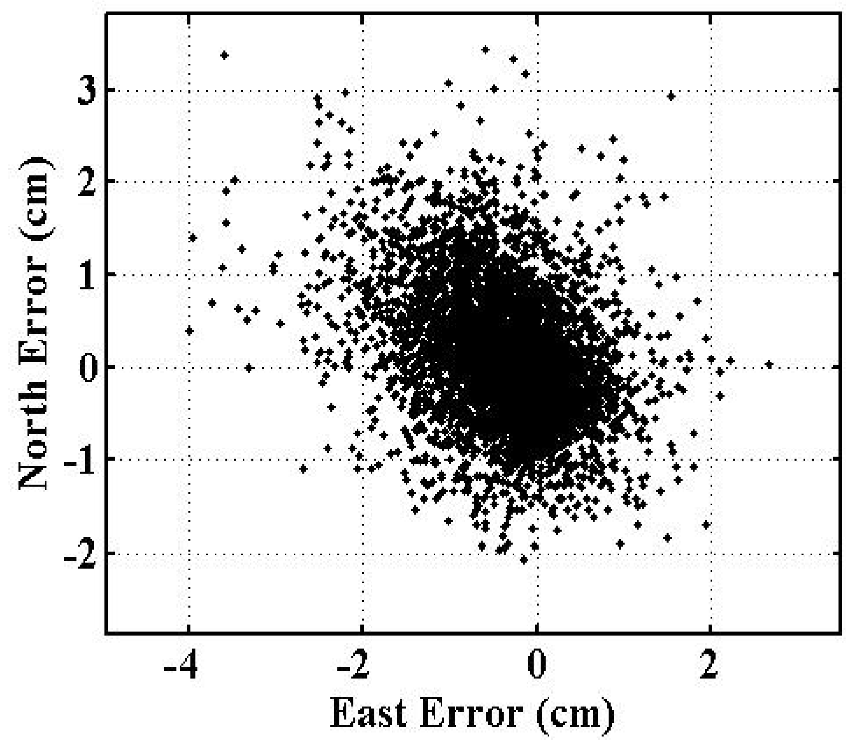
Single Difference

$$\Delta\phi_{AB}^j = \phi_{AB}^j(t) + N_{AB}^j + f^j\delta_{AB}(t) + Q_{AB}^j$$

$$\Delta\phi_{AB}^k = \phi_{AB}^k(t) + N_{AB}^k + f^k\delta_{AB}(t) + Q_{AB}^k$$

North Error STD = 0.70 cm

East Error STD = 0.68 cm

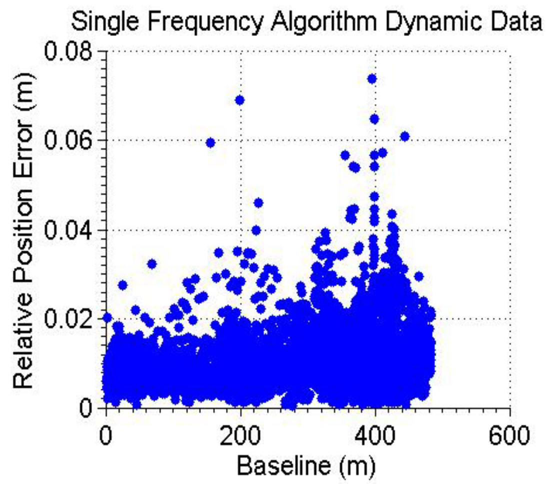


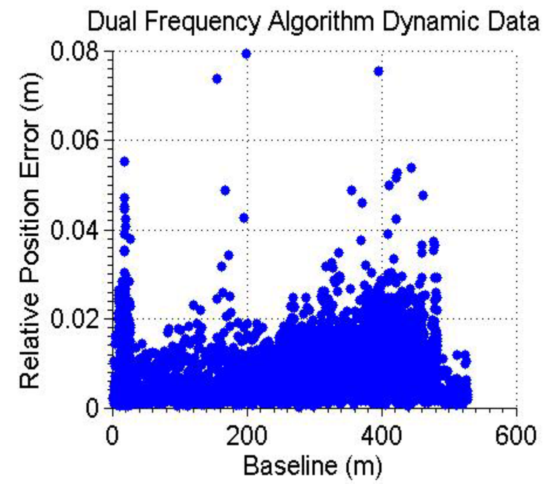
DRTK – L2/L1 and L1 Only Comparison

- DRTK accuracy and reliability analysis with single and dual frequency GPS
- Testing performed to determine feasibility of implementing DRTK with current ANS hardware

Accuracy

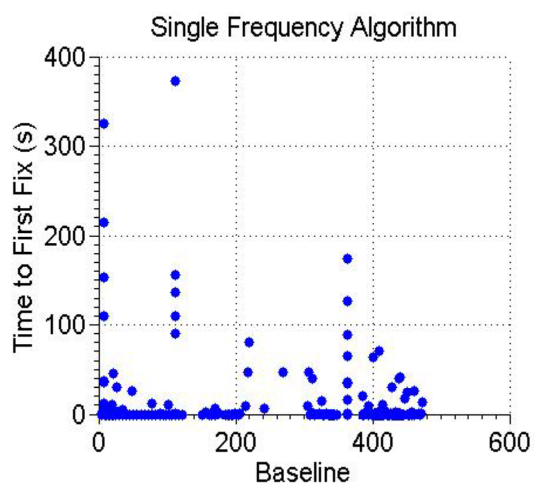
- Mean Error
  - Single – 1.1 cm
  - Dual – 0.9 cm
- Standard Deviation
  - Single – 0.7 cm
  - Dual – 0.6 cm

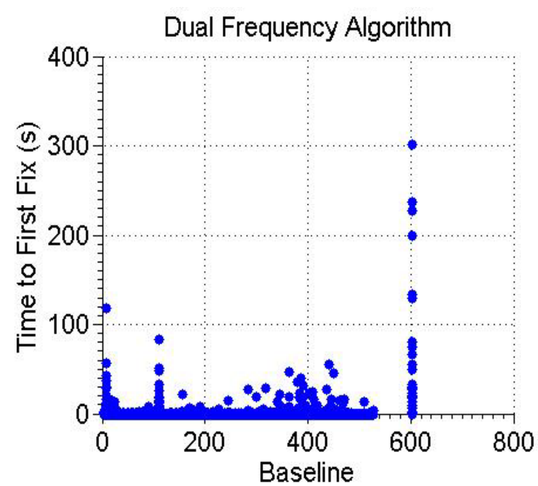




Time To First Fix

- Mean Time to First Fix
  - Single – 7.7 seconds
  - Dual – 0.2 seconds

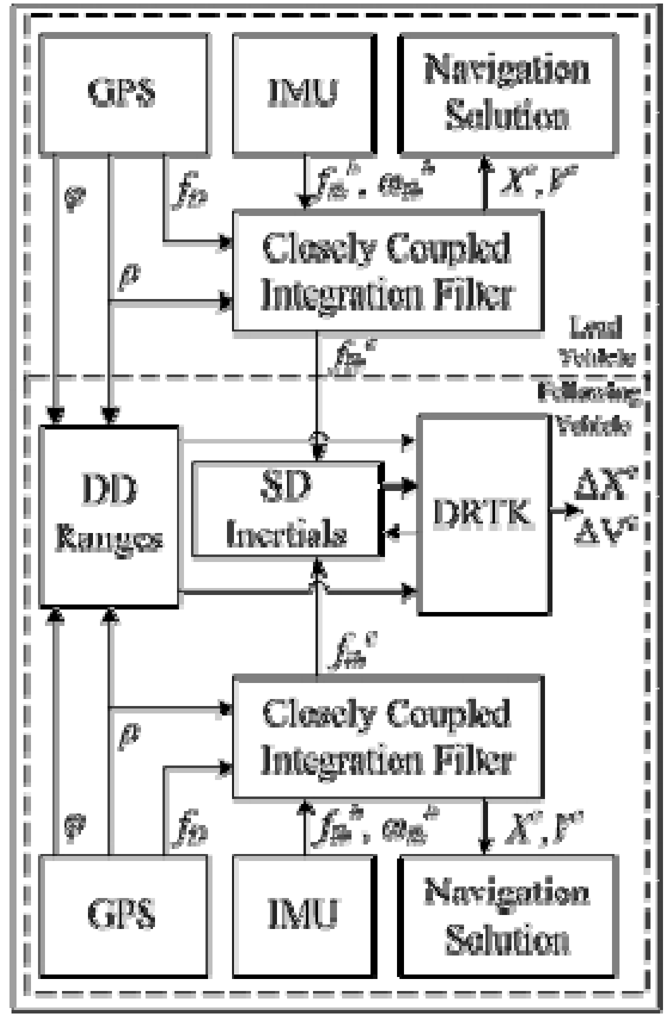




DRTK/INS – Inertial Integration

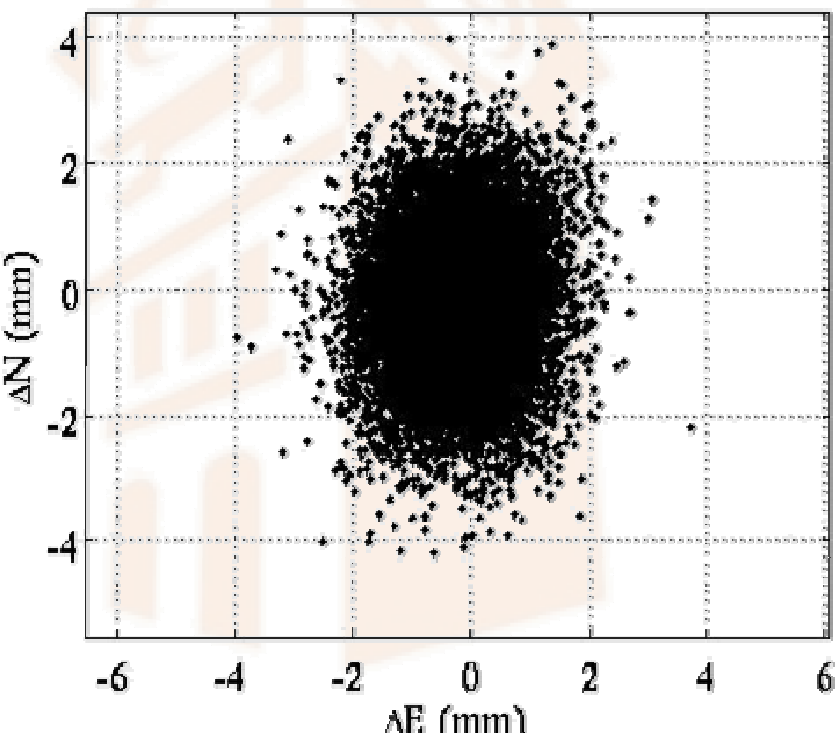
DRTK/INS Integration

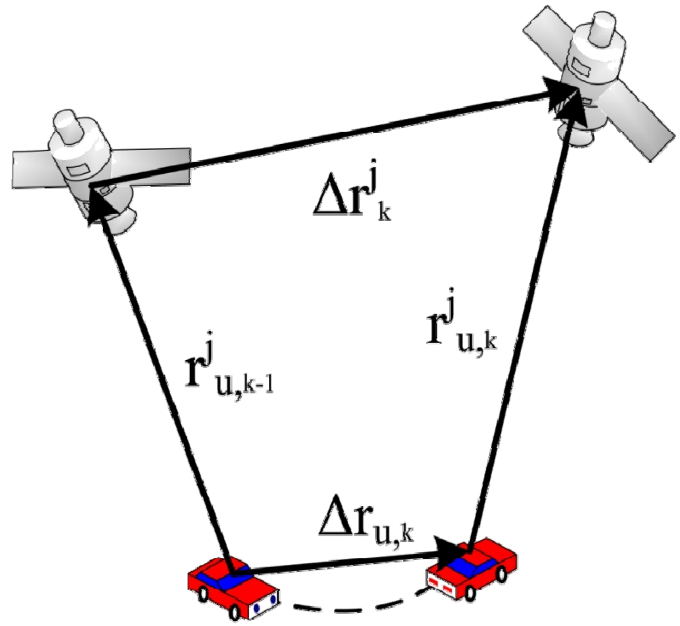
- Pseudo-range and Doppler data is fused with inertial data at each vehicle
- Relative inertial and state information is produced by differencing the corrected inertial measurements and states from each vehicle after a rotation into the navigation (ECEF) frame
- Double difference range and carrier phase measurements combine with the relative inertial measurements and/or state information, on the following vehicle, to produce a relative position to a lead vehicle



TDCP – Change in Position

- Accurate <u>change</u> in position can be estimated using *time differenced carrier phase* (TDCP) measurements
- Differencing two measurements across time "removes" atmospheric and SV clock errors, and the integer ambiguity, <u>assuming the time difference is small</u>





$$\Delta\phi^j_{Ak,k-\tau} = \lambda^{-1}\Delta\left|\vec{r}^{\,j}_A\right|_{k,k-\tau} + f\Delta\delta_{Ak-\tau} + Q^j_{Ak,k-\tau}$$

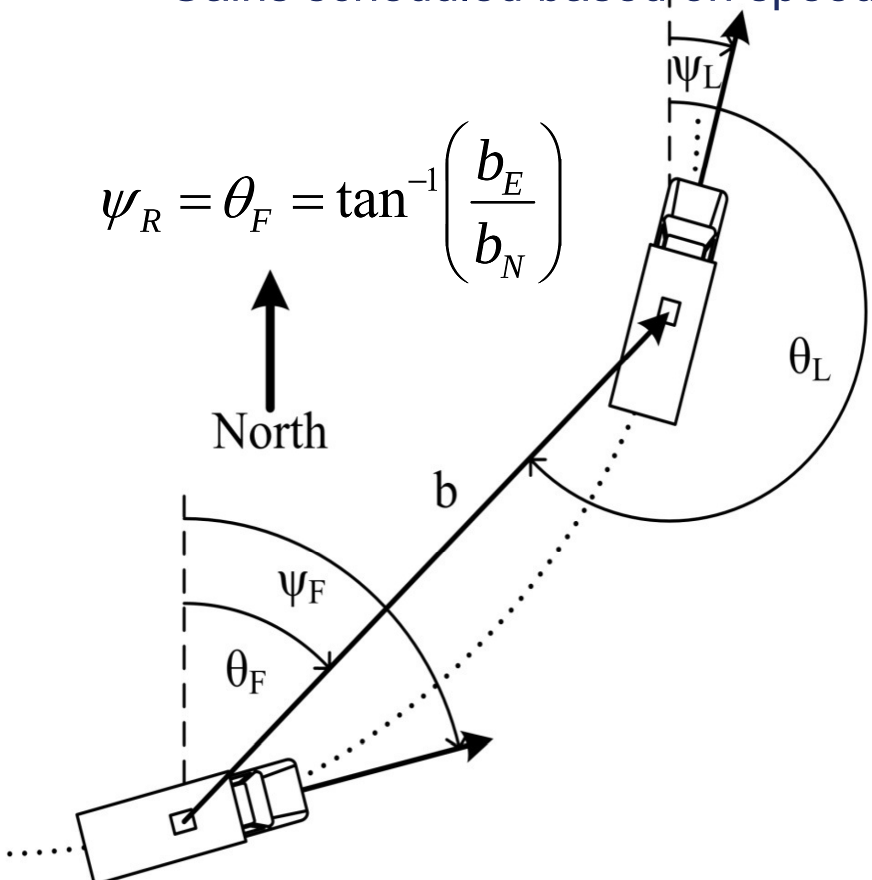
ΔNorth Error STD = 0.75 mm

Δ East Error STD = 1.09 mm

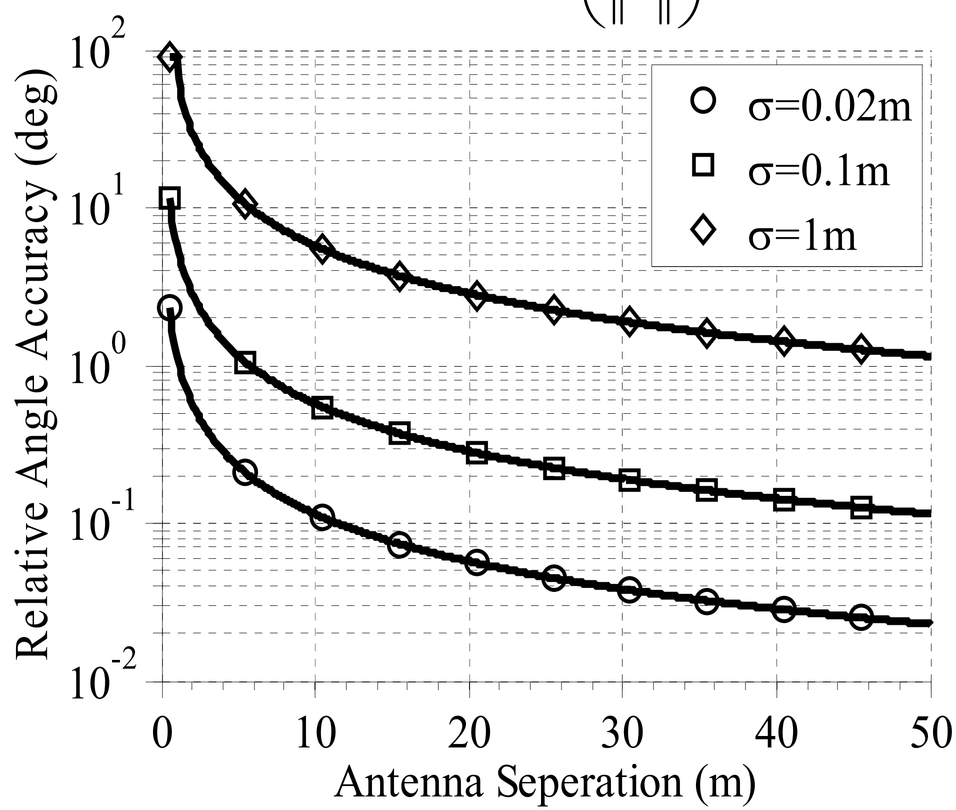
Path Duplication – Short Distance Following

- The short distance following approach was to control the following vehicle as if it were a trailer
  - The following vehicle's navigation system provided its heading estimate and yaw rate
  - The heading reference was set equal to the global relative angle between the vehicles determined from the DRTK solution
  - Gains scheduled based on speed

$$\psi_R = \theta_F = \tan^{-1}\left(\frac{b_E}{b_N}\right)$$



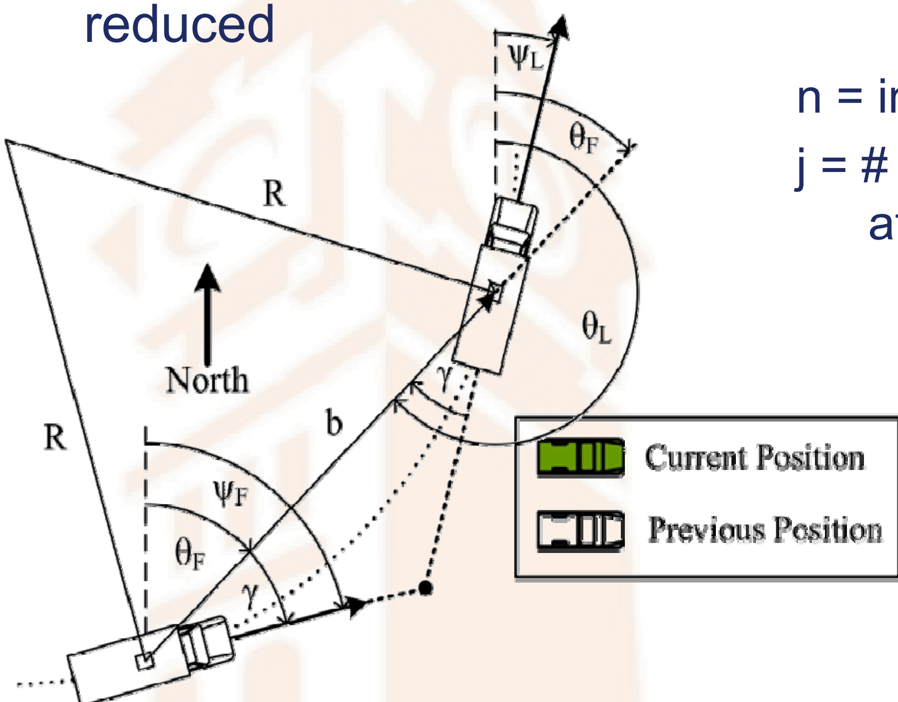
$$\sigma_{\theta_F} = \sin^{-1}\left(\frac{\sigma_b}{\left\|\vec{b}\right\|}\right)$$



Path Duplication – Experimental Results

Path Duplication – Long Distance Following

- If the change in vehicle position can be obtained with sufficient accuracy, the relative position vector from a previous time can be translated to the current time
- This new RPV is between a past position of the lead vehicle and the current position of the following vehicle, so the effective following distance has been reduced

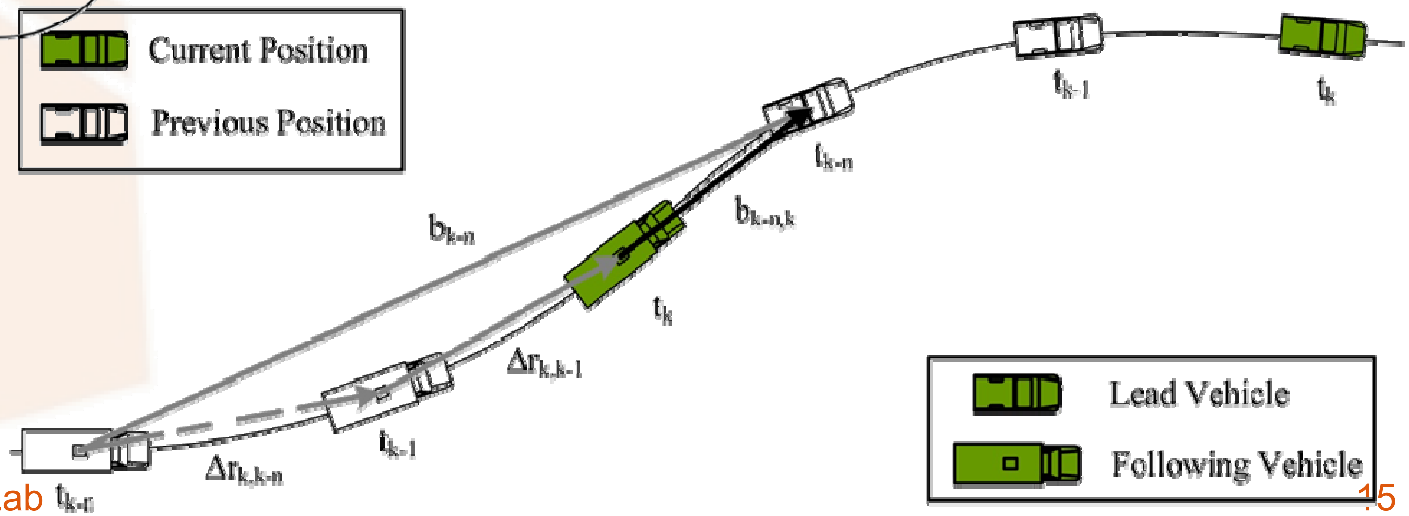


$$\psi_R = \theta_F + \gamma = 2\theta_F - \psi_L$$

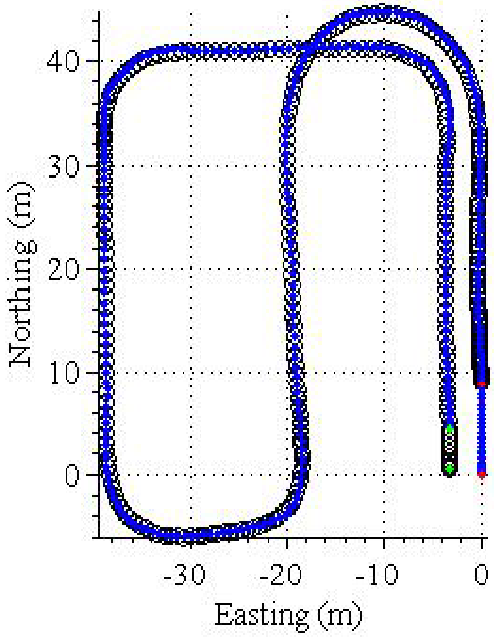
n = index of closest point of past leader position

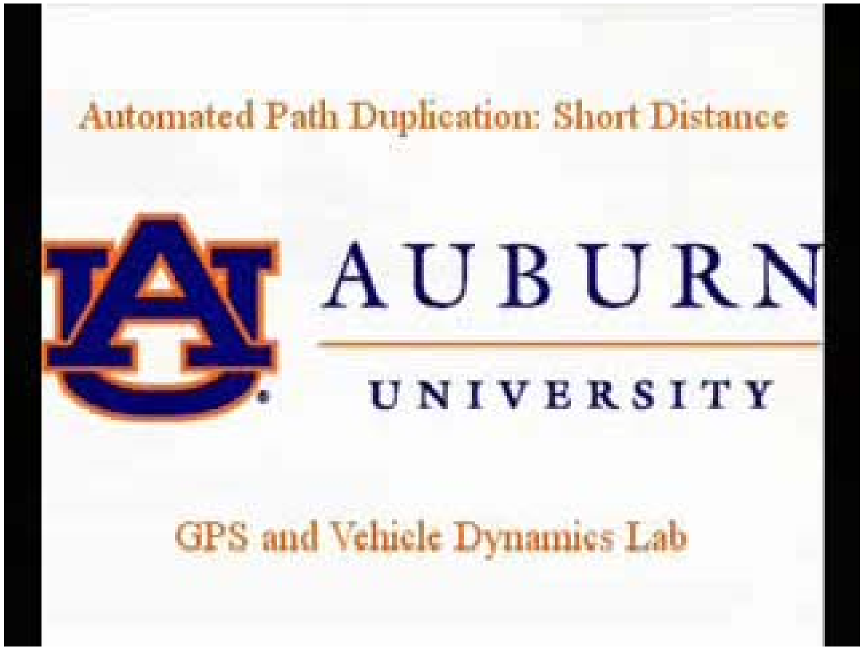
j = # of measurements between follower and leader at index n

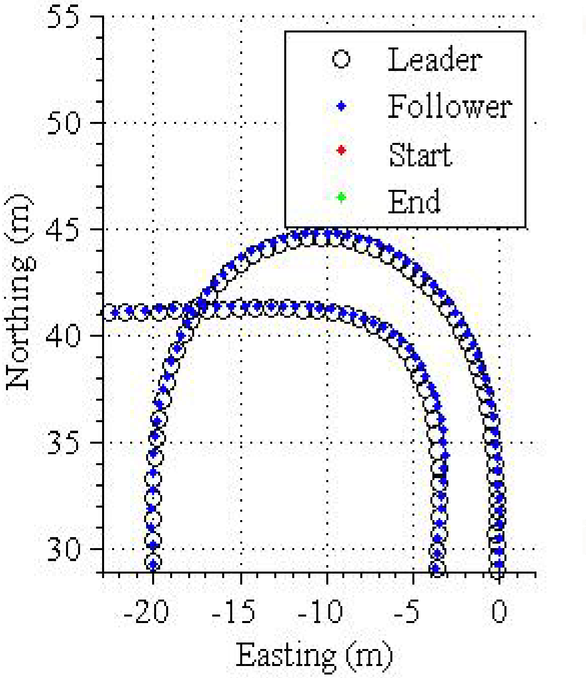
$$\vec{b}_{k,k-n} = \vec{b}_{k-n} - \sum_{j=n}^{k} \Delta\vec{r}_j$$

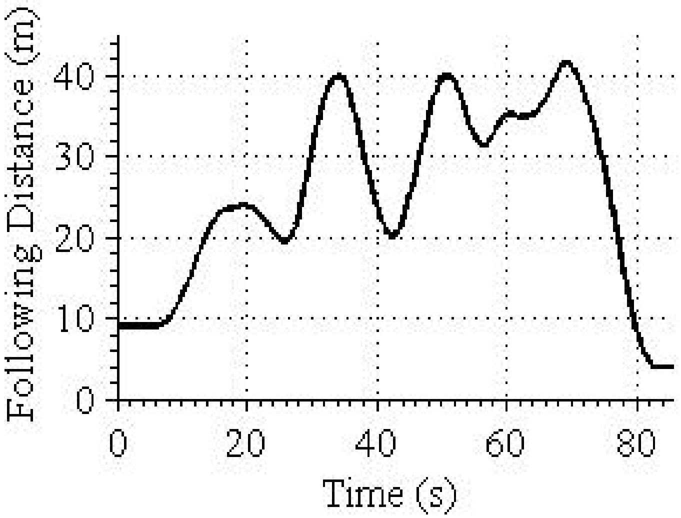


Path Duplication – Long Distance

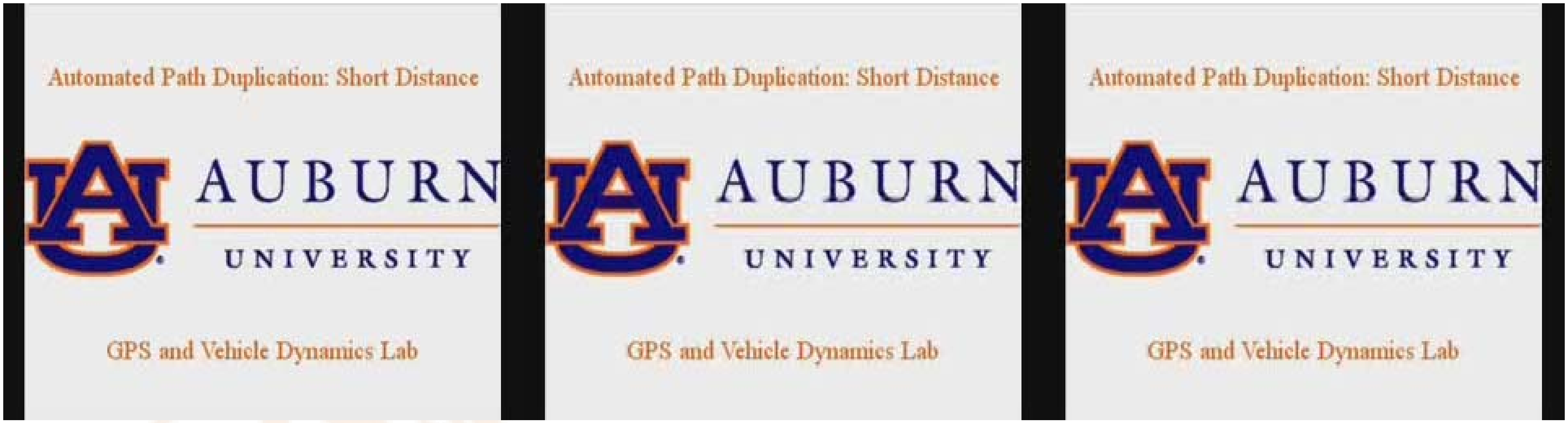




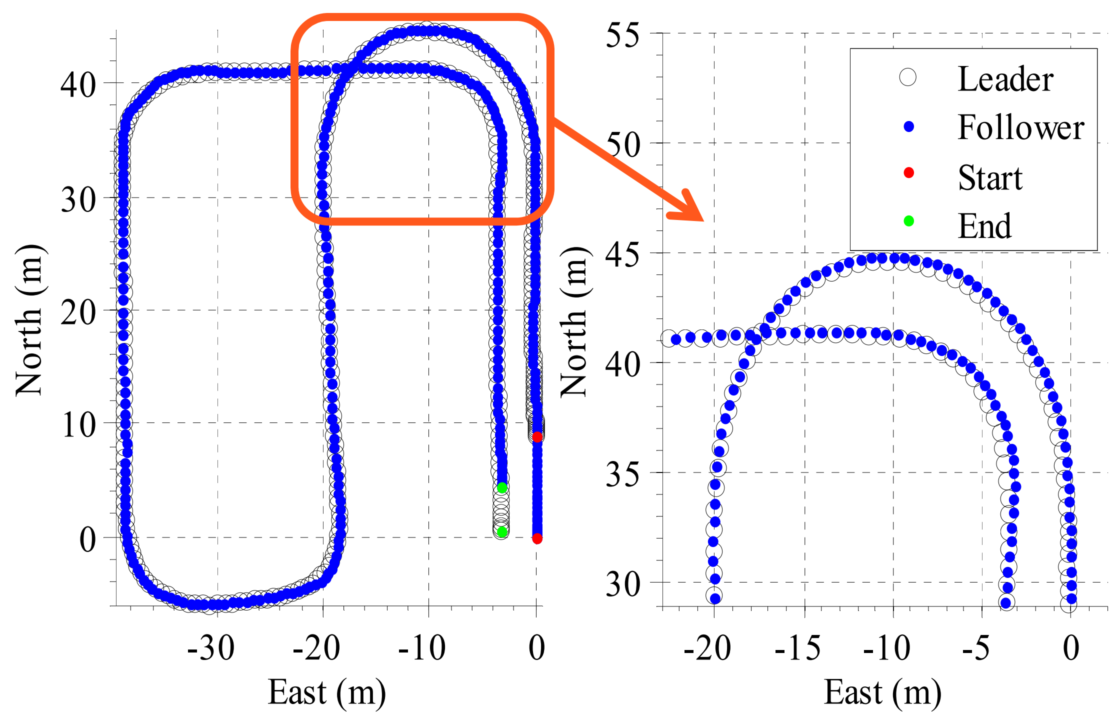




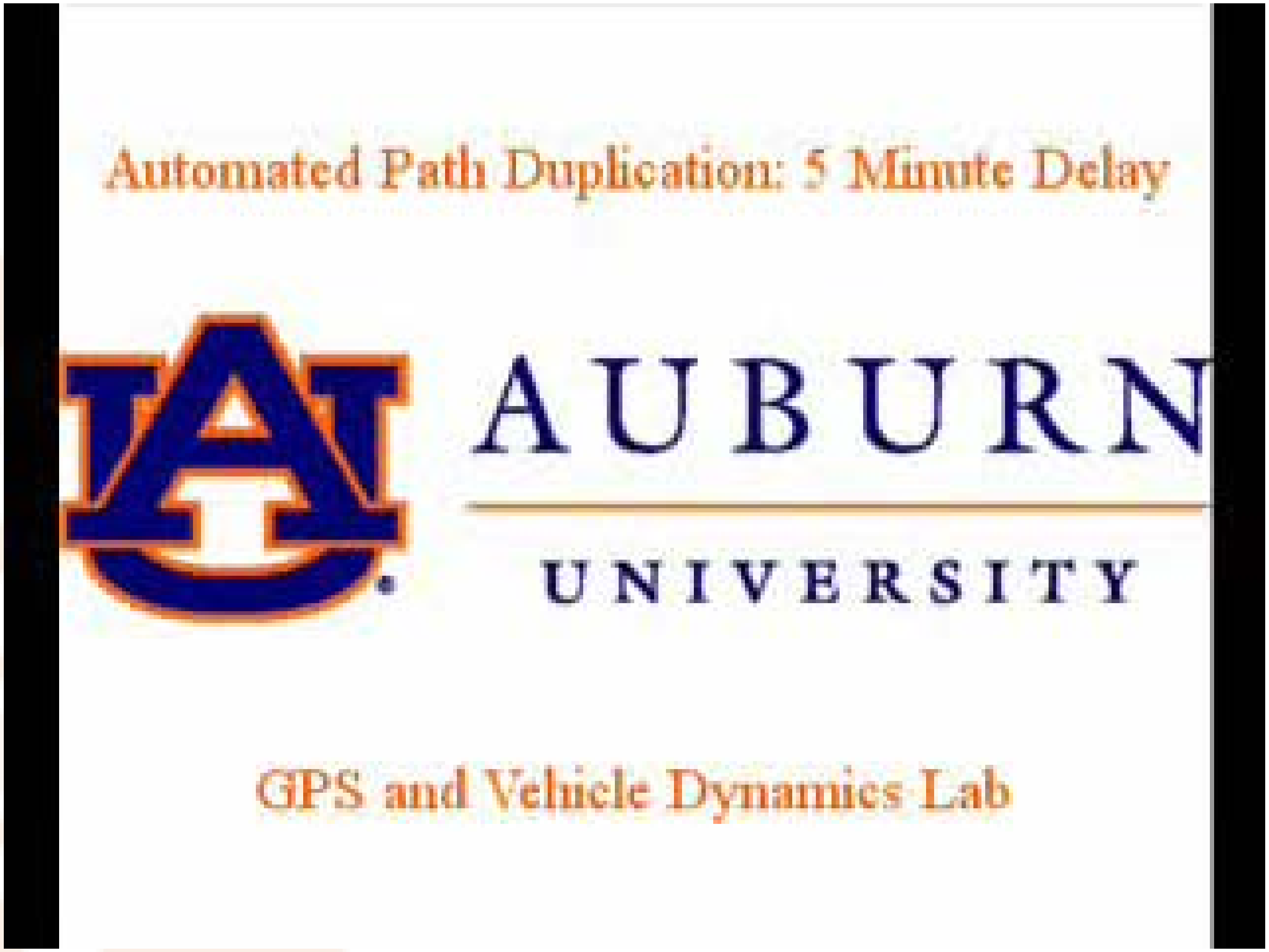
Long Distance Following



- NLOS method implemented in real time on UGV
  - Tested with dynamic paths through parking lot and on NCAT track
  - Following distances varied from 10 to 120 m

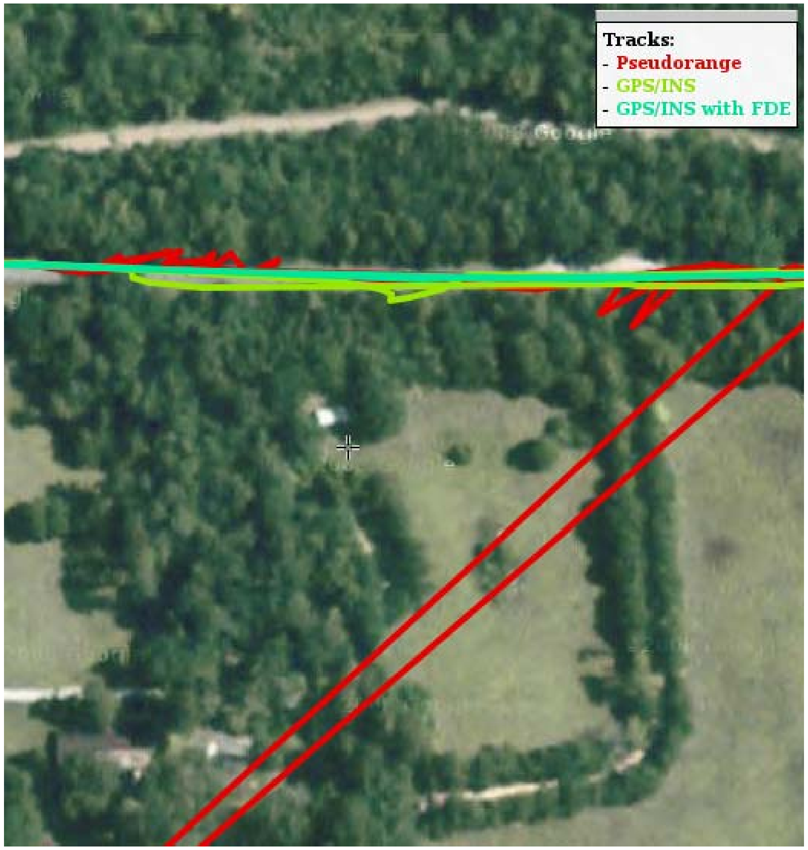


Path Duplication – Delayed Following



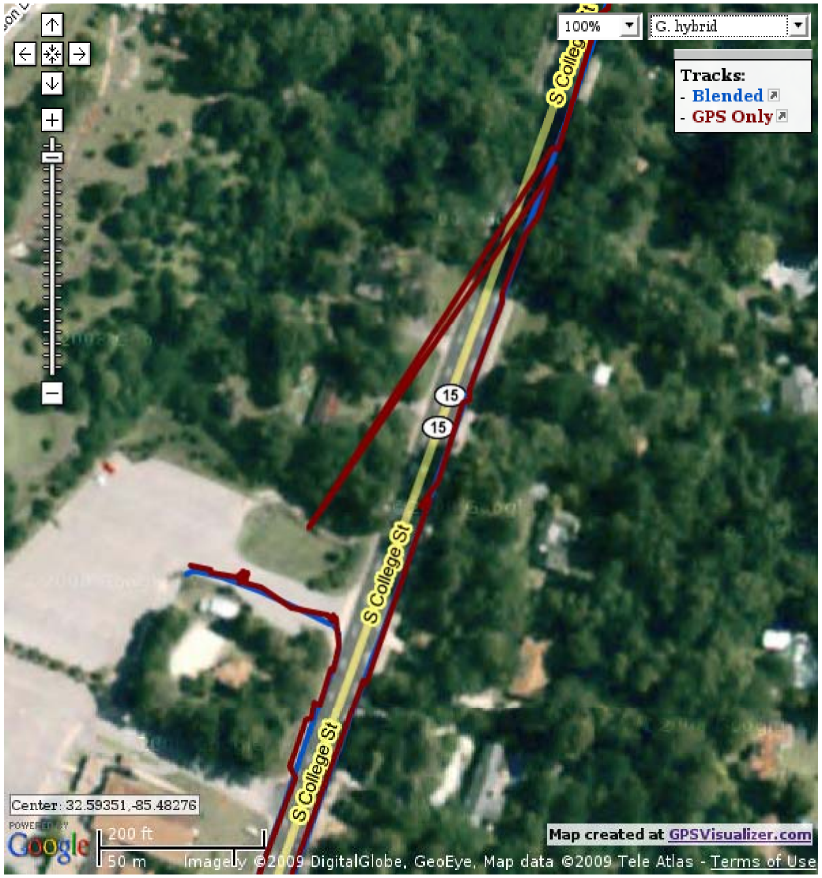
GPS/INS with FDE

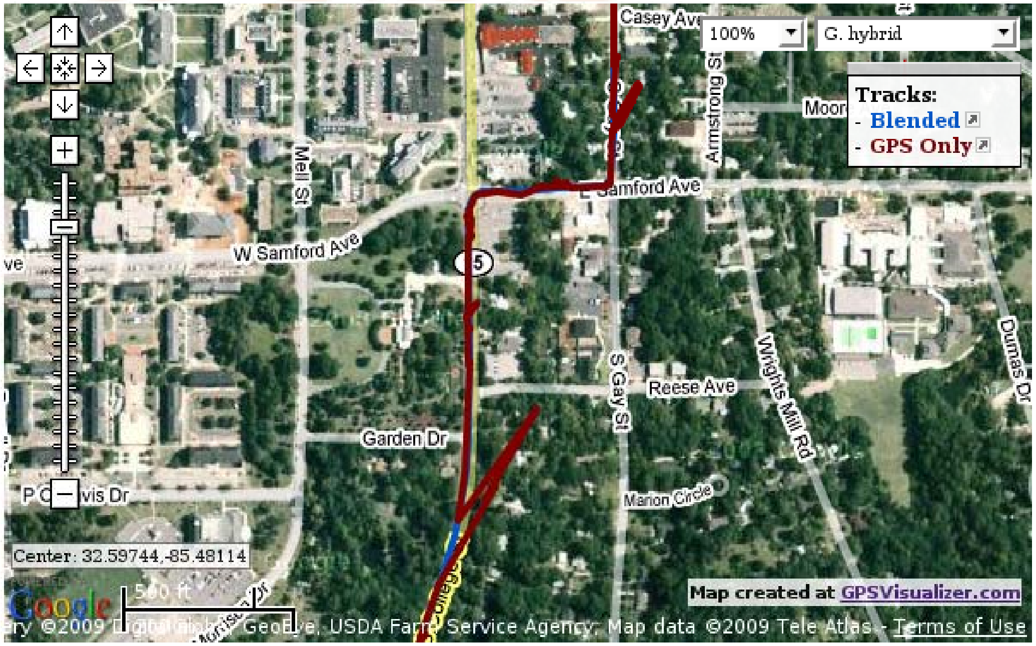
- Pseudorange-only positions suffer large jumps in foliage (red)
- Inertial Navigation System (INS) aids position solution (yellow)
- Fault Detection and Exclusion (FDE) further improves performance in degraded environments by detecting signal errors (green)



GPS/INS with FDE

- Integration and Fault Detection performed in real-time
- Removes faults in individual GPS signals (blue)
- Uses remaining signals to navigate

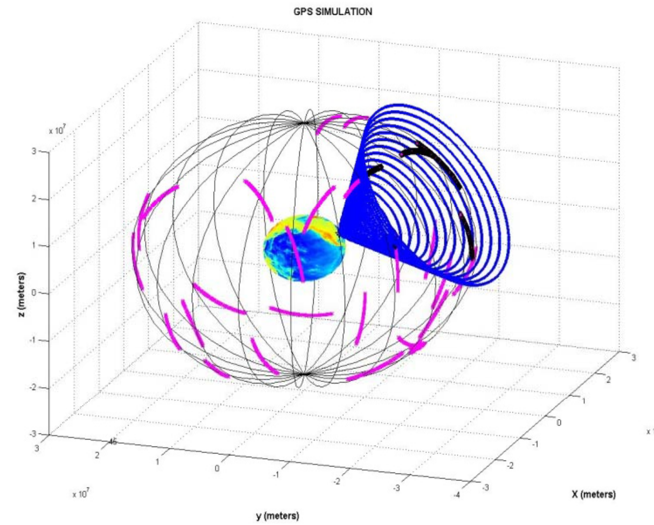




- NovAtel GPS
- Crossbow IMU

GPS Simulator

Motivation – create an accurate simulation of satellite and receiver positions



Satellite Positions

Simulation Capabilities:

Collect Ephemeris Data

Plot satellite positions with time

Plot receiver position with time

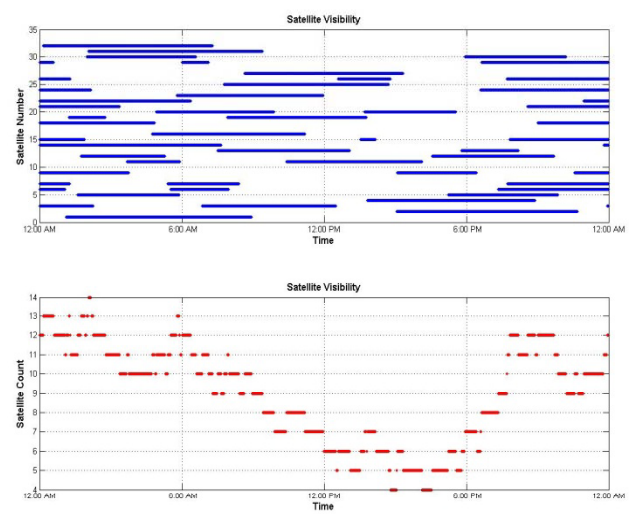
- Given receiver speed and heading

Detect Satellite visibility

- Given receiver envelope mask angle

Receiver position estimation

- Using known pseudo-ranges of satellite and receiver positions



Satellite Visibility

Vehicle Modeling

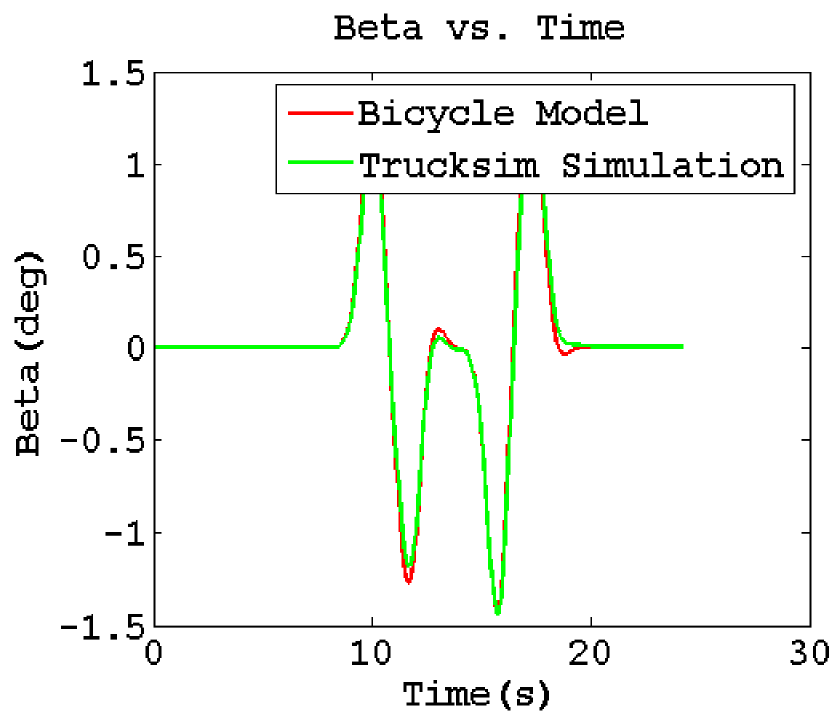
- Dynamic vehicle models have been developed
  - Wheel Slip
  - Steer Angle
  - Tire Parameters
  - Roll, Pitch, Yaw
- Vehicle Models validated against Carsim
- Initial terrain modeling methods developed
- Preliminary model converted to C++ for integration into GDRS simulation environment
- Computer has been set up for simulation environment at Auburn

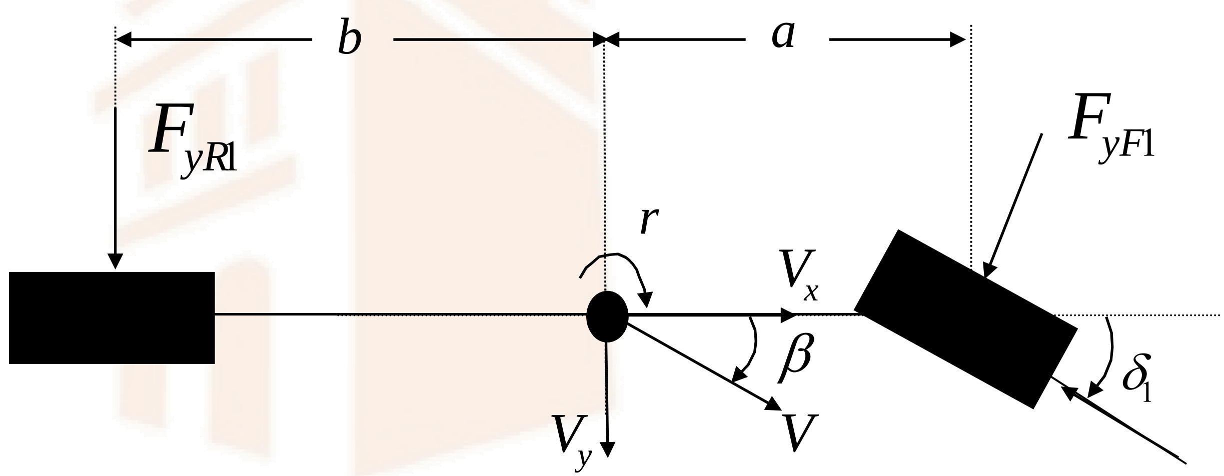
Vehicle Modeling

Model

- Simple Single-track
- Bicycle Model
- 2 DOF (Yaw, y)
- Assumptions
  - No weight transfer
  - Equal inner/outer slip angles (α) & steer angles (δ)
  - Same tires inner/outer

Validation





Vehicle Modeling – Next Steps

- Test vehicle models in simulation environment
- Implement terrain modeling in simulation environment
- Acquire parameters from vehicle experimentally
- Compare simulation results to actual vehicle test data

Object Based Relative Navigation

- Looking to use relative position to landmarks (object registration) to perform non-GPS based leader follower capability
  - Vision and LIDAR systems can provide range and bearing measurements to landmarks measured using vision or LIDAR to augment a GPS/INS navigation system.
  - Landmarks positions are measured relative to current vehicle position
  - Landmarks are then used to determine position when GPS is absent or degraded
- Typical SLAM approach – 1 vehicle sees the same landmark many times
- Modify approach to allow multiple vehicles to see the landmark 1 time
  - Only maps are shared between the vehicles (not sensor data)

Vision Navigation – Lead Vehicle

- Goals
  - Develop algorithms for the leader vehicle to “see” natural or man-made landmarks (i.e. signs, trees, etc).
  - Perform without a visual line of sight to the leader
  - Extracted features contain color information and contours
- Feature Extraction
  - Use the Shi and Tomasi corner detection algorithm

$$G = \sum_{x=p_x-w_x}^{p_x+w_x} \sum_{y=p_y-w_y}^{p_y+w_y} \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix}$$

    - Large eigenvalues indicate a corner
    - Small eigenvalues indicate a smooth surface
    - One large and one small eigenvalue indicates an edge
- Machine Learning
  - K -means Clustering
    - Iteratively assigns each corner to a cluster
    - Assumption: that all of the corners of an object will be grouped in the same cluster
- Extract a 50 x 50 pixel region around

Vision Navigation – Follow Vehicle

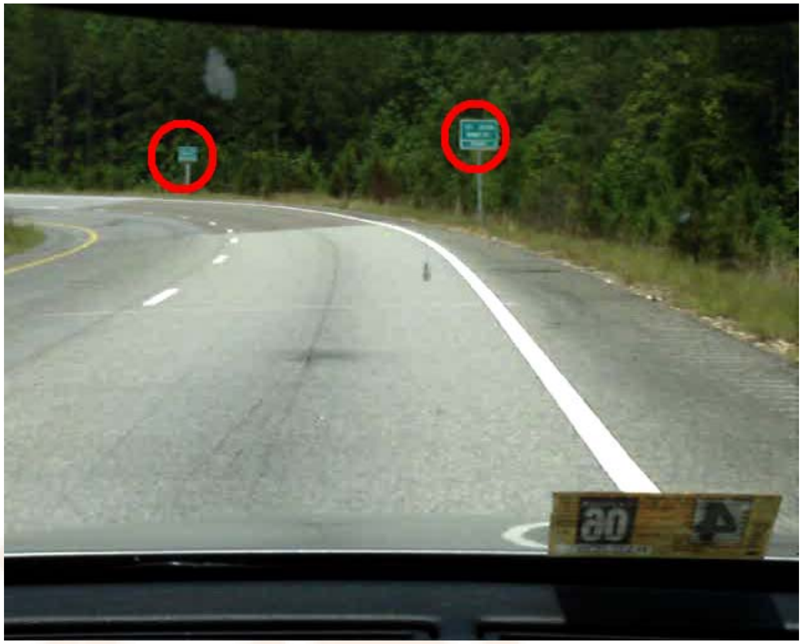
- Goals
  - Use a database created by the leader vehicle to aid in navigation
  - Locate the objects or landmarks that the leader extracts

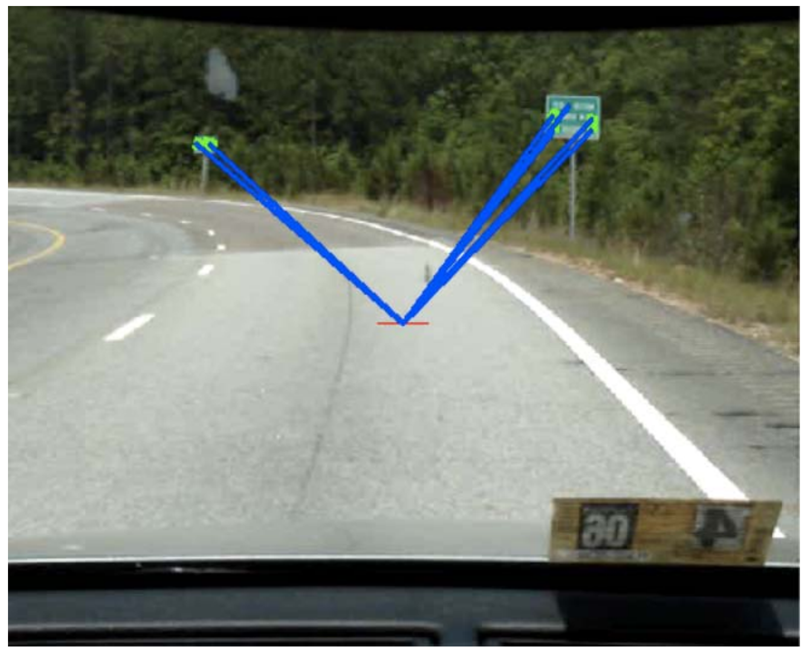
A sign extracted by the leader

- Approach
  - Characterize the landmark according to color statistics and edges
  - Perform a search for any locations that match the data of the landmark extracted from the leader

Vision Navigation – Results

Algorithm on lead vehicle extracts two signs

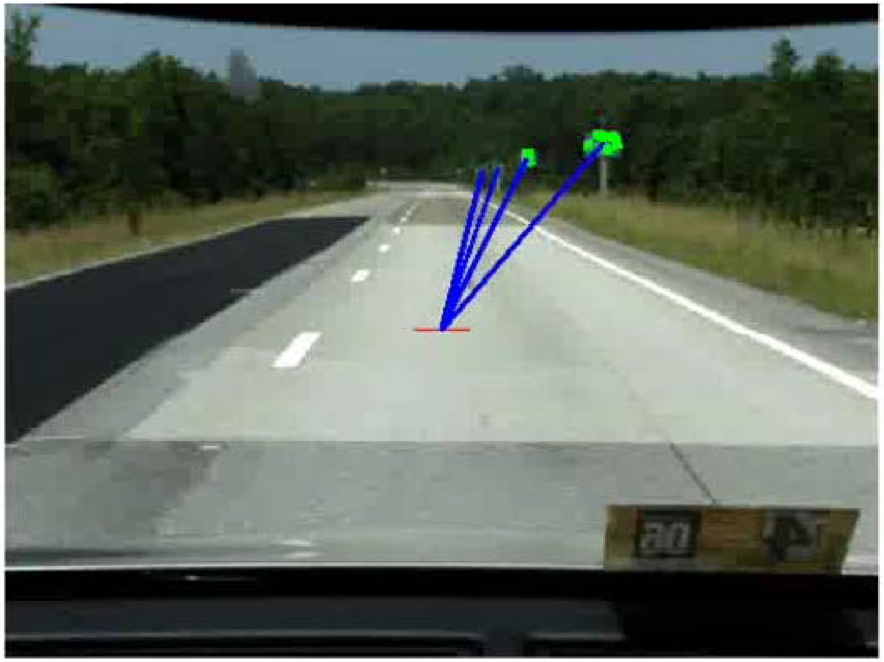




Following vehicle detects signs

Vision Navigation – Video

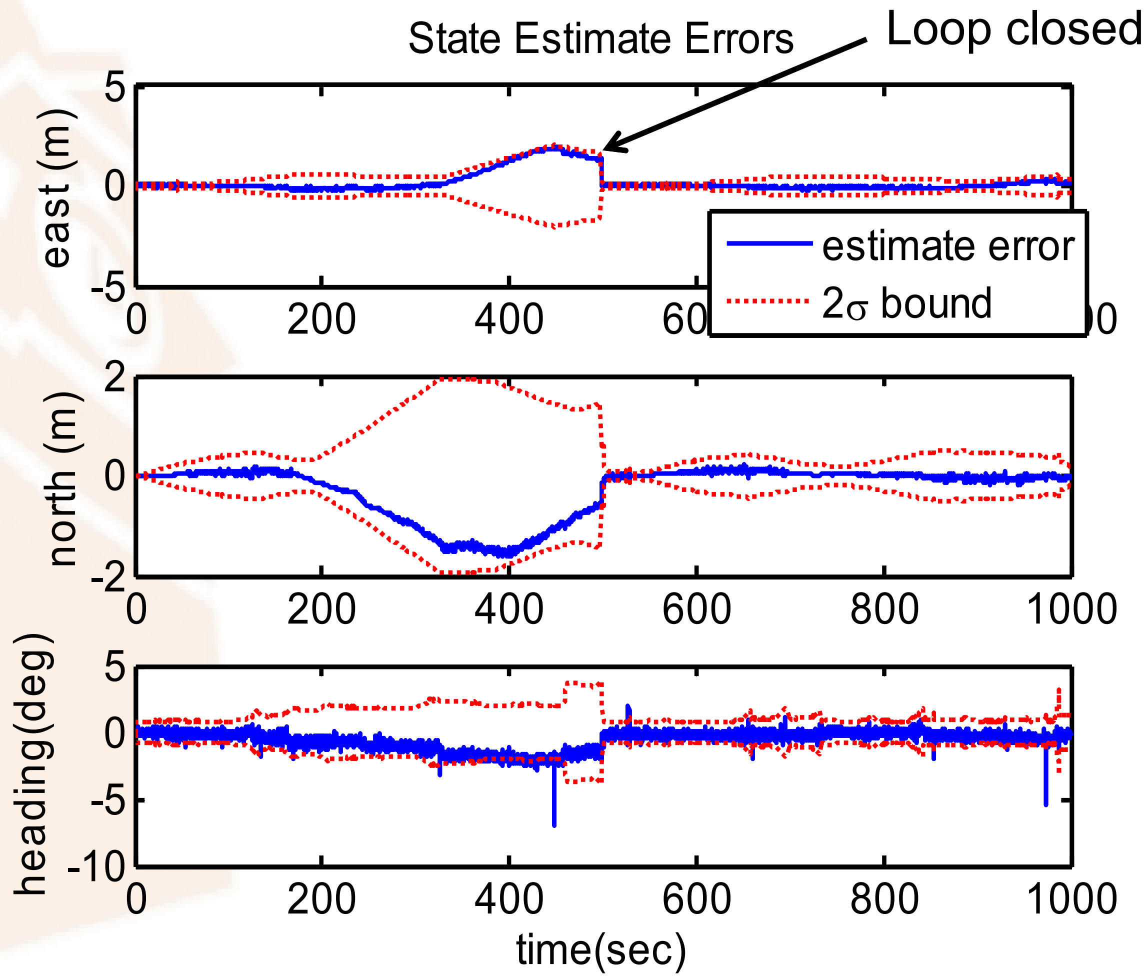
Lead vehicle extracts features



Following vehicle detects signs

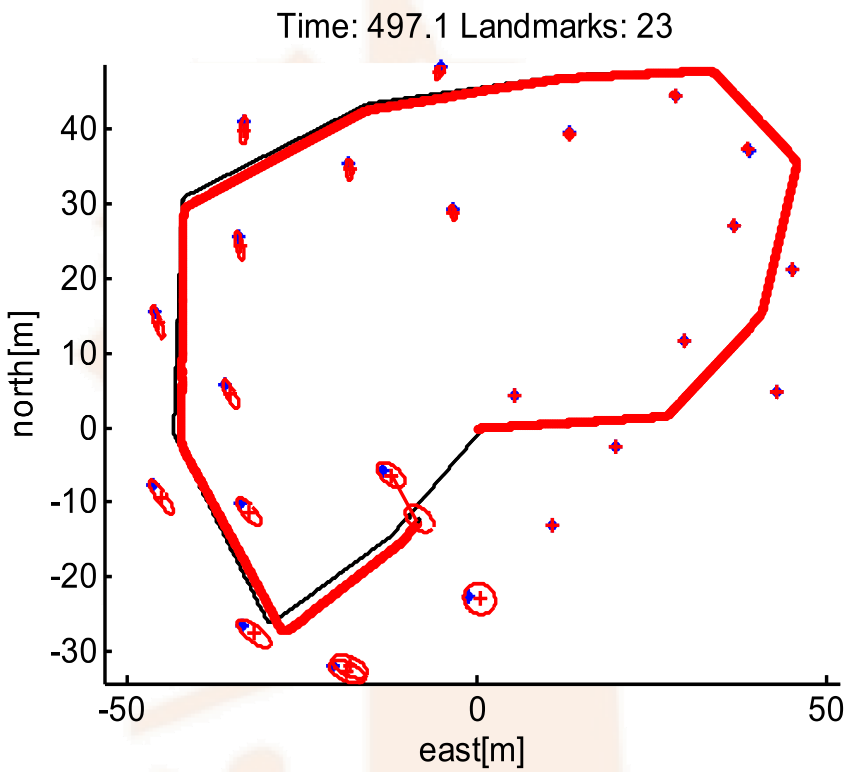
Landmark Navigation Benefits

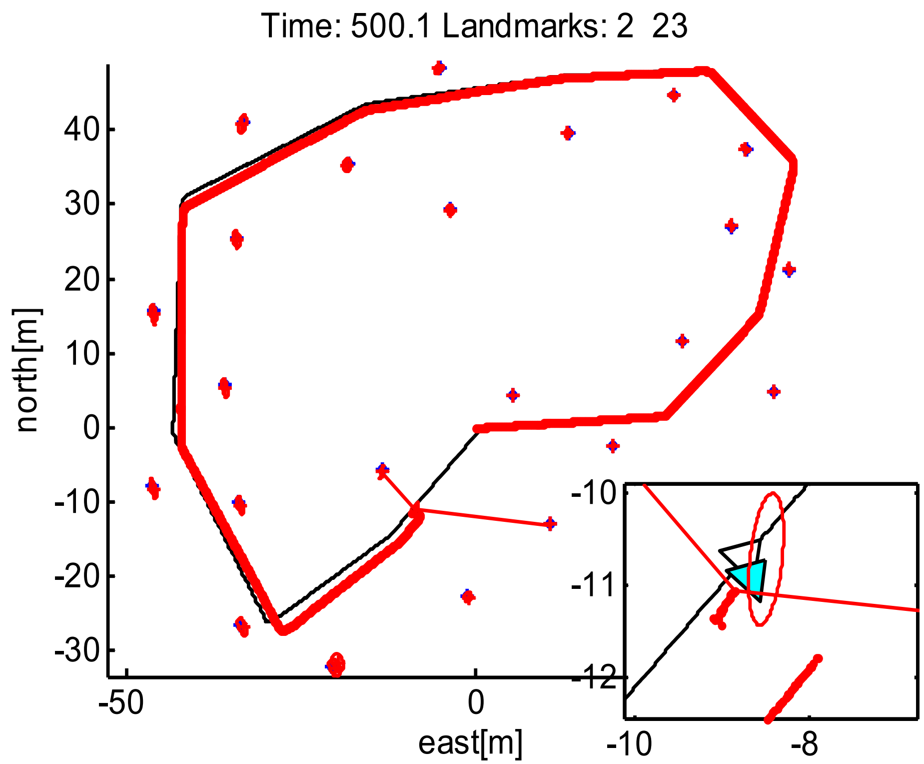
- Slows dead-reckoning error growth
- Bounds error when traveling a cyclical path



Simulation Results

- Simulated cyclical path using odometry and landmark measurements





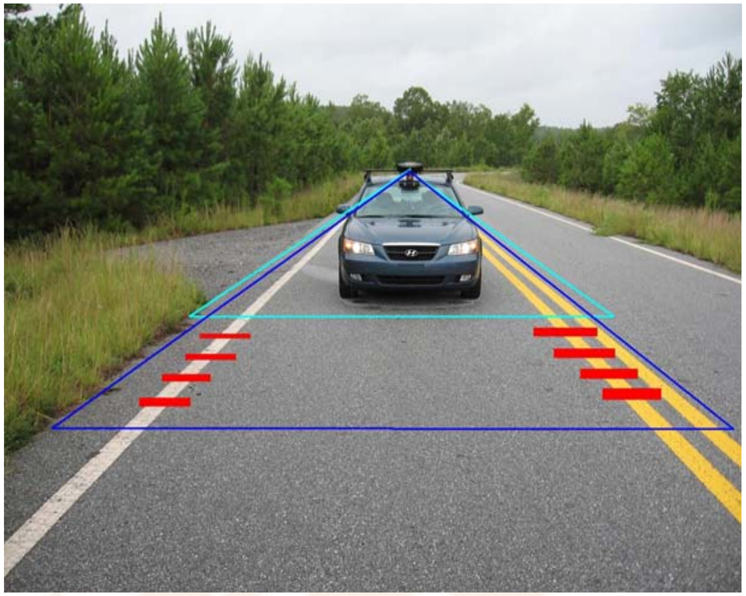
What's Next

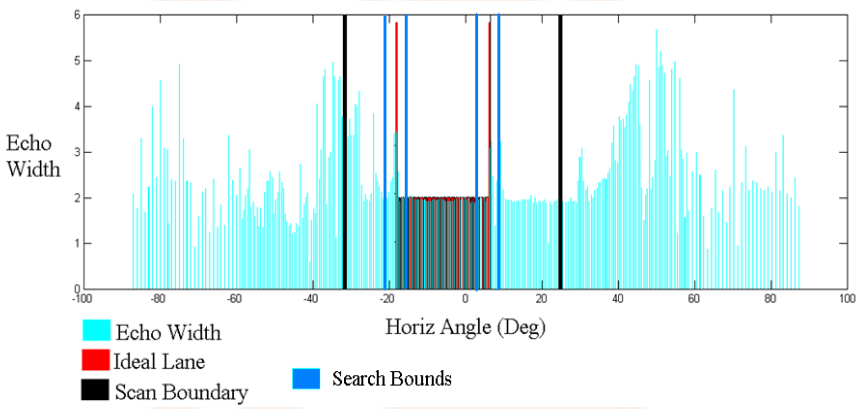
- Integration of DRTK with Perception Sensors
  - – Provide Robustness when GPS not available
  - – Provide DRTK with limited GPS satellites
- Low-cost DRTK/FDE Implementation
  - – Implement using on-board sensors (i.e. DAGR)
- FCS LSI Needs/Requests for Research
- Vector Tracking
  - – Novel GPS tracking algorithms developed at Auburn
    - Provides instantaneous GPS reacquisition
    - Improves noise resistance (jamming, multi-path, etc.)
    - Improves tracking in heavy foliage
  - – Extend to provide DRTK in harsh GPS environments
- Collaboration in Future ATOs?

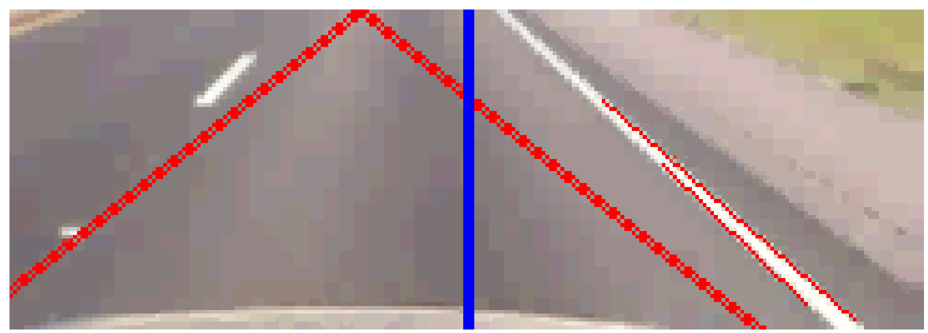
Integration of DRTK with Perception Sensors

- Provide relative navigation for leader-follower systems with limited, poor, or reduced GPS coverage
- Use relative position to landmarks measured using vision or LIDAR to augment or constrain the GPS/INS DRTK navigation system
  - Lane marking or road edges
  - Object registration
- Exploring 2 approaches
  - Feature based SLAM
  - Scan-matching SLAM

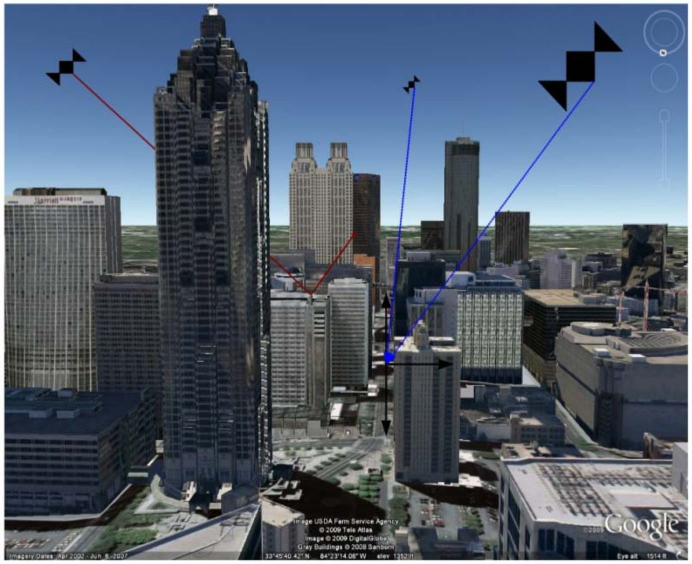
LiDAR and Vision based Lane Detection







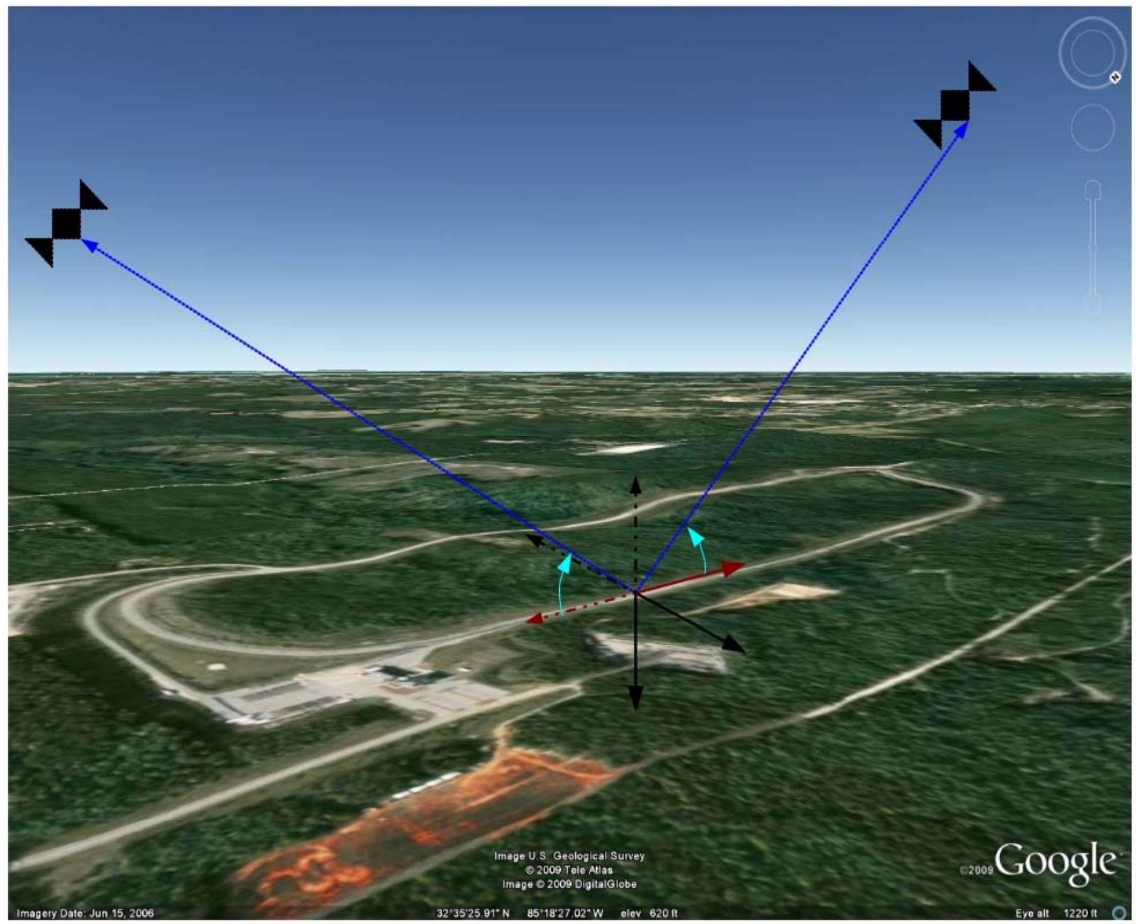
Positioning w/ Limited GPS Satellites



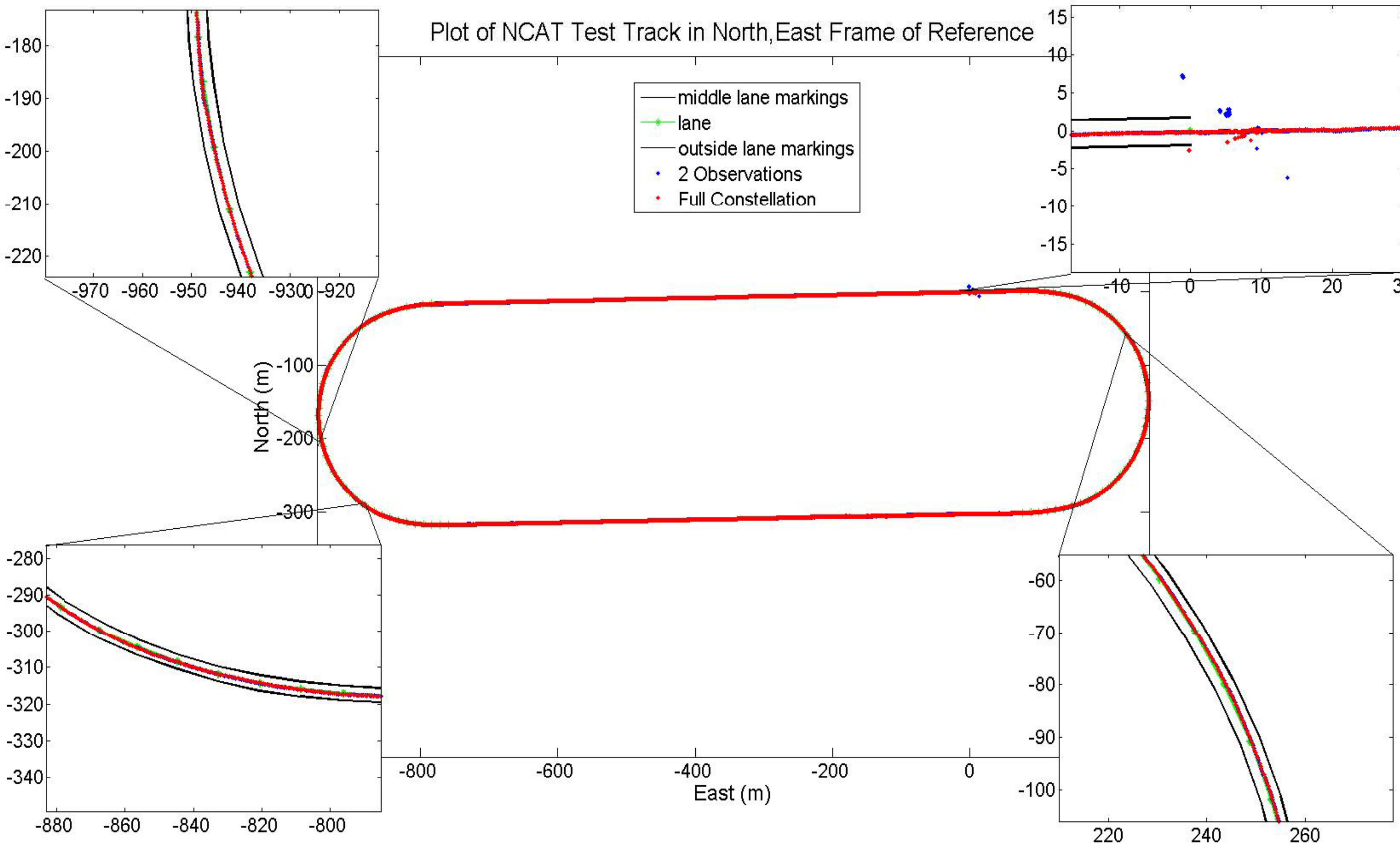
Urban Environment where only a few GPS Satellites may be available

Validated at Auburn's NCAT Test Track using:

- Lateral Constraint
- Vertical Constraint
- 2 GPS Satellites

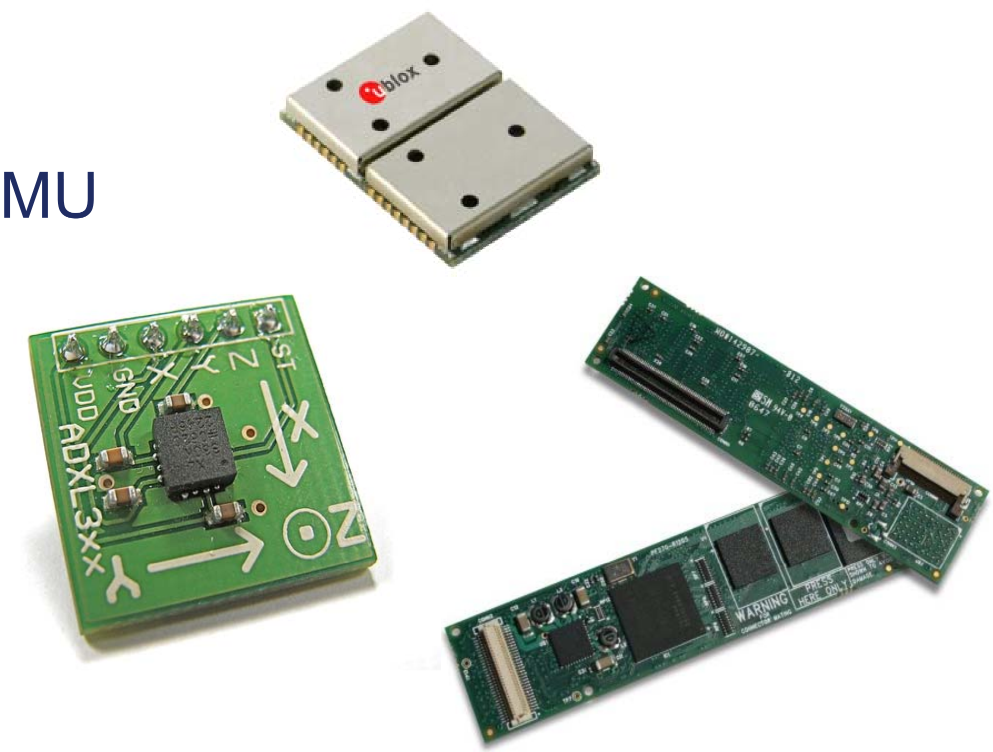


Positioning Results



Low-cost FDE/DRTK Integration

- Develop onto a low-cost GPS/INS module or using DAGR
  - Use on-board GPS (DAGR) and IMU or vehicle sensors (wheel speed, steer angle, etc).
- Alternatively use low-cost OEM receiver
  - Gumstix computer
  - uBlox GPS receiver
  - Analog Devices MEMS IMU
  - Prototype Cost ~ $600



Needs/Requests from FCS LSI

- DRTK on GB-GRAM
  - Use on-board GPS (DAGR) and IMU (wheel speed, steer angle, etc).
- DRTK with CRPA Antenna
  - Effects on accuracy and robustness
  - Effects on integer ambiguity solution
- Tele-op/indirect driving issues (especially at high speeds)
  - Effect of displays (resolution, 2D vs 3D information, field of view)
  - Effect of latency
  - Additional information to aid operator (visual, haptics, contour topography, birds eye view, etc.)
  - Local low-level control (allow operator to provide higher level commands)

AUBURN
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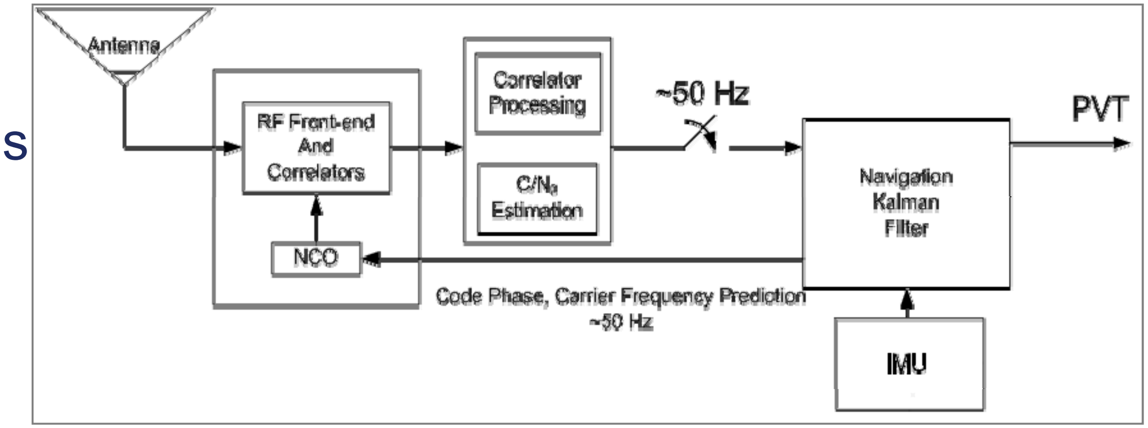
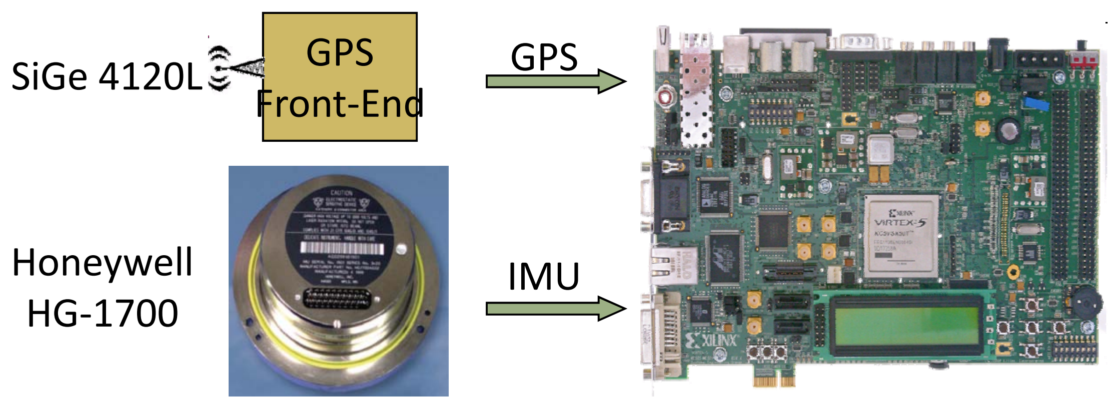
Auburn University’s Vector Tracking and Deeply Integrated GPS/INS

Vector Tracking

- No tracking loops are used, signal tracking and navigation state estimation are combined into one algorithm
- Provides near instantaneous signal reacquisition after short GPS blockage
- Provides improved tracking in noisy environments
- Implementing on a Xilinx Virtex-5 FPGA
  - Real-time capable
- Ability to interface with multiple sensors
  - INS, LIDAR, vision
- Need to modify algorithms to provide carrier outputs for DRTK

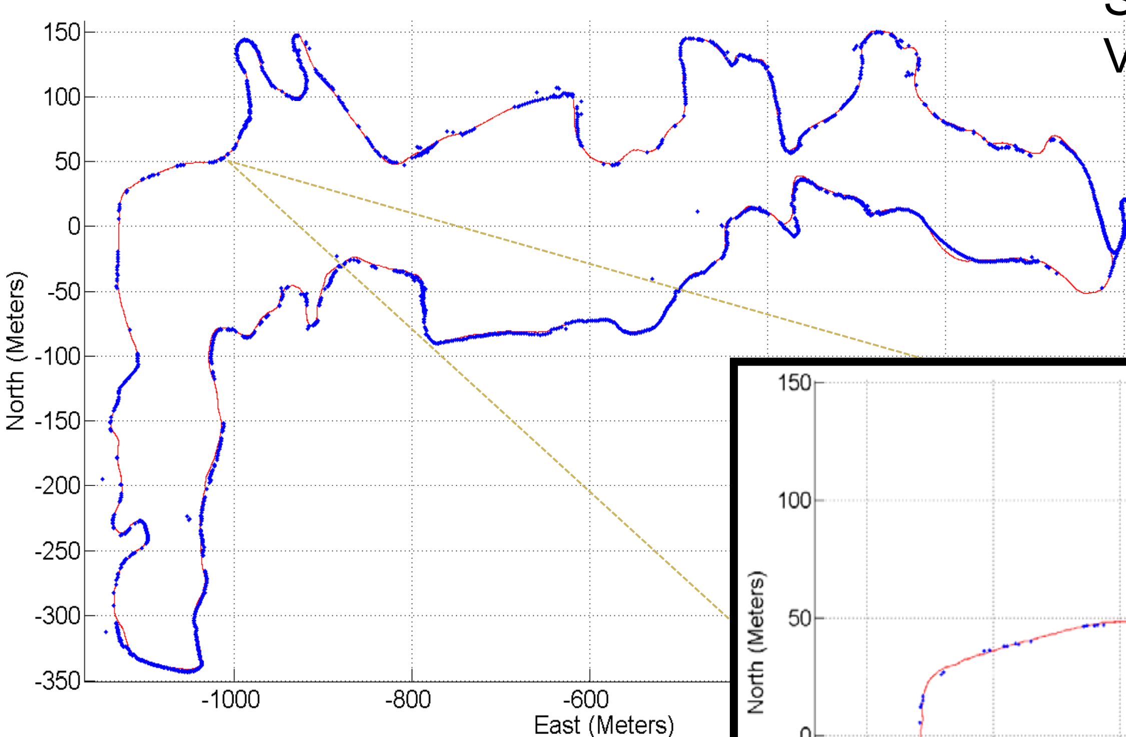


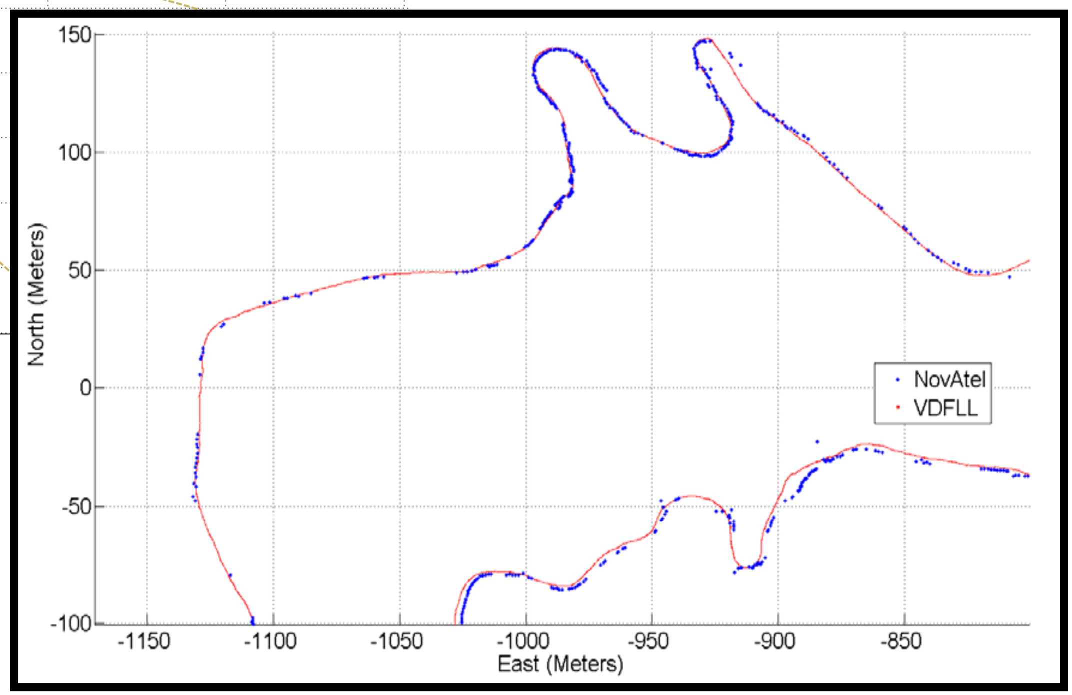


Xilinx Virtex-5 FPGA

Baja Course: NovAtel and VDFLL Comparison

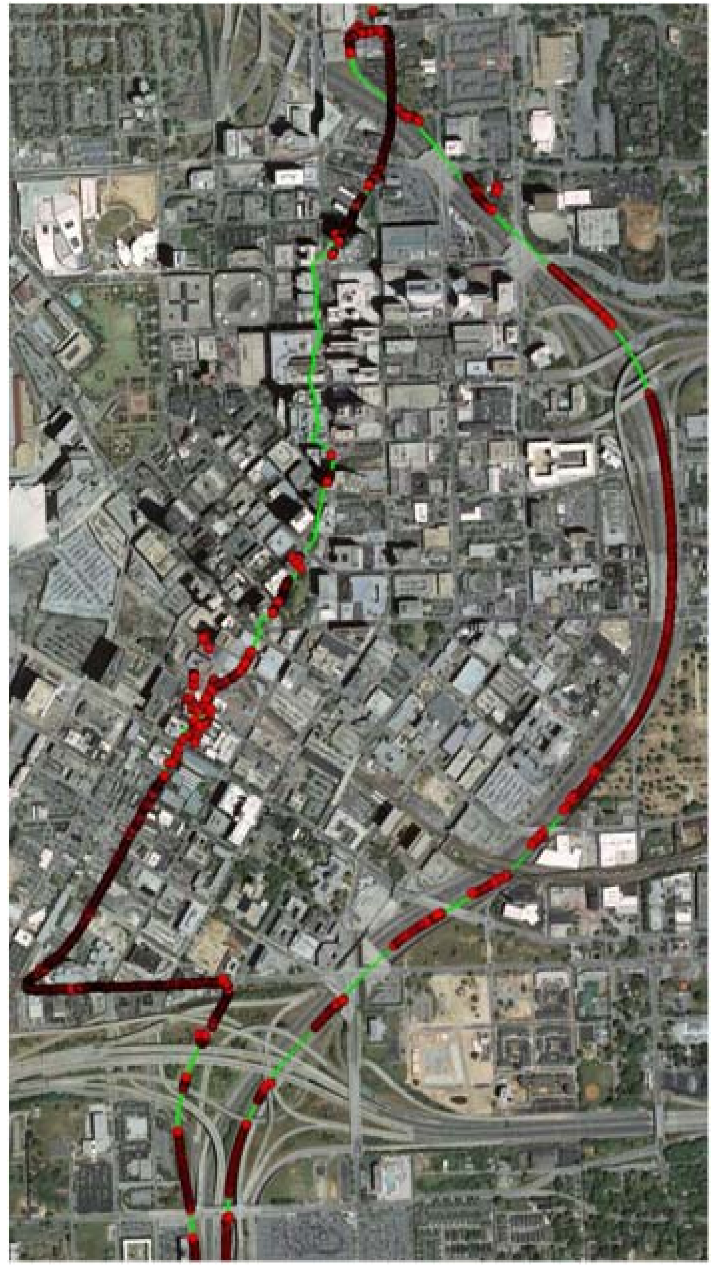
Comparison of Coverage:
Standard GPS Receiver ~ 70%
VDFLL 100%





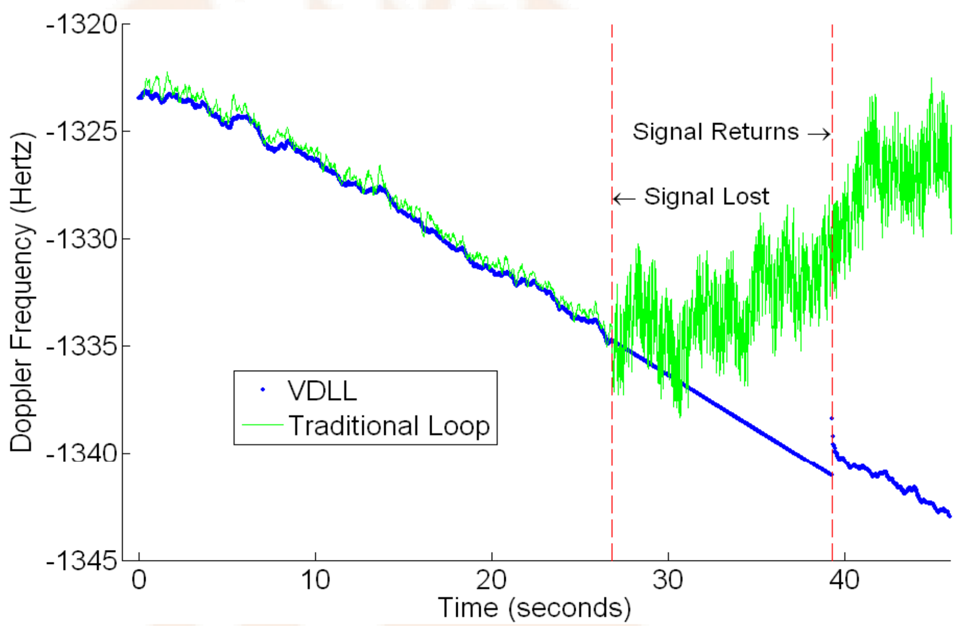
Heavy Foliage Test Course

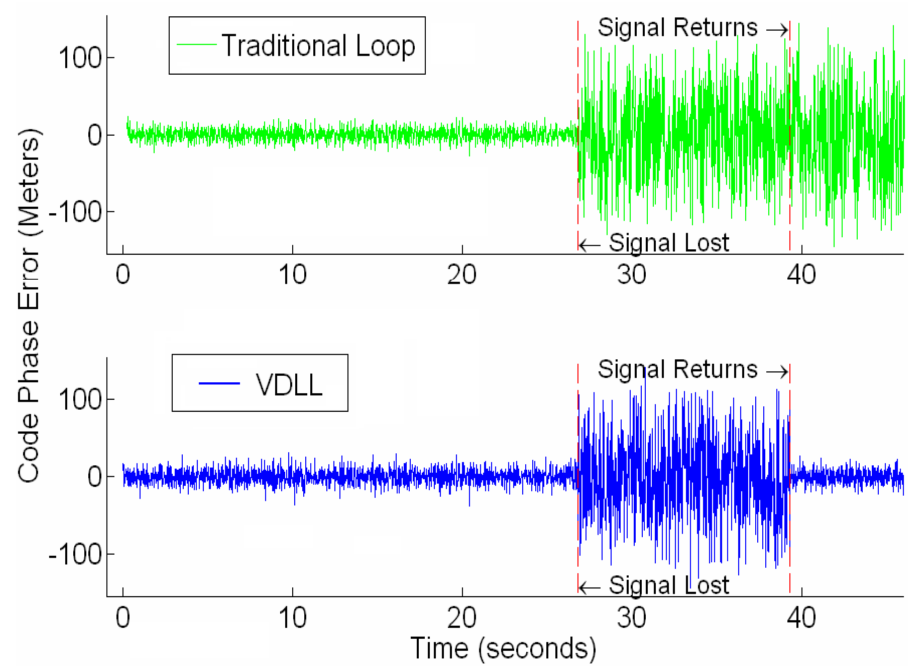
Downtown Atlanta w/ Vector Tracking



Vector Tracking Signal Tracking

- Vector tracking benefits include
  - Correlation among channels allows for tracking signals with lower C/N0s
  - Instant signal reacquisition after outage
  - Solution inherently aids tracking





The VDFLL tracks the correct Doppler when the signal is lost (left) and instantly reacquires the code phase when the signal returns.

FHWA – Lane Level Navigation

Lane Detection and Lateral Distance Estimation

Lateral Distance Estimation

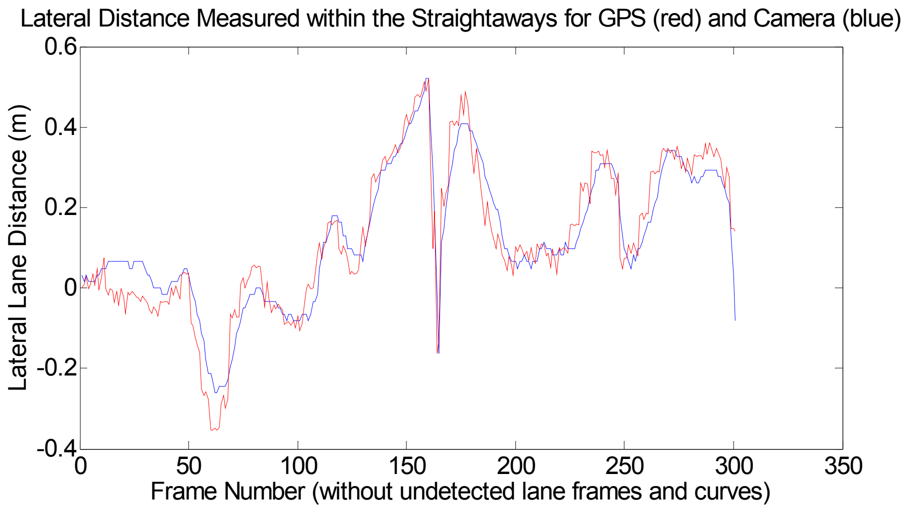
- Sensor fusion with camera and LiDAR for robustness of lateral distance measurement
- Used for lane level localization in multipath environments

Lane Detection Sensors

- Logitech QuickCam Pro 9000
- IBEO ALASCA XT laser scanner
- both sensors have a update rate of 10Hz

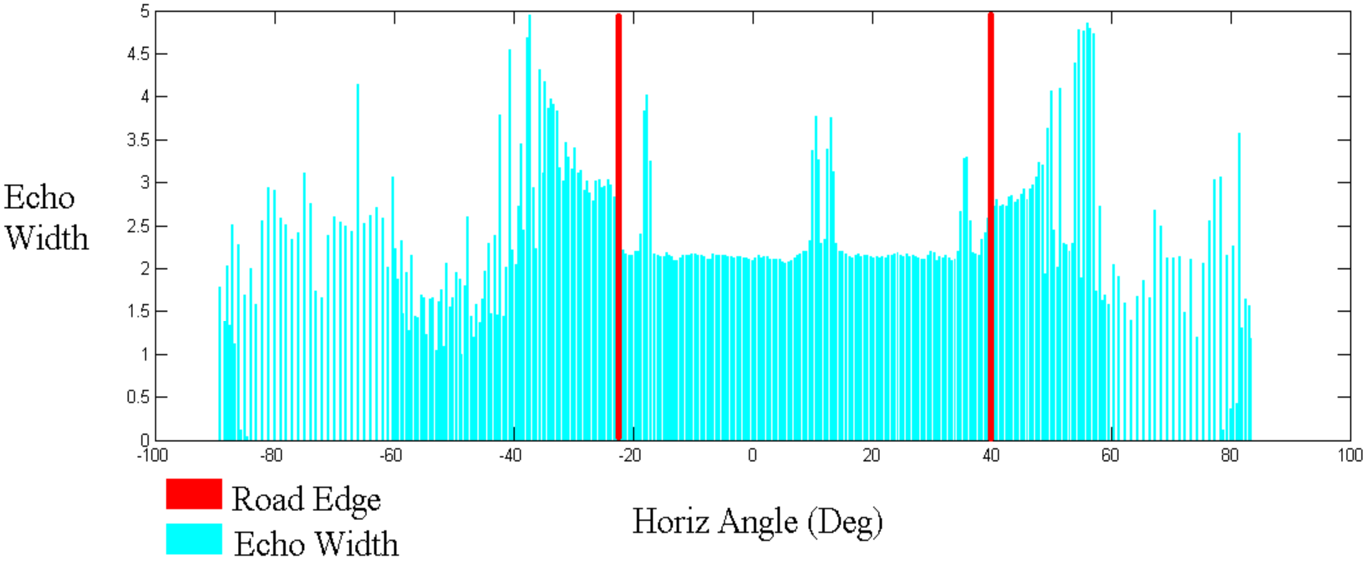
Lane Detection with Camera

- Thresholding / Edge Detection
- Hough Transform
- Least Squares Interpolation
  - Interpolate 2nd order polynomial as model for lane
- Kalman filter
  - states are the coefficients of the polynomial
- Polynomial Bounds
  - Lines for subsequent frames lie within polynomial boundary curves
- <10 cm accuracy on straight roads



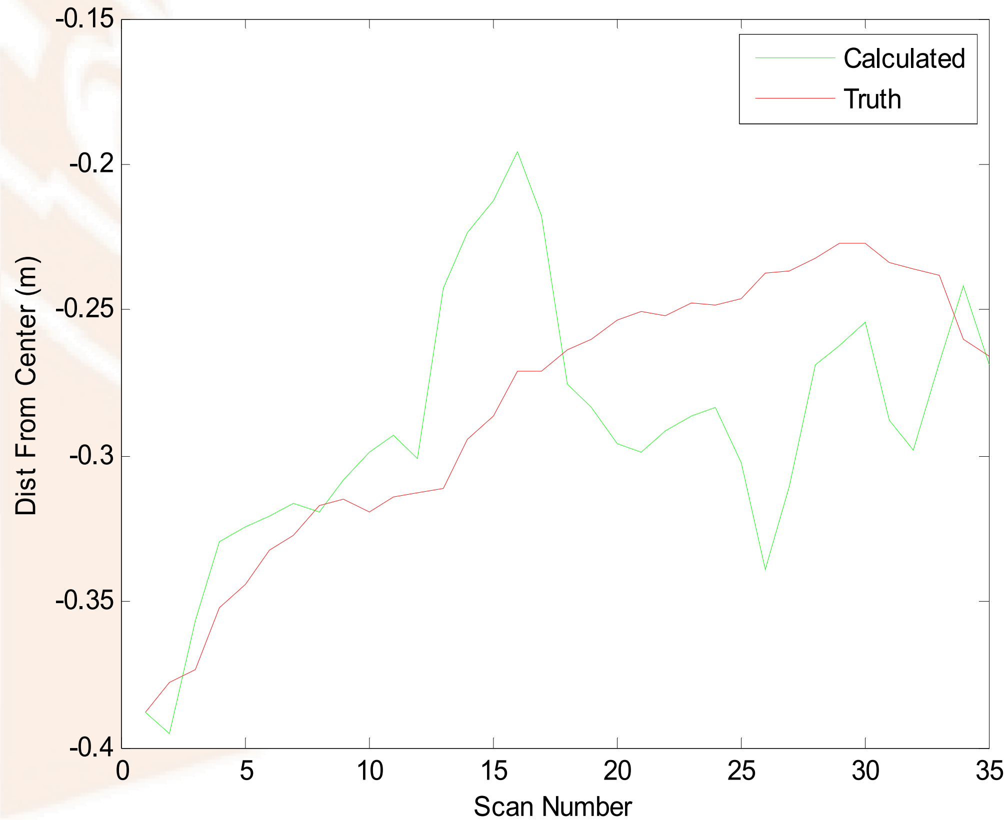
Detecting Lane Markings

- Detect lines using increased Echo Width
- Find minimum RMS error

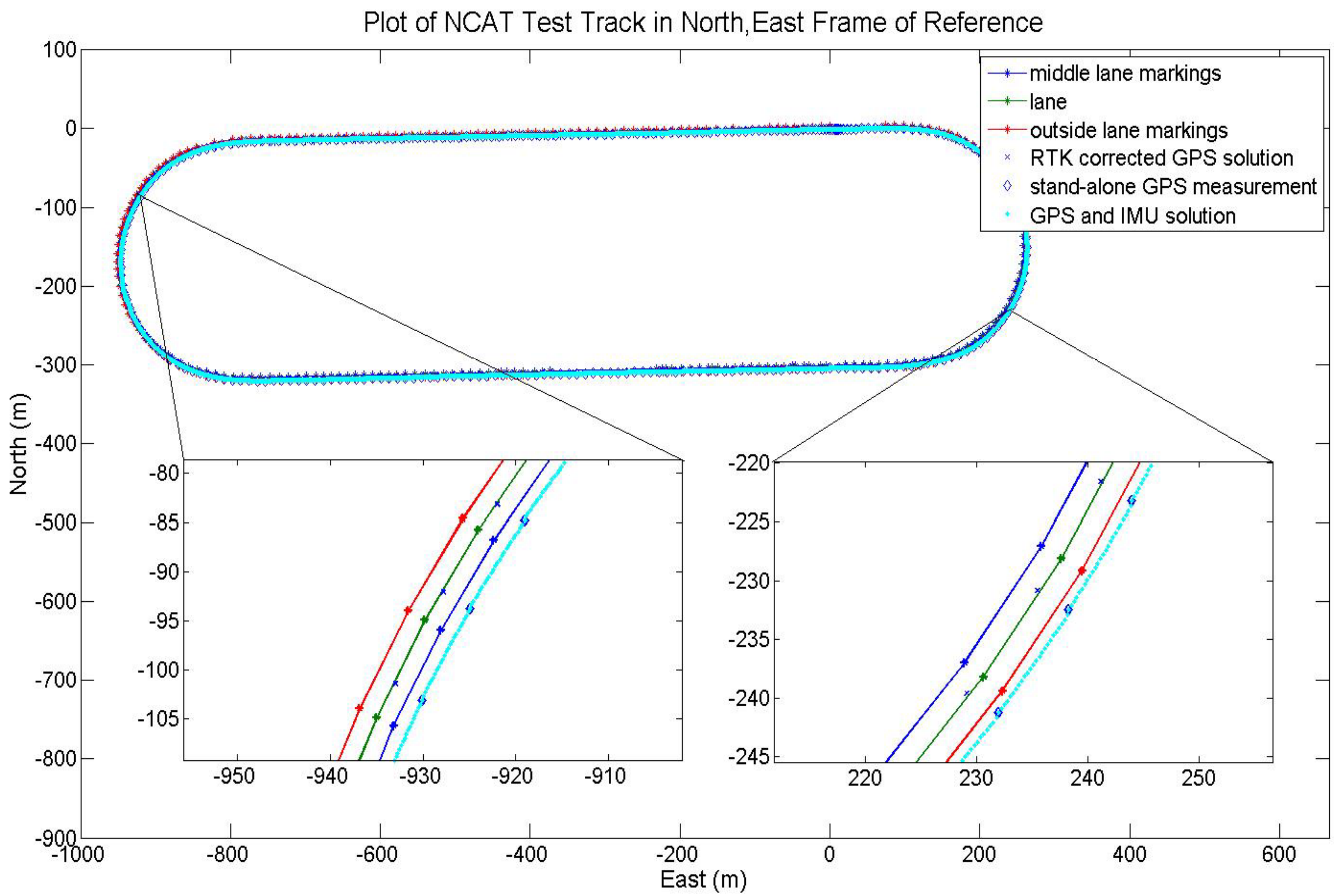


Results

- Best on Straights
- STD of Error = .0435m
- Avg Error = .0355m

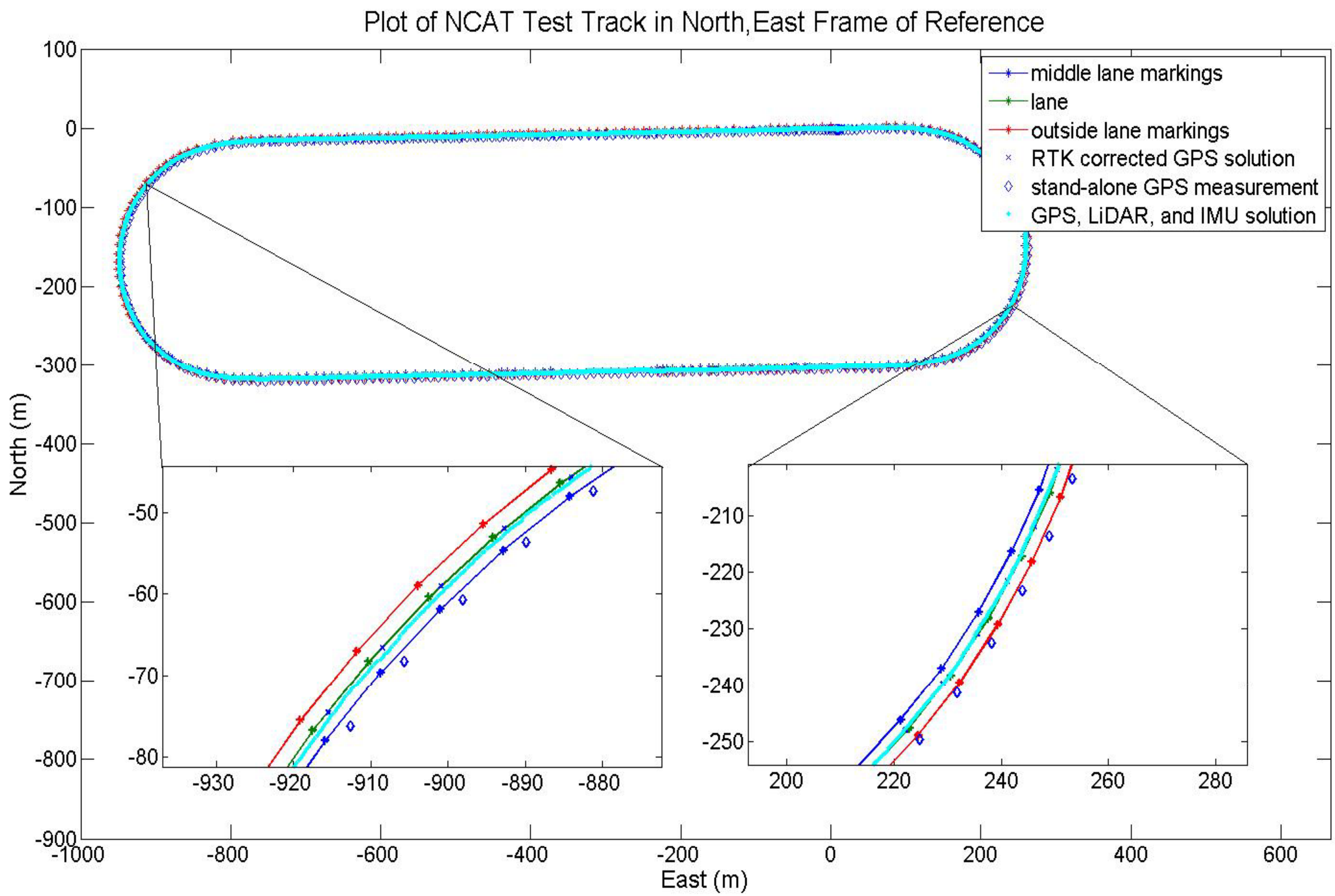


GPS / INS



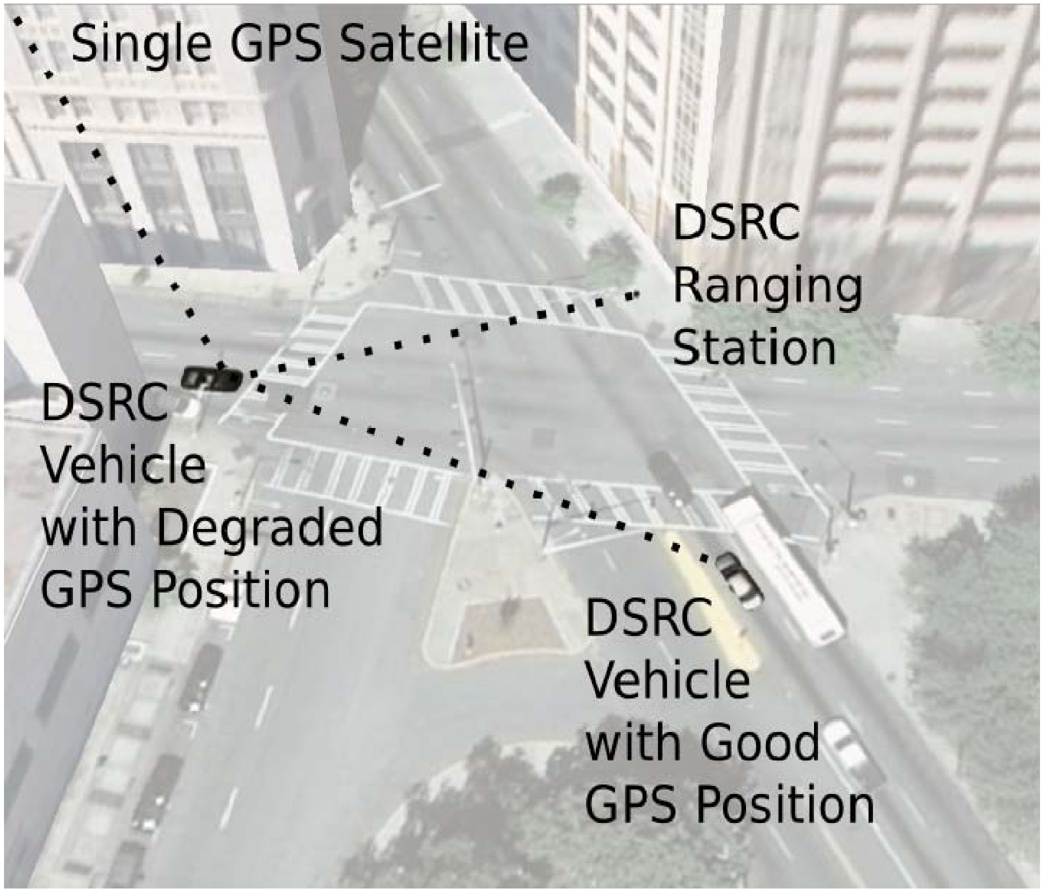
Plot of NCAT Test Track in North,East Frame of Reference
middle lane markings
lane
outside lane markings
RTK corrected GPS solution
stand-alone GPS measurement
GPS and IMU solution
North (m)
East (m)
100
0
-100
-200
-300
-400
-500
-600
-700
-800
-900
-1000
-800
-600
-400
-200
0
200
400
600
-80
-85
-90
-95
-100
-105
-950
-940
-930
-920
-910
-220
-225
-230
-235
-240
-245
220
230
240
250

GPS / Camera / LiDAR / INS



Positioning With Additional Ranges

- Some scenarios provide poor GPS position
- Augment navigation with ranges to known positions
- Provides more seamless operation



Vehicle Modeling

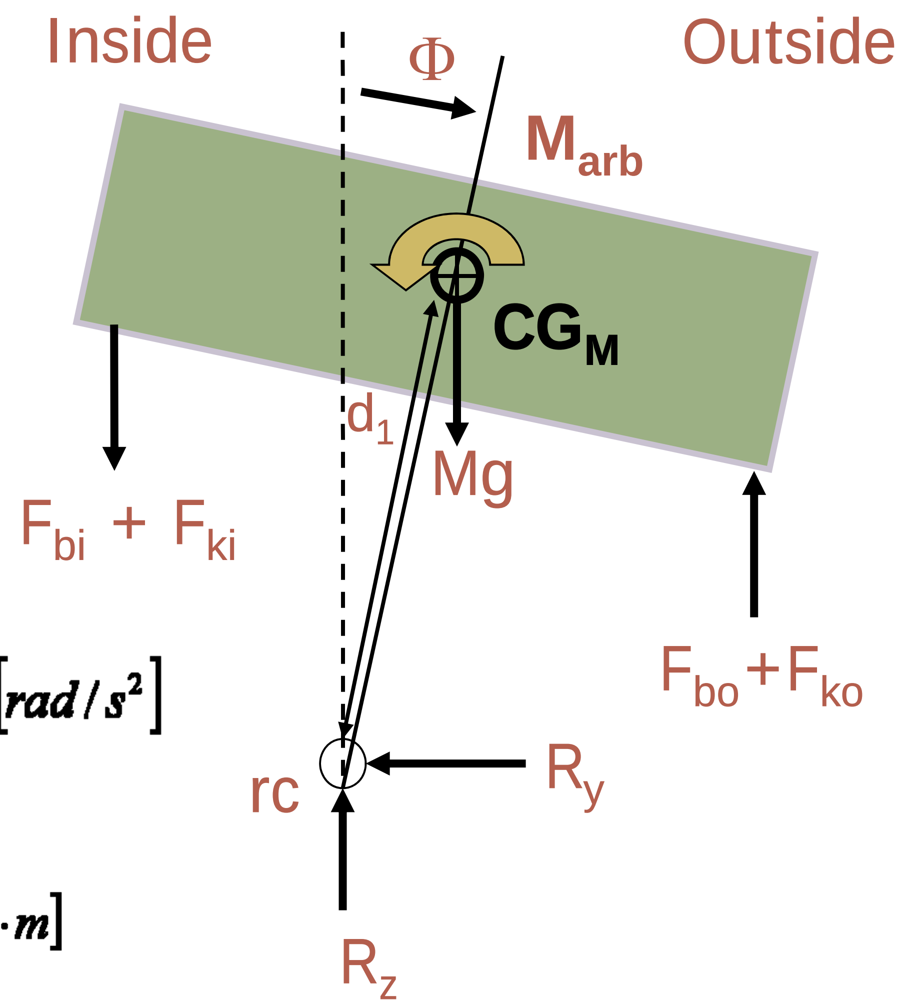
Roll FBD: Sprung Mass

R = Reaction Forces
rc = roll center
F_b = Damper Force
F_k = Spring Force

$$\Sigma M_x = I_x \cdot \ddot{\Phi}$$

$$\ddot{\Phi} = \left(\frac{1}{I_x}\right) \cdot \begin{bmatrix} -RSM - RDM + \left(R_z \cdot d_1 \cdot \sin(\Phi)\right) \\ +\left(R_y \cdot d_1 \cdot \cos(\Phi)\right) \end{bmatrix} \cdot \left[rad/s^2\right]$$

$$RSM = \left[\begin{bmatrix} \left(0.5 \cdot k_{sf} \cdot S_{kf}^{\ 2}\right) + \left(0.5 \cdot k_{sr} \cdot S_{kr}^{\ 2}\right) \\ + k_{arbf} + k_{arbr} \end{bmatrix} \cdot \Phi\right] \cdot \left[N \cdot m\right]$$



Roll FBD: Un-Sprung Mass

- Lateral Weight Transfer

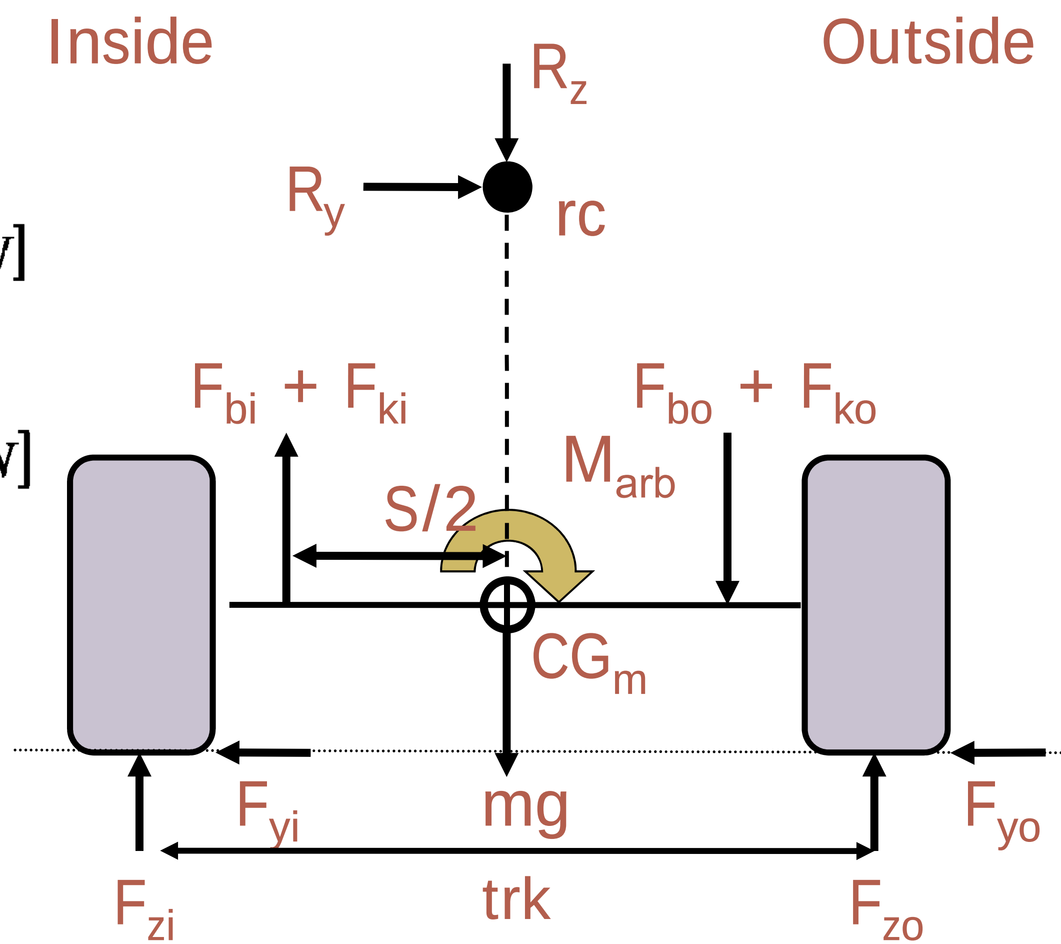
$$dF_z = [F_{zo} - F_{zi}] \cdot [N]$$

$$dF_{zf} = \frac{2}{trk_f} \cdot \begin{bmatrix} M_{arbf} + S_{kf} \cdot F_{kf} + S_{bf} \cdot F_{bf} \\ + R_{yf} \cdot (h_{rcf} - h_{cgm}) + F_{yf} \cdot h_{cgm} \end{bmatrix} \cdot [N]$$

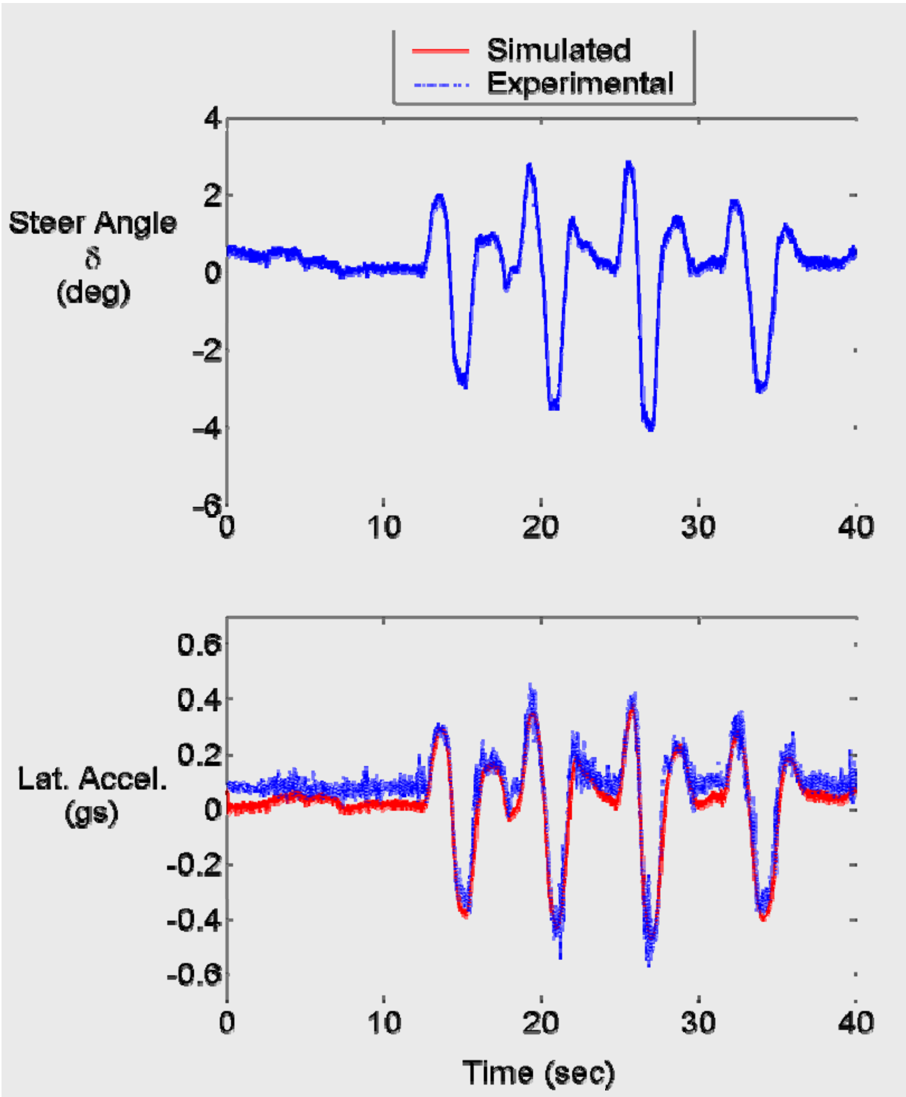
$$dF_{zr} = \frac{2}{trk_r} \cdot \begin{bmatrix} M_{arbr} + S_{kr} \cdot F_{kr} + S_{br} \cdot F_{br} \\ + R_{yr} \cdot (h_{rcr} - h_{cgm}) + F_{yr} \cdot h_{cgm} \end{bmatrix} \cdot [N]$$

F_z = Normal Force

F_y = Tire Lateral Force

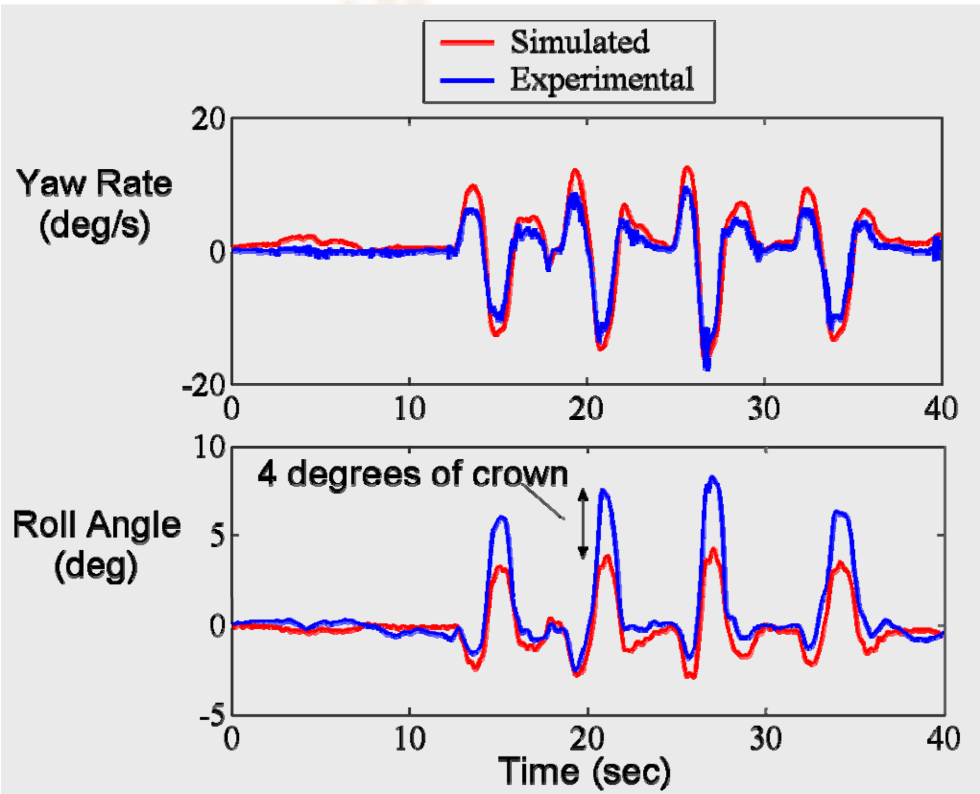


GAVLAB Blazer Data



- Lane Change Maneuver
- Velocity ~ 40 mph
- Steer Rate ~ 6 deg/s
- Data collected at Auburn NCAT facility

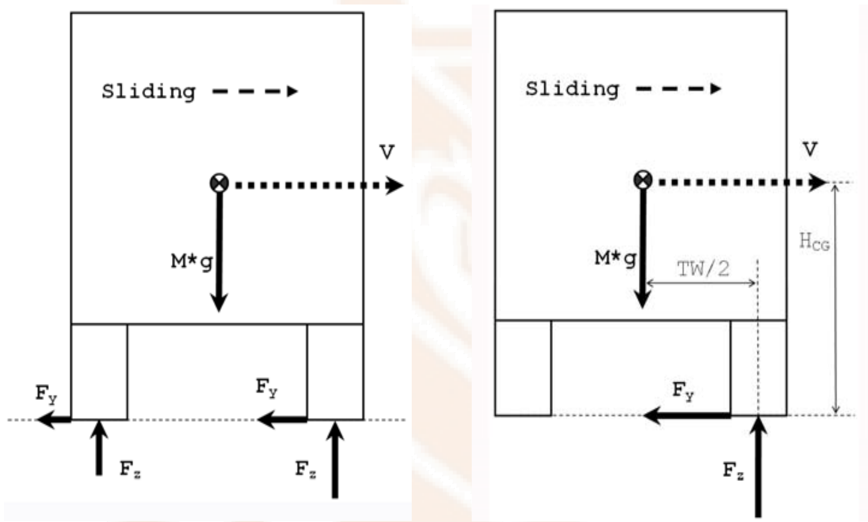
GAVLAB Blazer Data (2)



- Simulation Matches Well
- Vehicle Model for the Blazer is same as used for the NHTSA Data
  - No Tuning Between the Two Blazers
- Crown of 4 degrees visible in the roll angle measurement

NHTSA's Static Stability Factor (SSF) Test

$$SSF = \frac{TW}{2 \cdot H_{CG}}$$



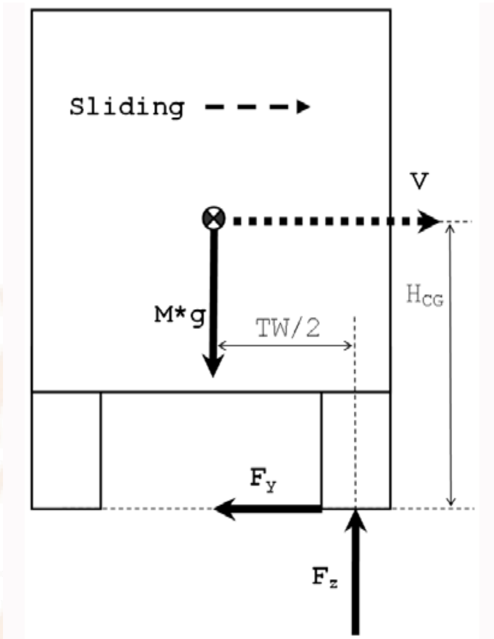
$$\sum F_y = M \cdot a_y = F_y$$

$$\sum F_z = M \cdot a_z = M \cdot g - F_z$$

$$\sum M_{CG} = \frac{TW}{2} \cdot F_z - H_{CG} \cdot F_y = 0$$

- The standard test for vehicle rollover resistance comparison for the National Highway Traffic Safety Administration (NHTSA)
- Calculated when $Fz_{inner}=0$
- Pros:
  - Simple calculation of the lateral acceleration (g's) needed for tripping a stationary vehicle
  - Good for vehicle comparisons
  - Includes the two largest rollover contributors
- Cons:
  - Ignores dynamic behaviors
  - Overlooks all other vehicle properties

Improved Rollover Prediction Formula



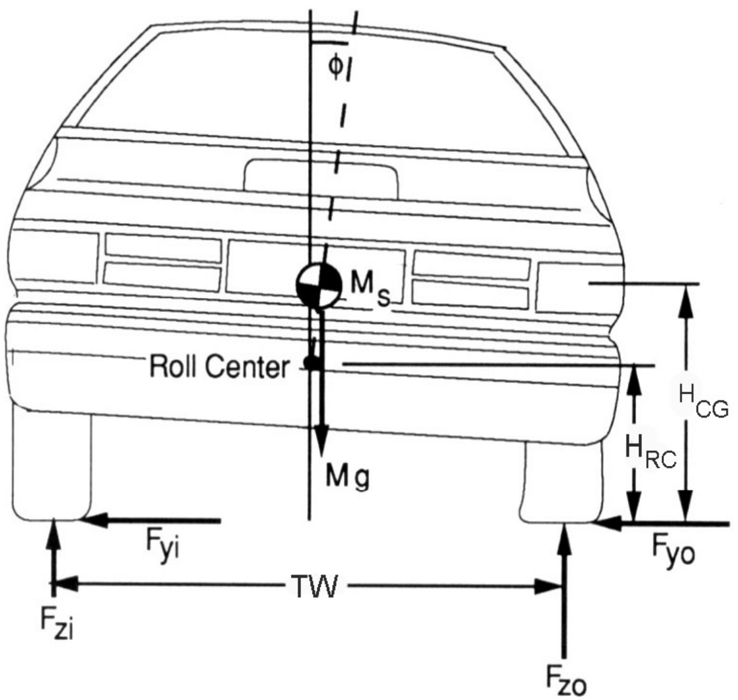
$$SSF = \frac{a_y}{g} = \frac{TW}{2 \cdot H_{CG}}$$

$$a_{y_{Rollover}} = V \cdot r = \frac{V^2}{R} = \frac{TW \cdot g}{2 \cdot H_{CG}}$$

$$V_{Rollover} = \frac{TW \cdot g}{2 \cdot r \cdot H_{CG}} = \sqrt{\frac{TW \cdot R \cdot g}{2 \cdot H_{CG}}}$$

- The SSF can be expanded to estimate the rollover lateral acceleration and velocity
- Requires estimates of track width, CG height, radius of curve or a measurement of yaw rate
- Still ignores other vehicle properties and dynamic behaviors
- SSF <□ for rollover to occur typically
- Can also be used to calculate:
  - $H_{CG\ Rollover}$
  - $TW_{Rollover}$
  - $r_{Rollover}$
  - $R_{Rollover}$

Inclusion of Suspension Effects



From Gillespie: Fundamentals of Vehicle Dynamics

$$a_y = \kappa \cdot \frac{TW \cdot g}{2 \cdot H_{CG}}$$

$$V_{Rollover} = \kappa \cdot \frac{TW \cdot g}{2 \cdot r \cdot H_{CG}} = \kappa \cdot \sqrt{\frac{TW \cdot R \cdot g}{2 \cdot H_{CG}}}$$

From Gillespie:

$$a_y = \frac{TW \cdot g}{2 \cdot H_{CG}} \cdot \frac{1}{1 + R_\Phi \cdot \left(1 - \frac{H_{RC}}{H_{CG}}\right)}$$

For passenger cars:

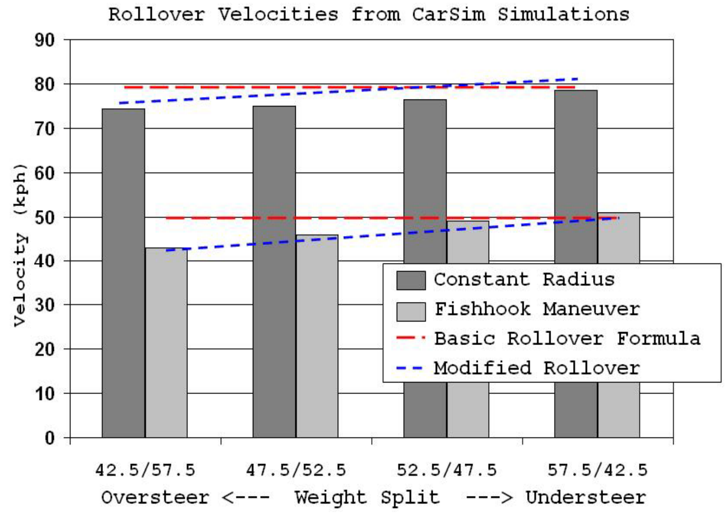
- R_Φ=.1 rad/g (roll rate)
- $H_{RC}/H_{CG} \sim 0.5$

For SUVs:

- R_Φ=.15 rad/g (roll rate)
- $H_{RC}/H_{CG} \sim 0.4$

Empirical Trends Noticed with Changes in Weight Split

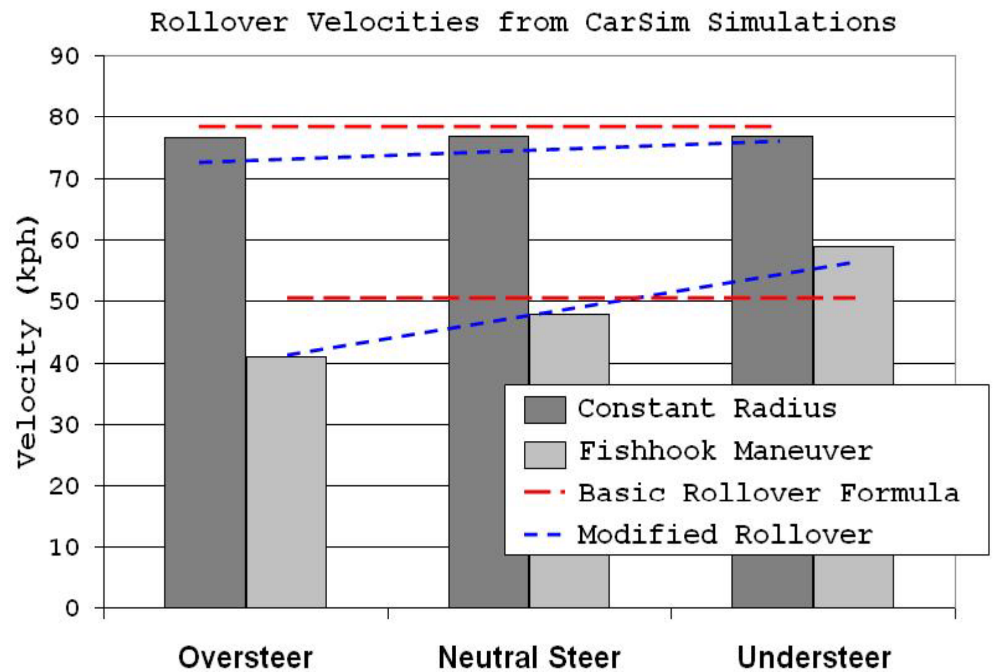
- Using simulation in CarSim of the CR and Fishhook maneuvers, rollover velocities were recorded for different weight splits
- A trend was observed, and a scale factor using the understeer gradient was added to the rollover prediction equations



Constant Radius						
WS (F/R)	$K_{US}(deg/g)$	CarSim	Eq. (3.15)	% err.	Eq. (3.41)	% err.
42.5 / 57.5	-0.139	74.2	79.7	7.4 %	71.6	3.6 %
47.5 / 52.5	-0.0464	74.7	79.7	6.7 %	72.8	2.5 %
52.5 / 47.5	0.0464	76.2	79.7	4.6 %	74.0	2.9 %
57.5 / 42.5	0.139	78.2	79.7	1.9 %	75.0	4.3 %
Fishhook						
42.5 / 57.5	-0.139	43	49.6	15.3 %	42.9	0.2 %
47.5 / 52.5	-0.0464	46	49.6	7.8 %	44.4	3.6 %
52.5 / 47.5	0.0464	49	49.6	1.2 %	46.9	4.5 %
57.5 / 42.5	0.139	51	49.6	2.8 %	49.6	2.8 %

Empirical Trends Noticed with Changes in Cornering Stiffness

- The same test procedures were performed with changes in cornering stiffness
- Similar trends in the rollover velocity can be shown
- Generally, the accuracy of the modified rollover prediction formula still holds true



Constant Radius						
Config.	$K_{US}(deg/g)$	CarSim	Eq. (3.15)	% err.	Eq. (3.41)	% err.
Oversteer	-1.82	76.6	79.7	4.1 %	71.0	7.9 %
Neutral Steer	0.0	76.8	79.7	3.8 %	73.3	4.8 %
Understeer	1.82	76.7	79.7	4.0 %	75.7	1.3 %
Fishhook						
Oversteer	-1.82	41	51.6	25.9 %	41.4	1.0 %
Neutral Steer	0.0	48	51.6	7.5 %	47.5	1.0 %
Understeer	1.82	59	51.6	14.3 %	56.0	5.3 %

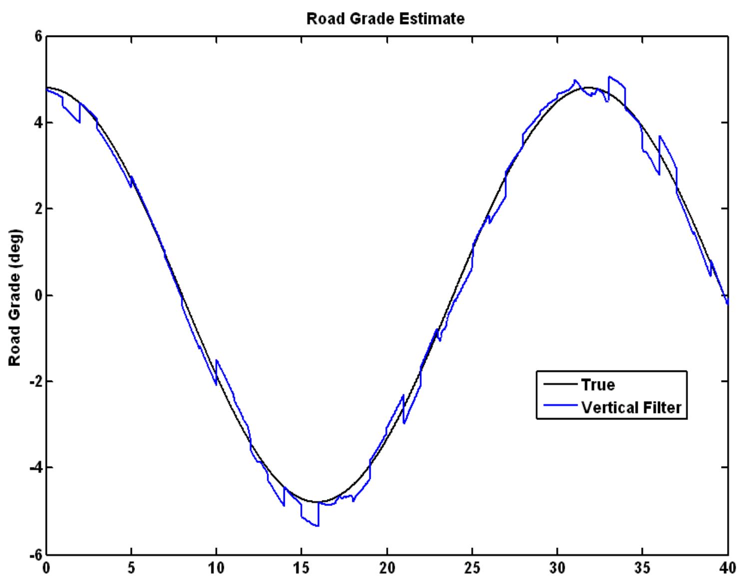
Vehicle State Estimation

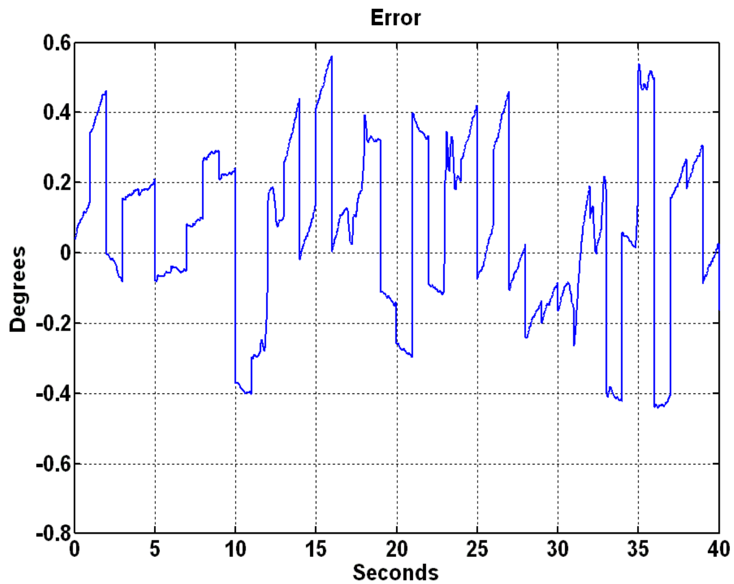
Road Grade Estimation

- GPS Velocity Based
  - Road Grade is generally much larger than the vehicle's suspension pitch.
  - Input from vertical accelerometer
  - GPS Velocity Accuracies 1σ ≈ 5cm/s
  - Θ ≈ atan(Vz/Vx)
  - Vx can be estimated the same way, or using wheel speed sensors.

$$\begin{bmatrix} \dot{V}_z \\ \dot{b}_z \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_z \\ b_z \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} a_z + \omega$$

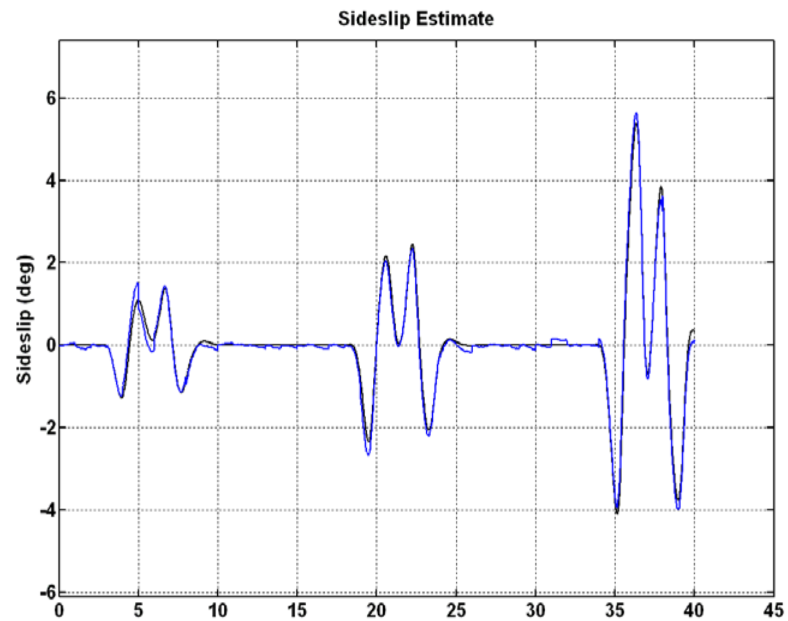
$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} V_z \\ b_z \end{bmatrix} + \eta$$

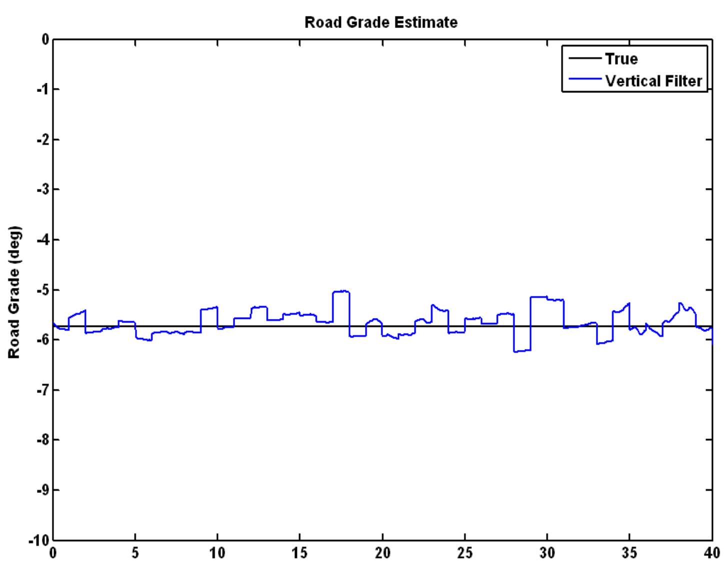


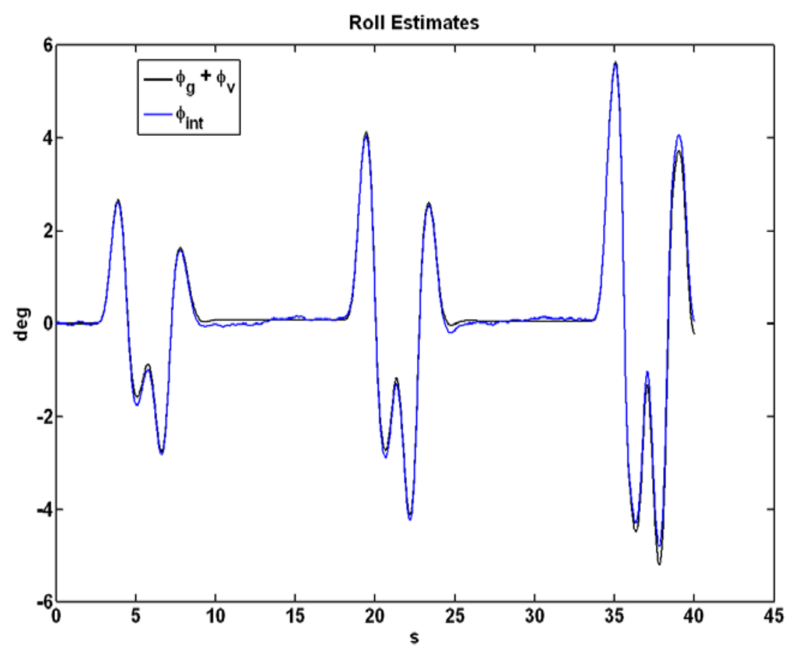


Sideslip Estimation

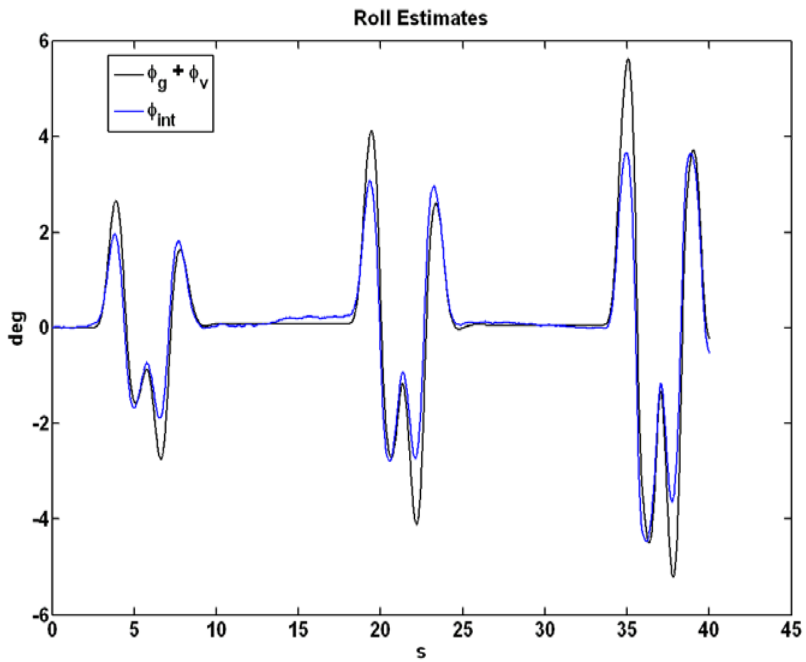
- GPS/INS Based (Single Antenna)
  - When driving straight vehicle heading = vehicle course (assuming no bank).
  - C is set to [1 0] , and the gyro bias is estimated.
  - When turning, C is set to [0 0] and the yaw gyro is integrated to obtain a heading estimate ψ*.

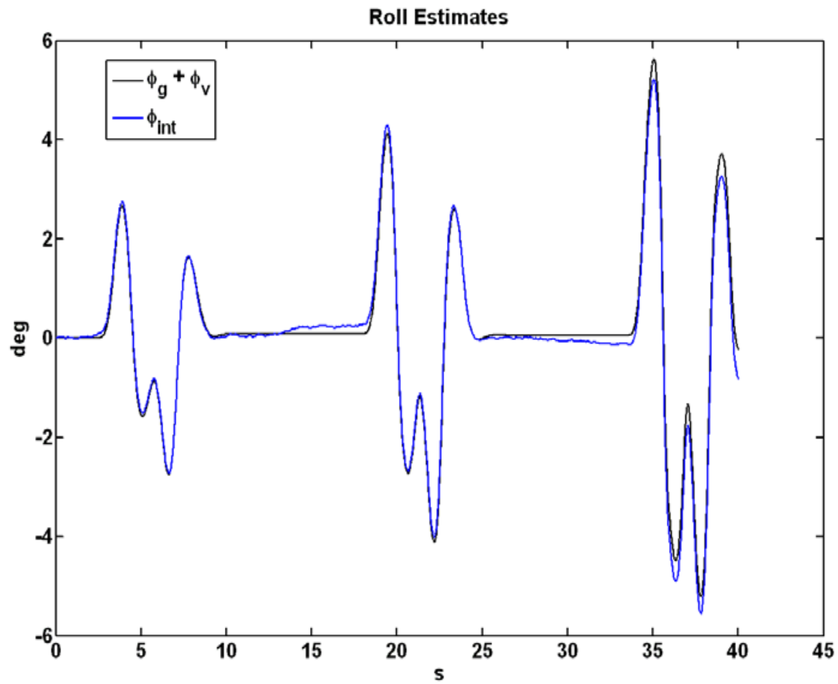






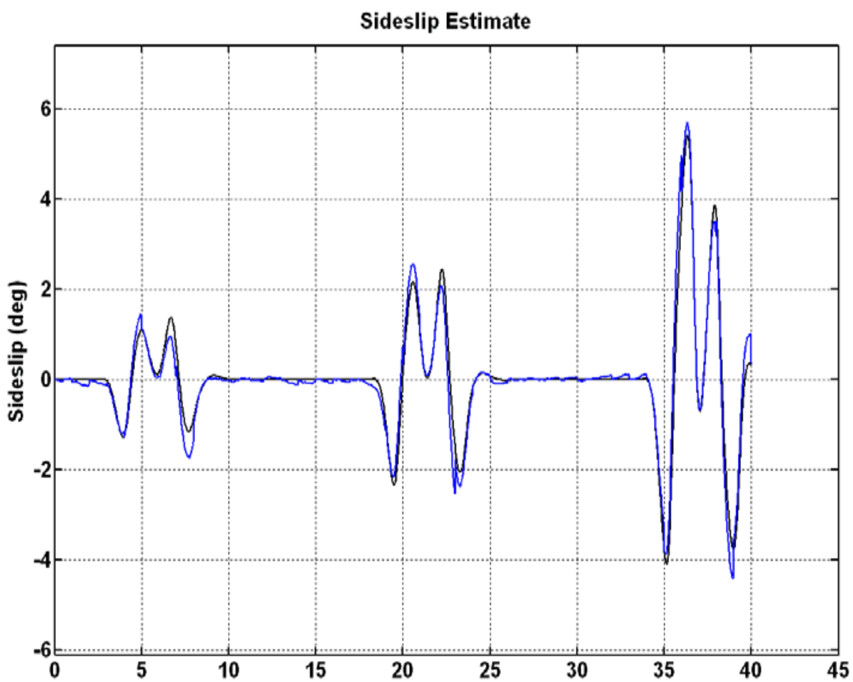
Roll Estimation

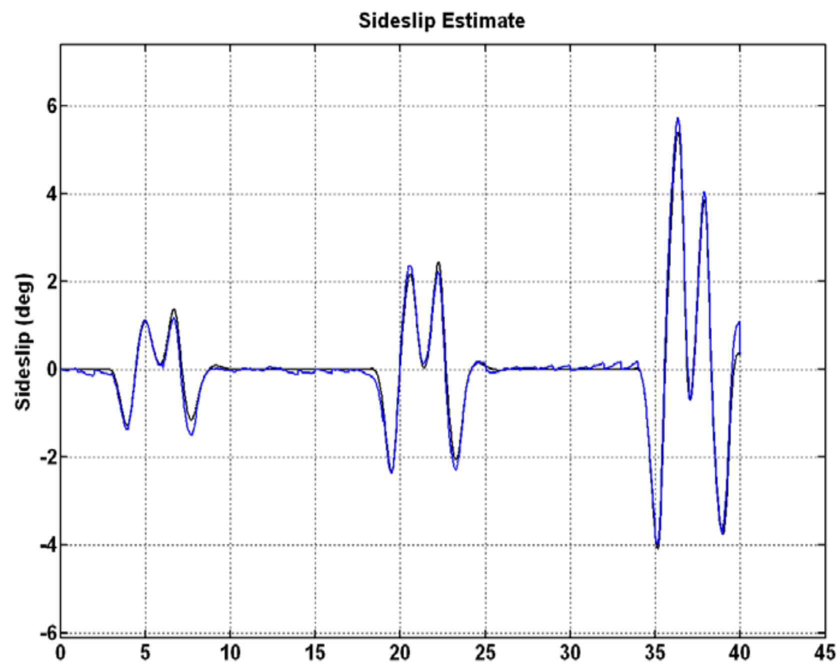




- Without Road Grade Information
- With Road Grade Information

Sideslip Estimation





- Without Road Grade Information
- With Road Grade Information

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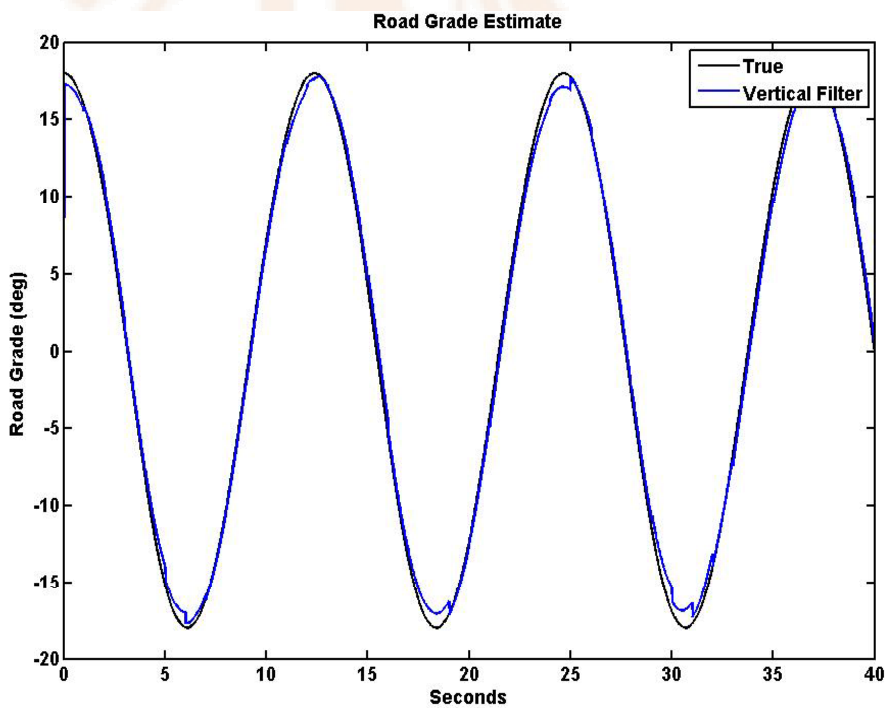
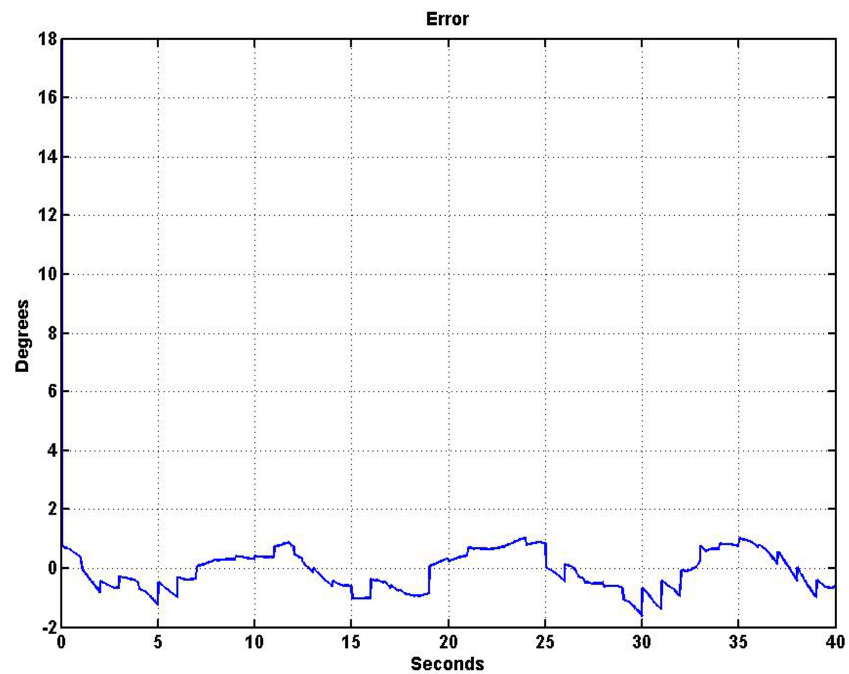
$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} V_z \\ b_z \end{bmatrix} + \eta$$



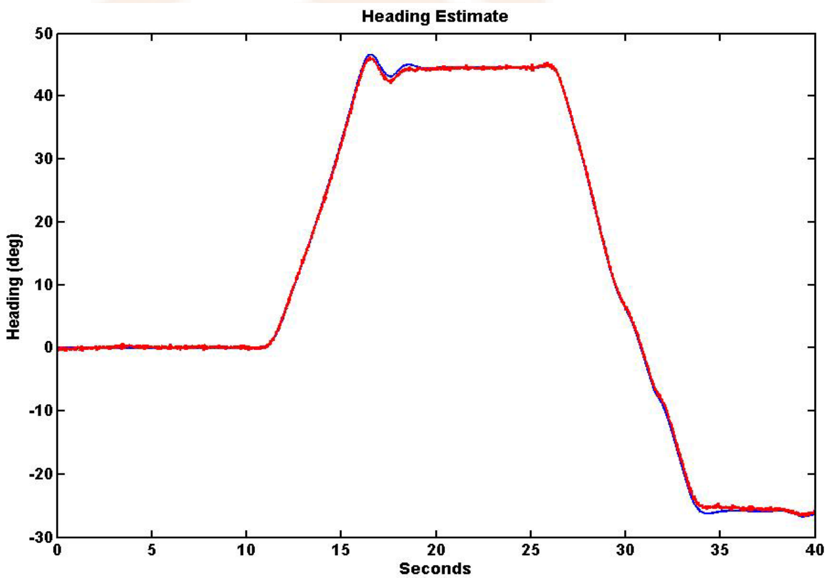


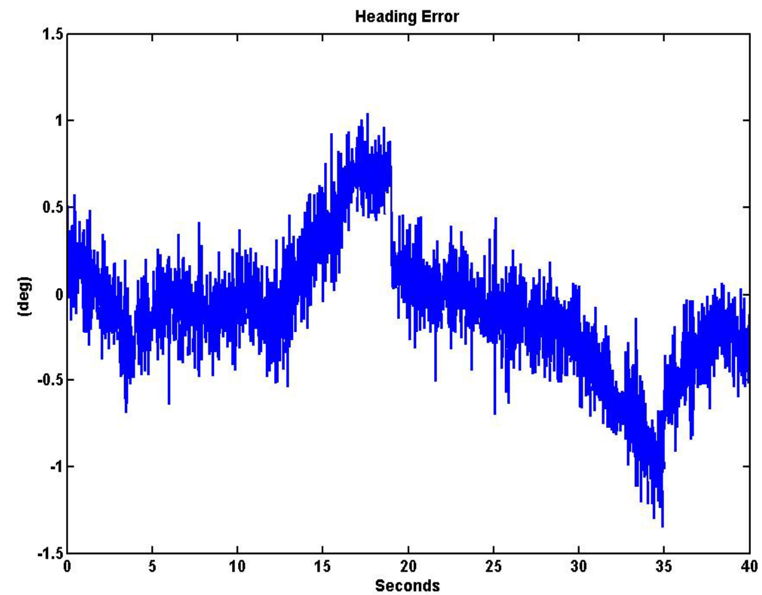
Heading Estimation

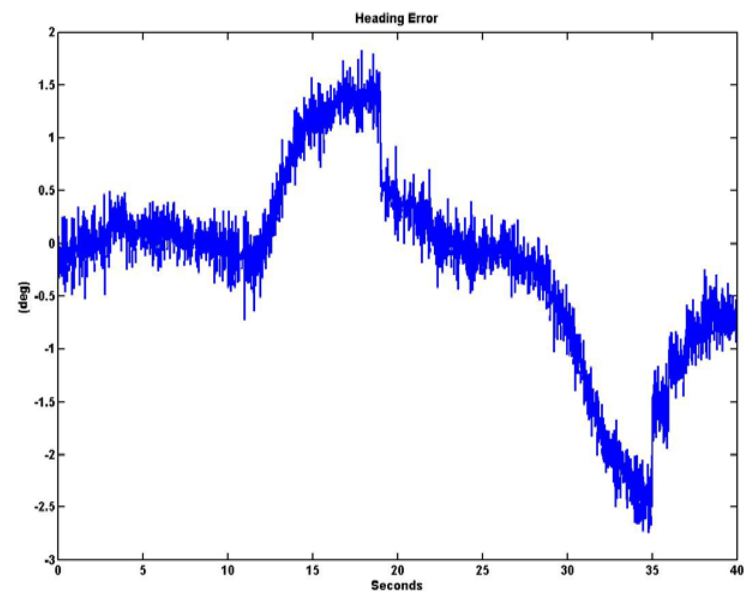
- GPS/INS Based (Single Antenna)
  - When driving straight vehicle heading = vehicle course (assuming no bank).
  - C is set to [1 0] , and the gyro bias is estimated.
  - When turning, C is set to [0 0] and the yaw gyro is integrated to obtain a heading estimate ψ*.

$$\begin{bmatrix}\psi\\ b_r\end{bmatrix} = \begin{bmatrix}0 & -1\\ 0 & 0\end{bmatrix}\begin{bmatrix}\psi\\ b_r\end{bmatrix} + \begin{bmatrix}1\\ 0\end{bmatrix} g_r + \omega$$

$$y = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}\psi\\ b_r\end{bmatrix} + \eta = \nu^{GPS} + \eta$$



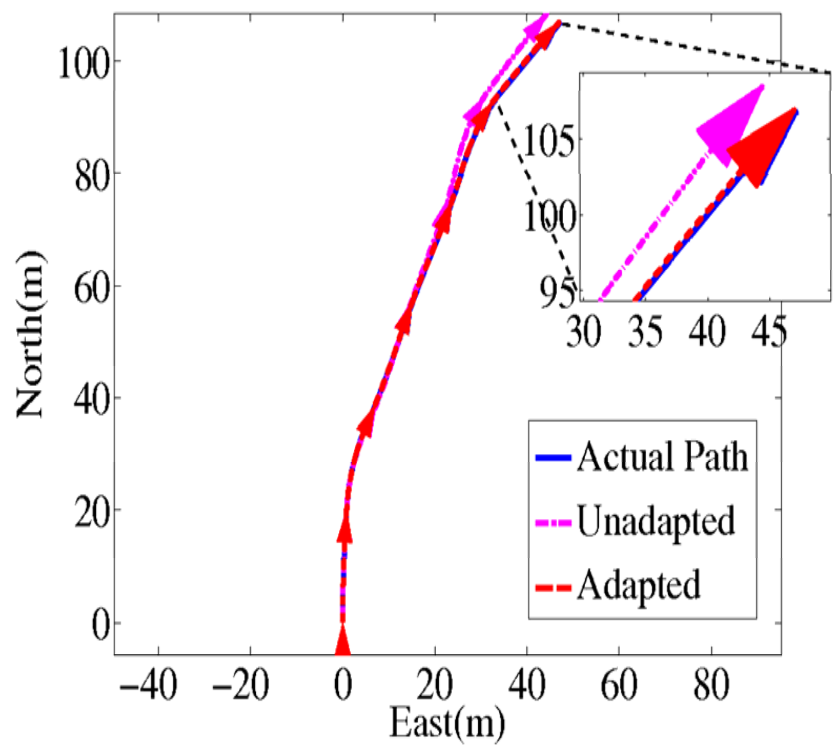




Neural Network Based Modeling

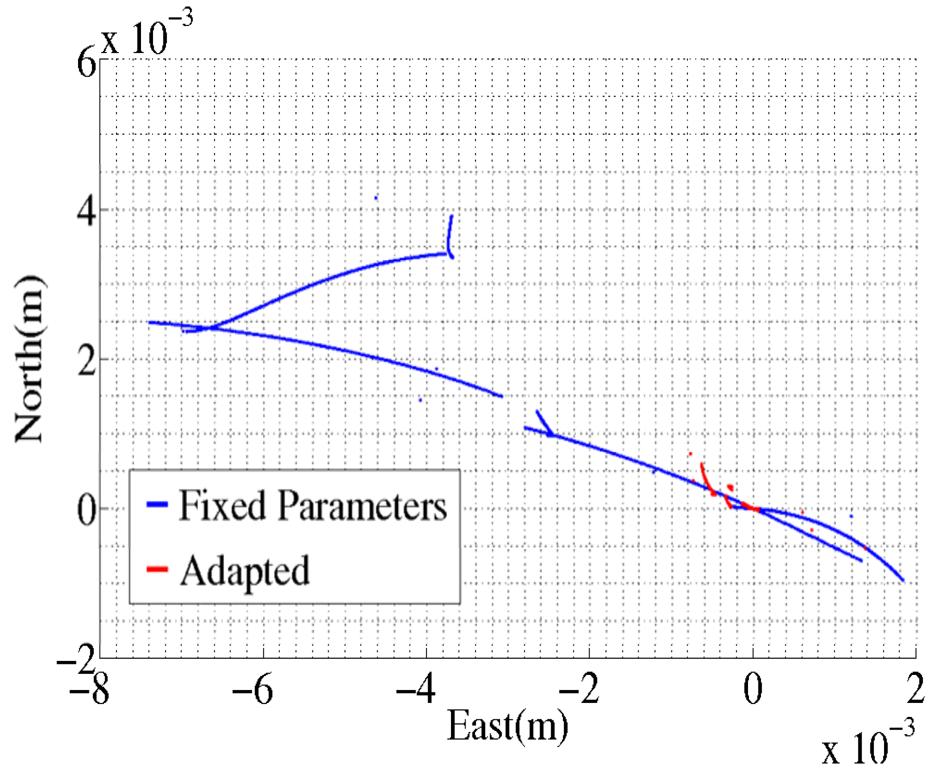
Adaptive Modeling

- Neural Networks can capture Nonlinear Dynamics
- Ability to approximate any continuous function
- A flat tire is a scenario that would alter the structure of the model



Adaptive Modeling

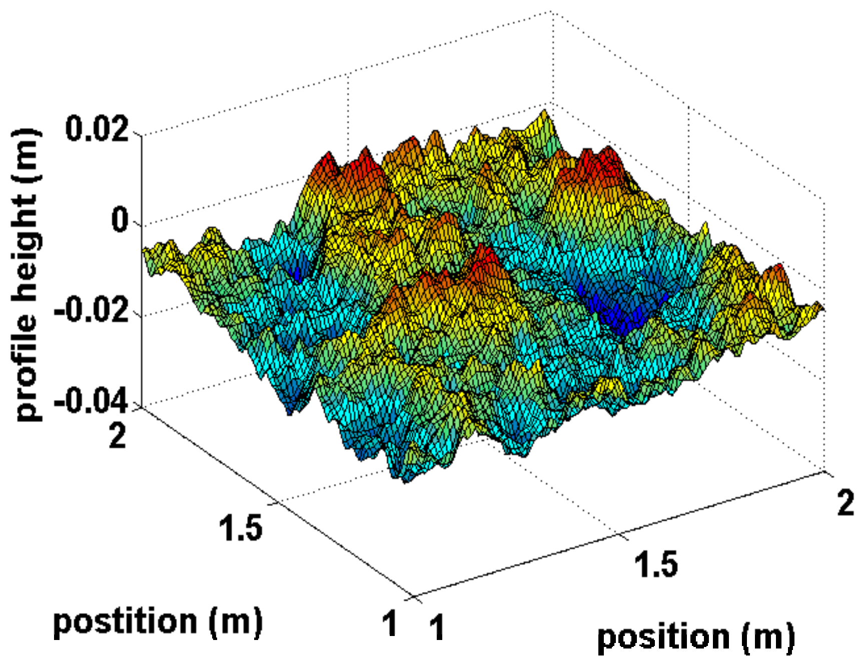
- Examine error introduced by each estimate
- Using fixed model: 0.0627m mean
- Using adapted model: 0.000217m mean

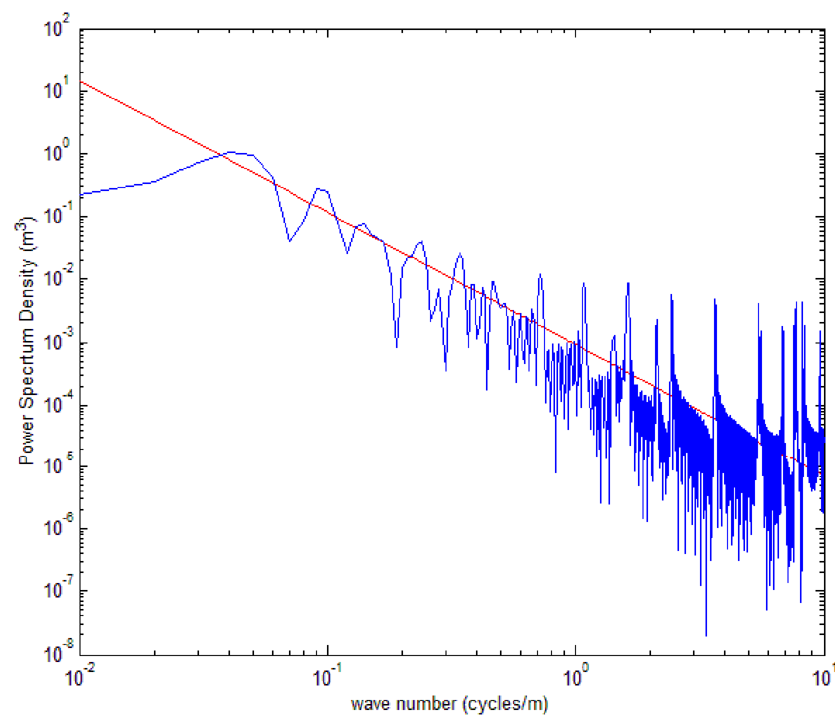


Terrain Characterization

Terrain Characterization – Profile Generation

- Methodologies have been developed to determine critical roughness parameters based on Power Spectral Density
- Rough Surfaces can be Generated based on the critical roughness parameters
- Rough terrain can be implemented to induce vehicle vibration into the simulation environment





Terrain Characterization

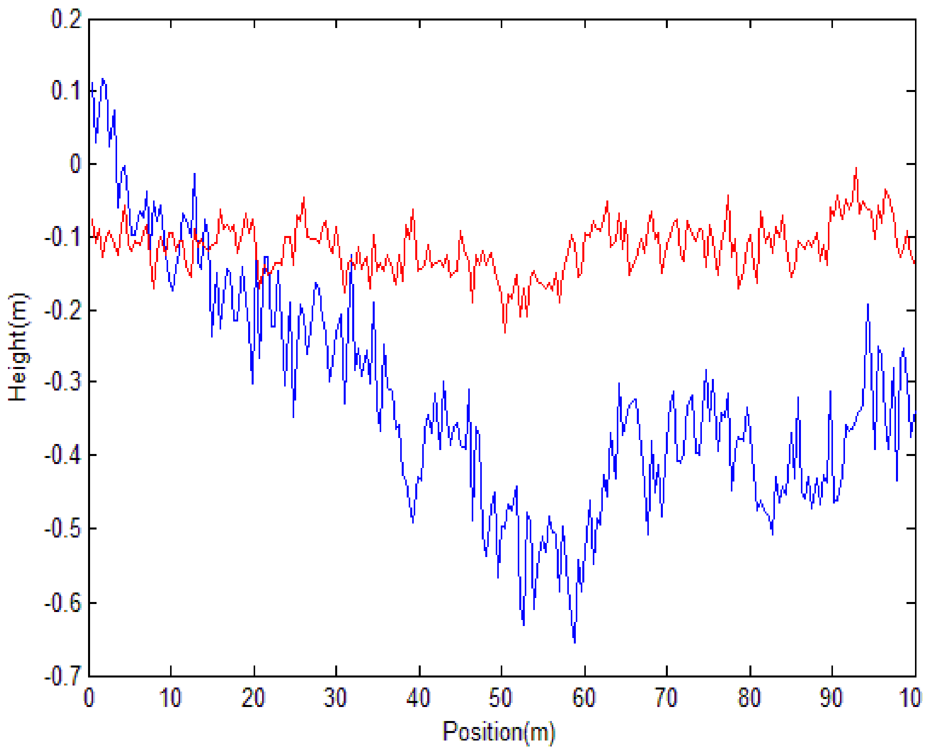
2D Terrain Profile Generation

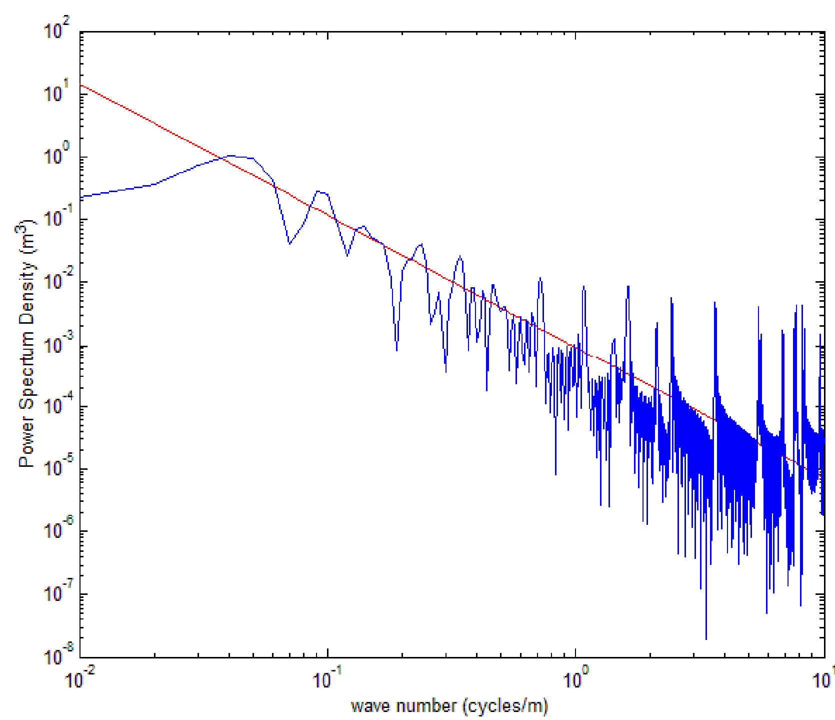
- Fractal profile using Weierstrass-Mandelbrot function
- Fit fractal parameters G & D

$$\bar{\Phi}(\omega) = \frac{G^{2(D-1)}}{2\ln\gamma}\frac{1}{\omega^{(5-2D)}}$$

$$\Phi(\omega) = R(\omega)^{-k}$$

$$h(x) = L\left(\frac{G}{L}\right)^{(D-1)} \sum_{n=1}^{n_{max}} \frac{\cos\left(\frac{2\pi\gamma^n}{L}+\phi_n\right)}{\gamma^{(2-D)n}}$$

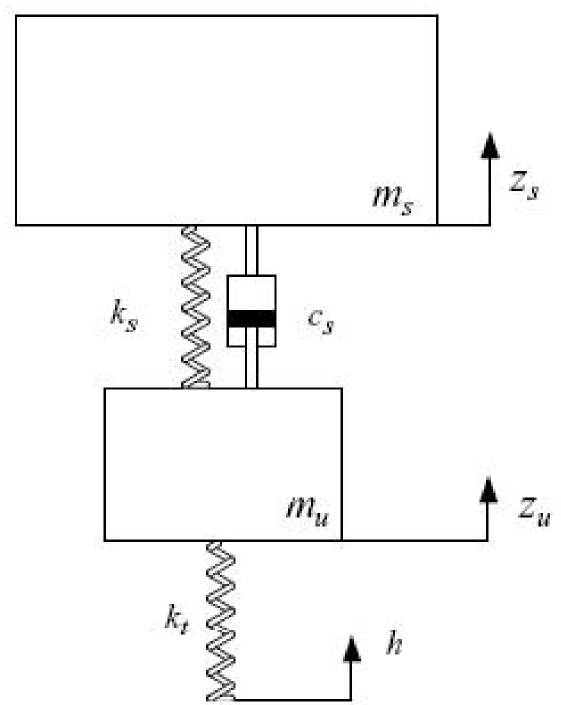




Terrain Characterization

Vehicle Simulations

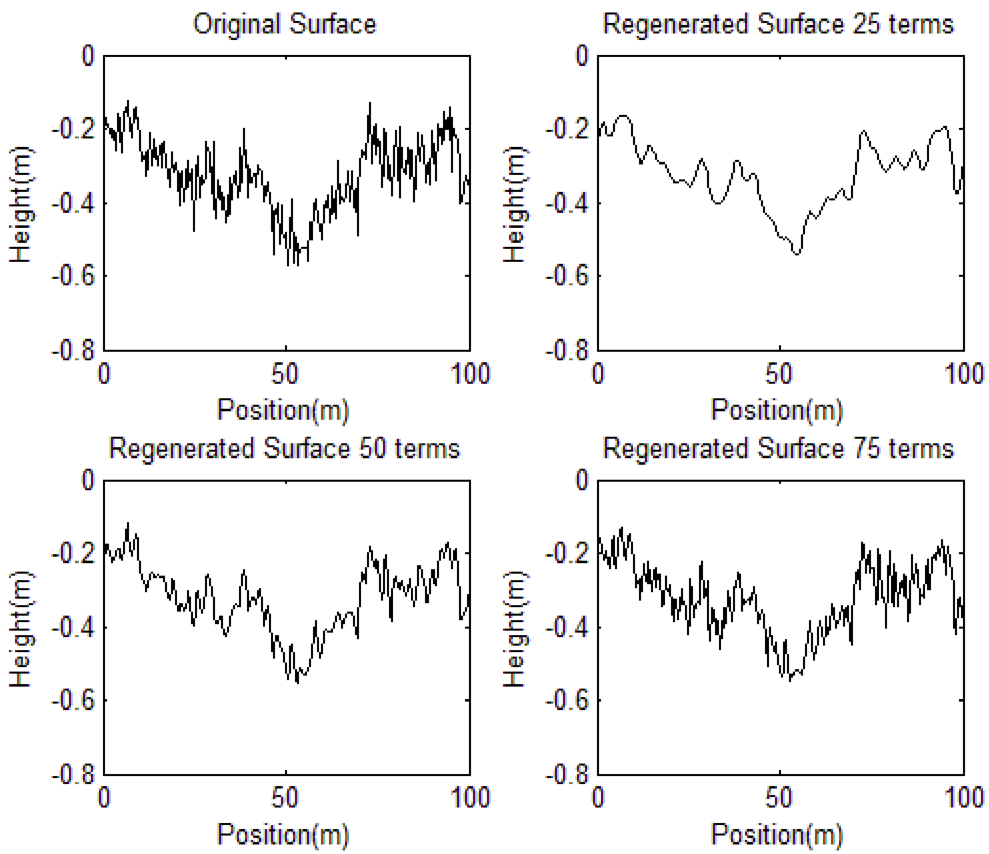
- Matlab/Simulink Quarter Car Model
  - Simple models to help better understand the effect of the terrain on the vehicle
- Carsim
  - More sophisticated models will ultimately be used to capture effects such as pitch and roll



Terrain Characterization

Fourier Transform

- Can be used to generate a simplified terrain
- Take FFT then take the IFFT with a limited number of terms

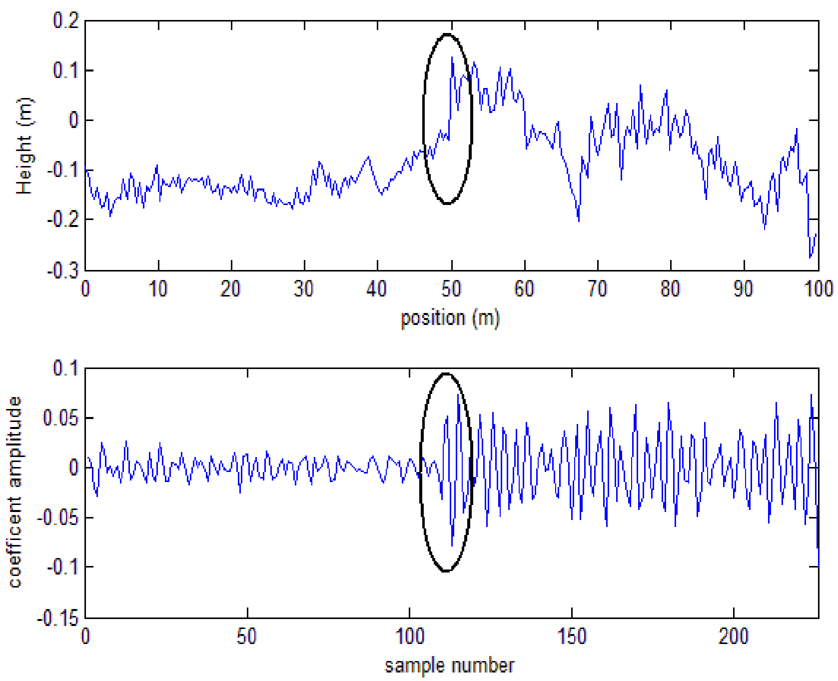


Terrain Characterization

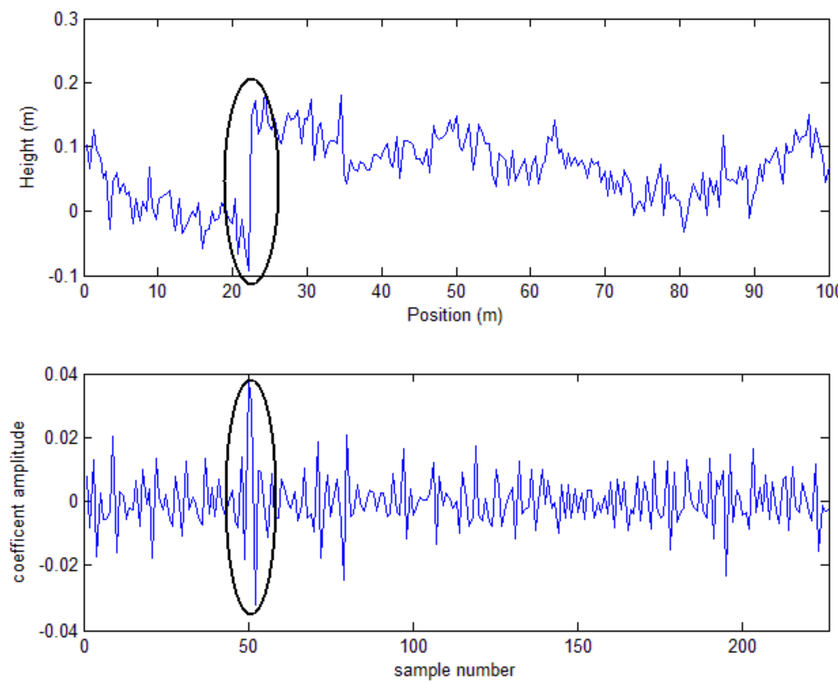
Wavelet transform

- Analyzes the profile at a resolution matched to each scale
- The high frequency components can be extracted to detect discontinuities and changes in roughness

Terrain Profile with a change in roughness



Terrain Profile with a step increase



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Prowler UGV

Vehicle – Prowler ATV

Power Train : Fully Automatic Transmission with Limited Slip 4WD, 4WD Diff Lock, and 2WD

Construction : Sealed Tubular Structure with Chrome-Moly Roll Cage and Cargo Racks

Top Speed : 63 mph (4WD, Hi Range)

Suspension : Independent Double Wishbone with Adjustable Preload Reservoir Shock Absorbers

Payload : 1000 lb (1+ : 1 payload to weight ratio exclusive of crew)

Towing Capacity : 2250 lb (terrain dependent)

Prowler ATV Automation

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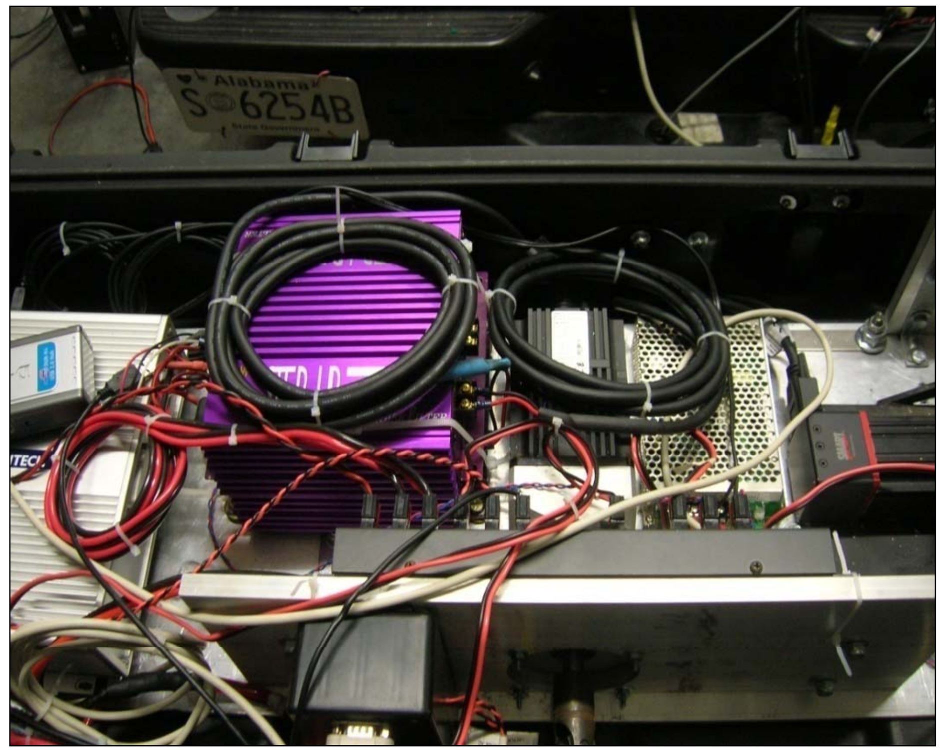
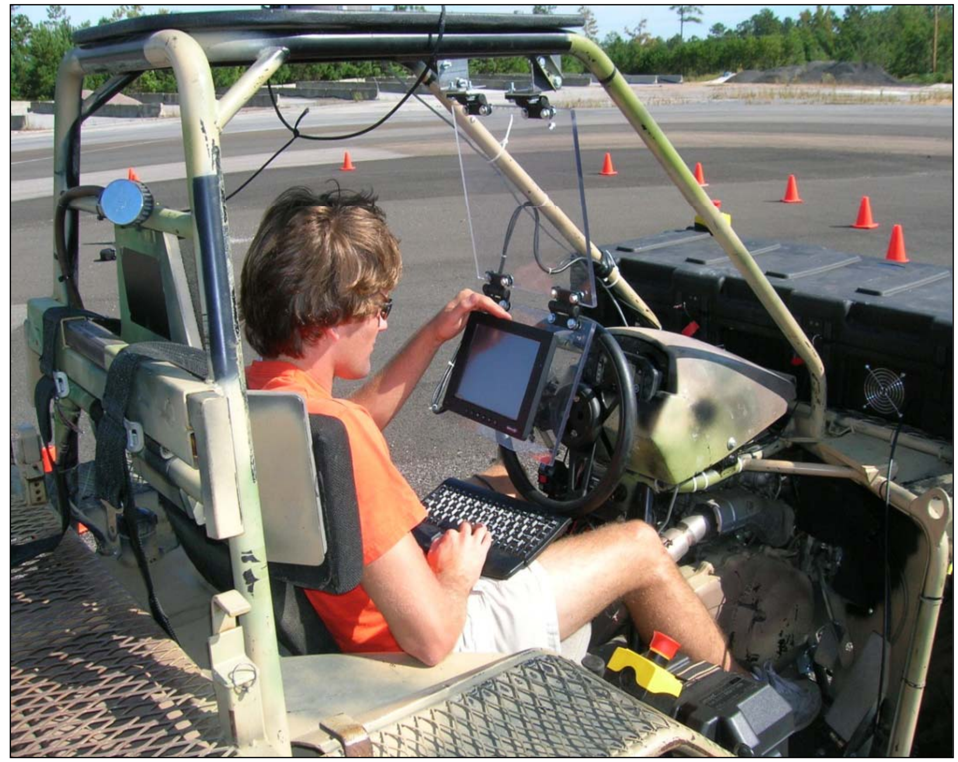
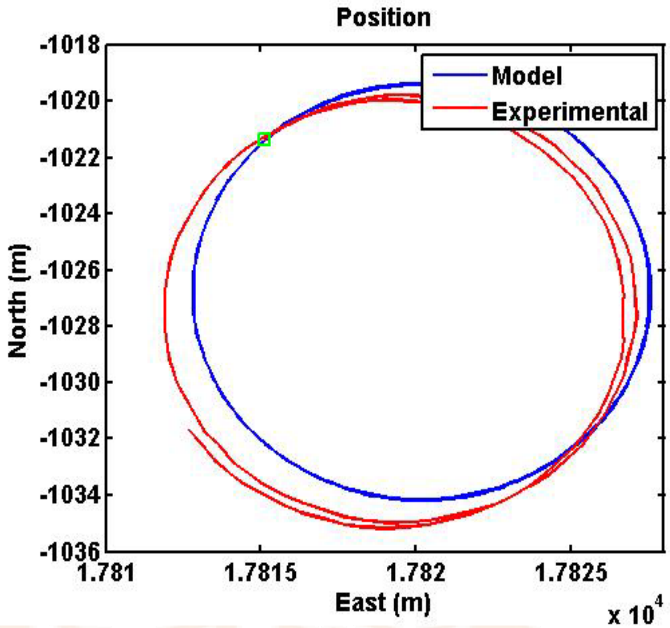


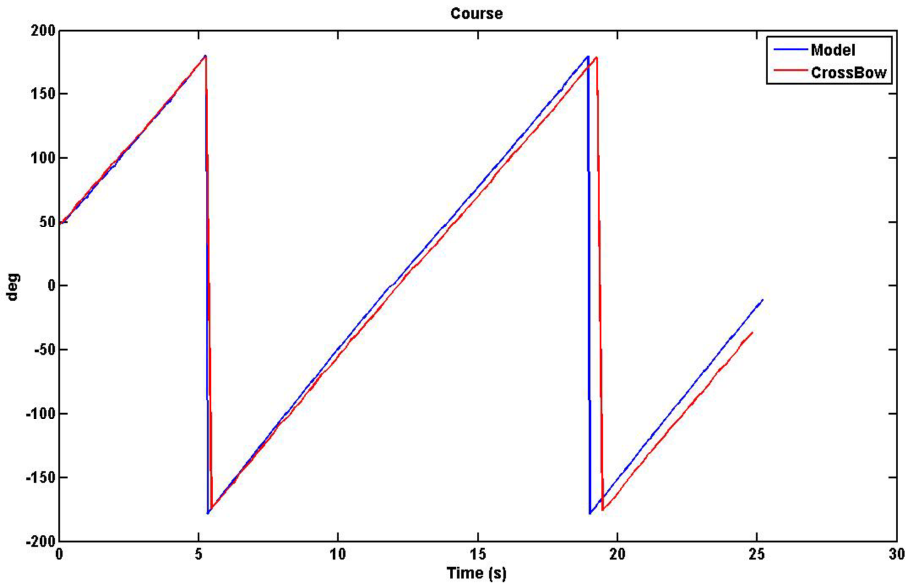
Prowler Autonomous Control

- Generate desired Waypoints manually
- Create output waypoint file
- Use heading error, yaw rate error, and velocity error to create desired steer angle and throttle position



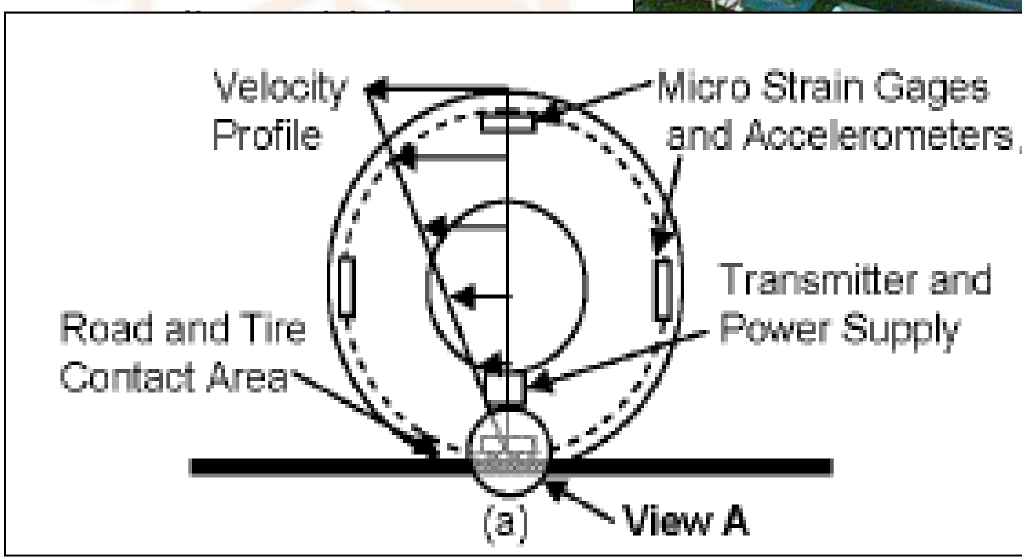
Model Validation



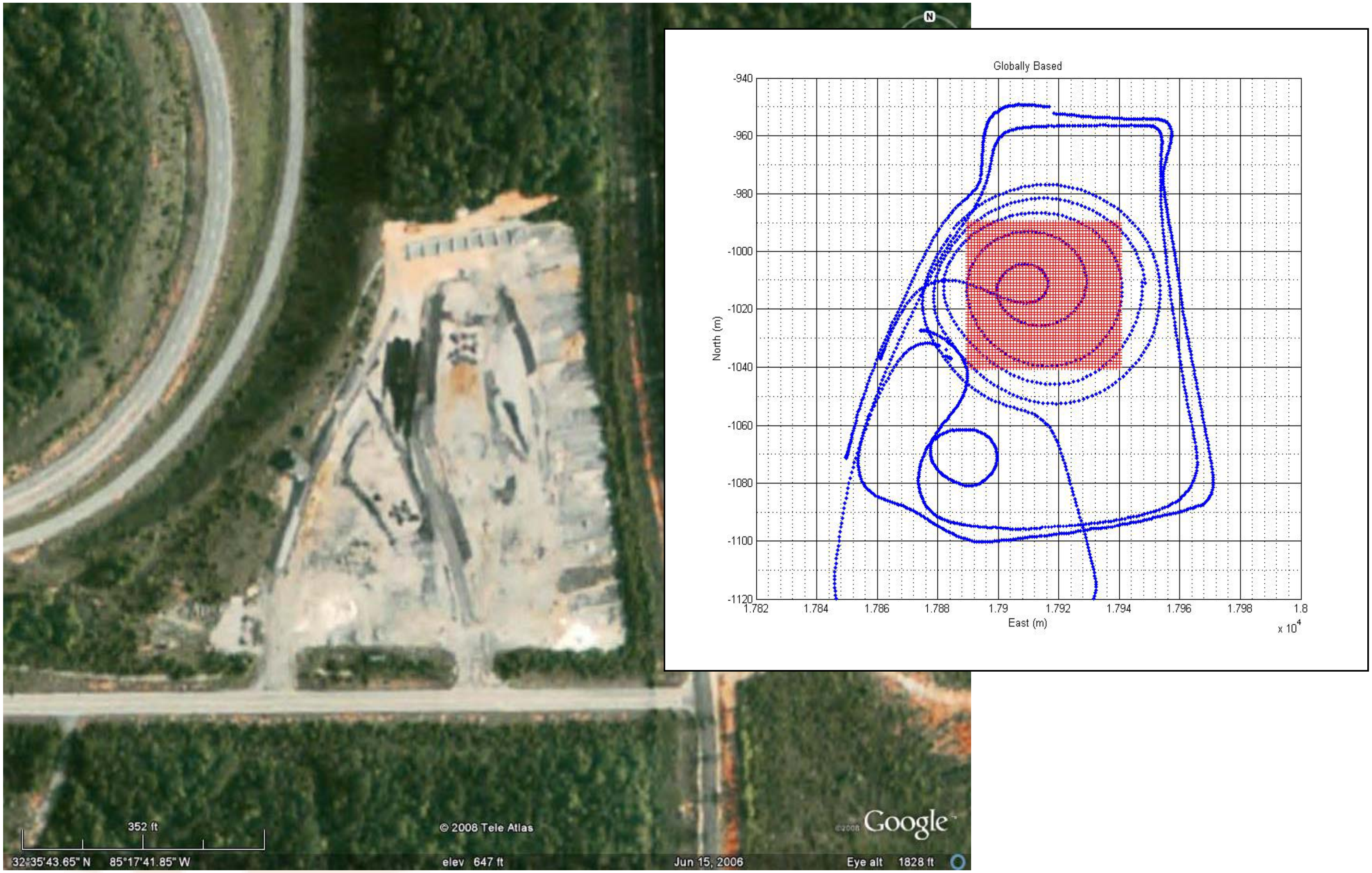


Tire Test Stand

- Strain Gauges mounted along inner tire surface
- Wireless Data transmission module
- Ability to monitor and model tires more accurately and provide valuable information to



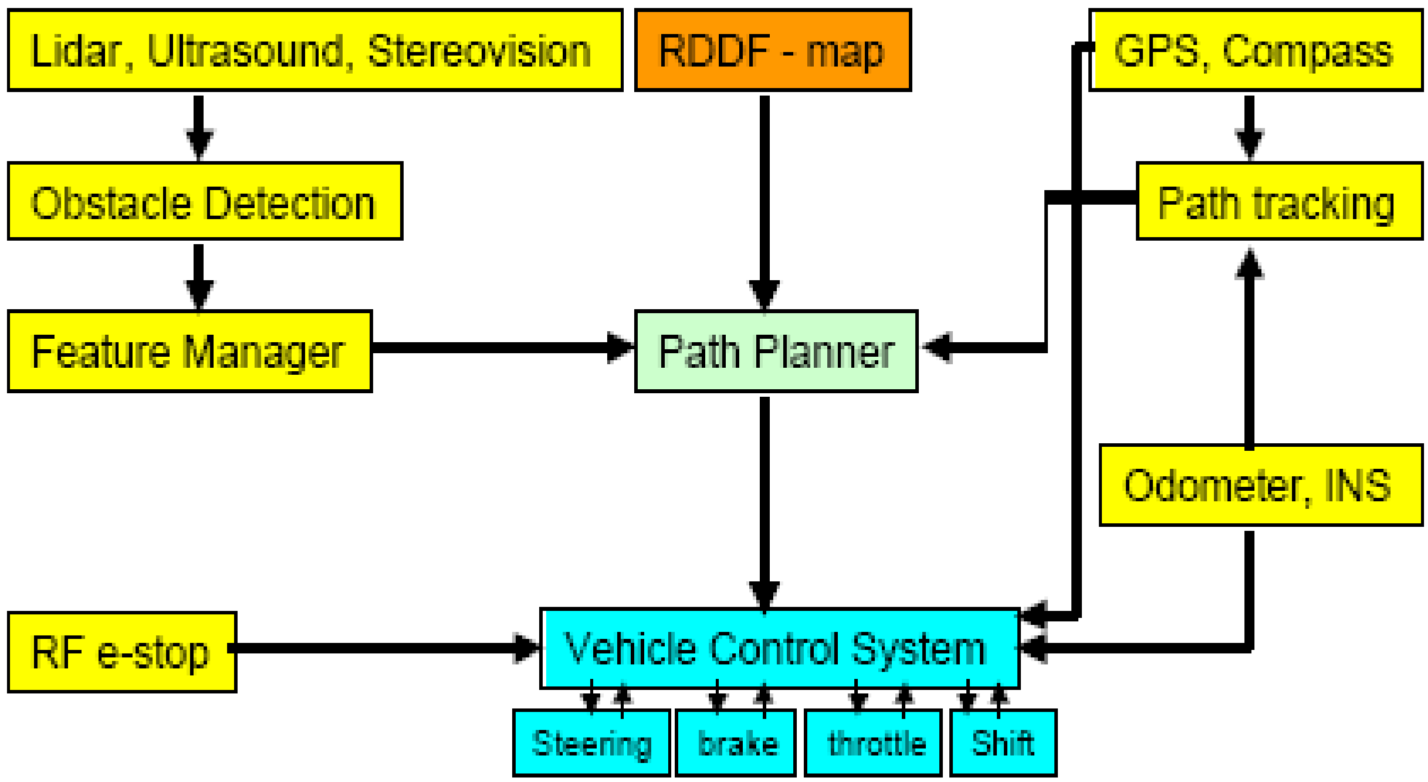
Experimental Test Grid



UGV Fault Diagnostics / Health Monitoring

- Corporate Partner:
  - *Global Technology Corporation (GTC), Atlanta, GA*
- UGV Platform – Prowler ATV
  - Automated and maintained by the Auburn University GAVLAB
- Tire Pressure System (TPS)
  - Wireless sensor network that transmits temperature and pressure from inside of the tire to the primary vehicle computer
- Goal: Fault Diagnostics / Mission Planning
  - Path Planning
  - Vehicle Modeling
  - Automation
  - Online Vehicle Monitoring

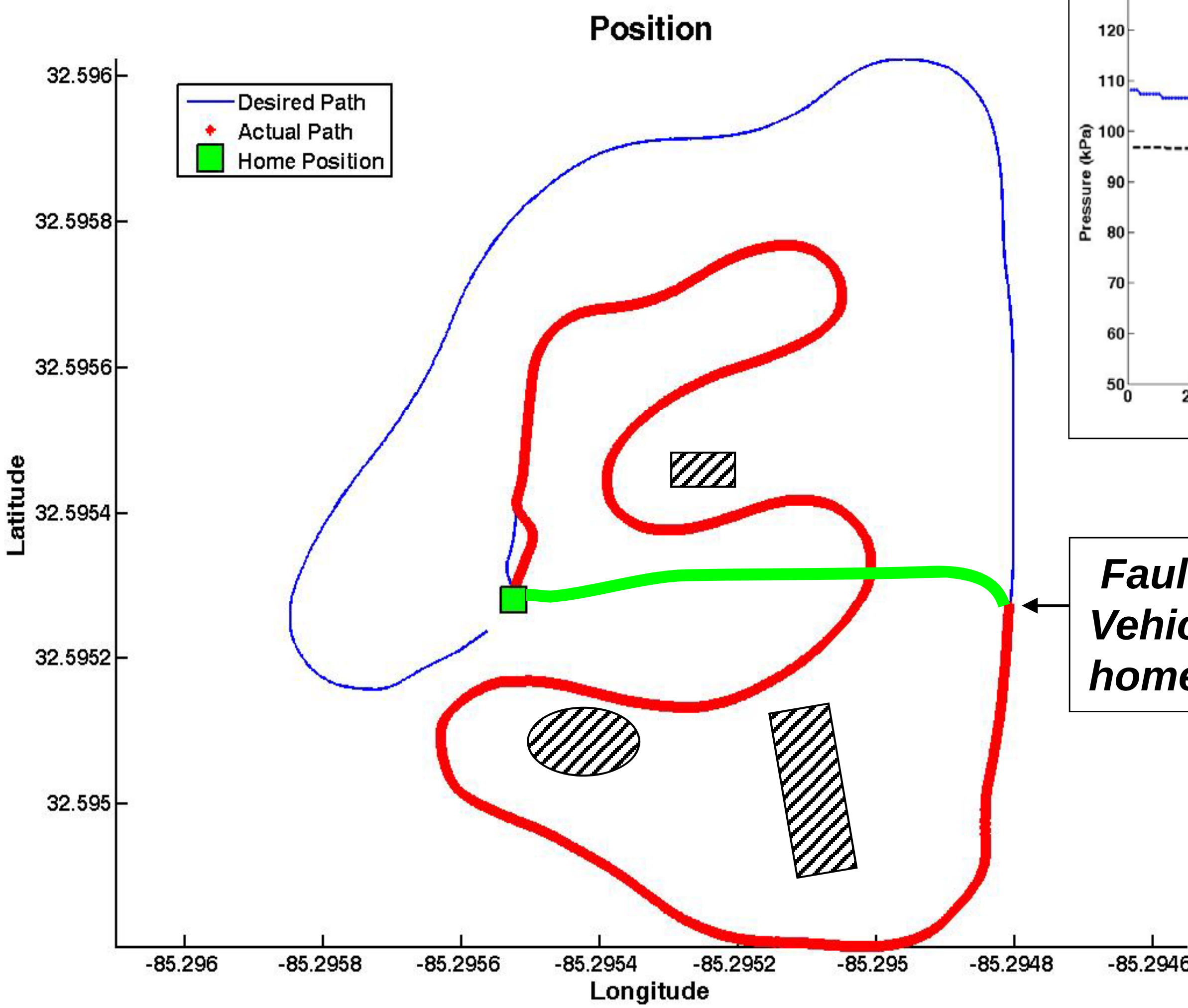
Fault Tolerant Control with Goal Modification

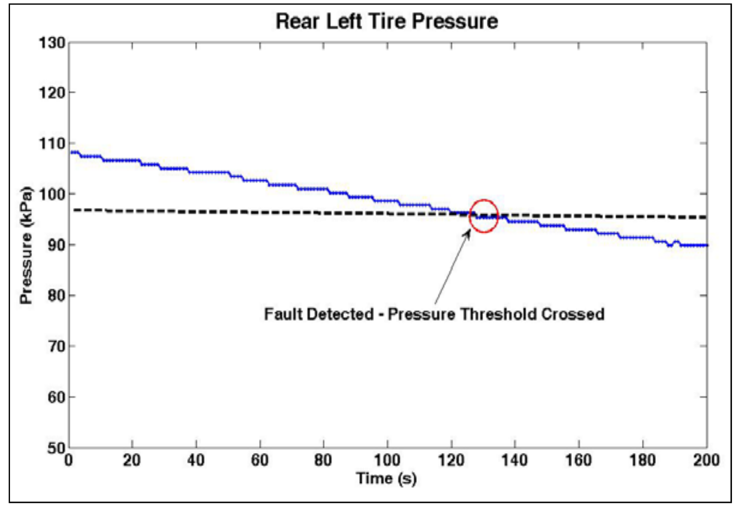


The purpose of the goal modification module is to adjust the cost functions of the path planner and the low-level control parameters due to detected and identified failure modes.

UGV Fault Diagnostics – Flat Tire

Work done in collaboration with Globatal





Fault Detected - Vehicle returns to home position

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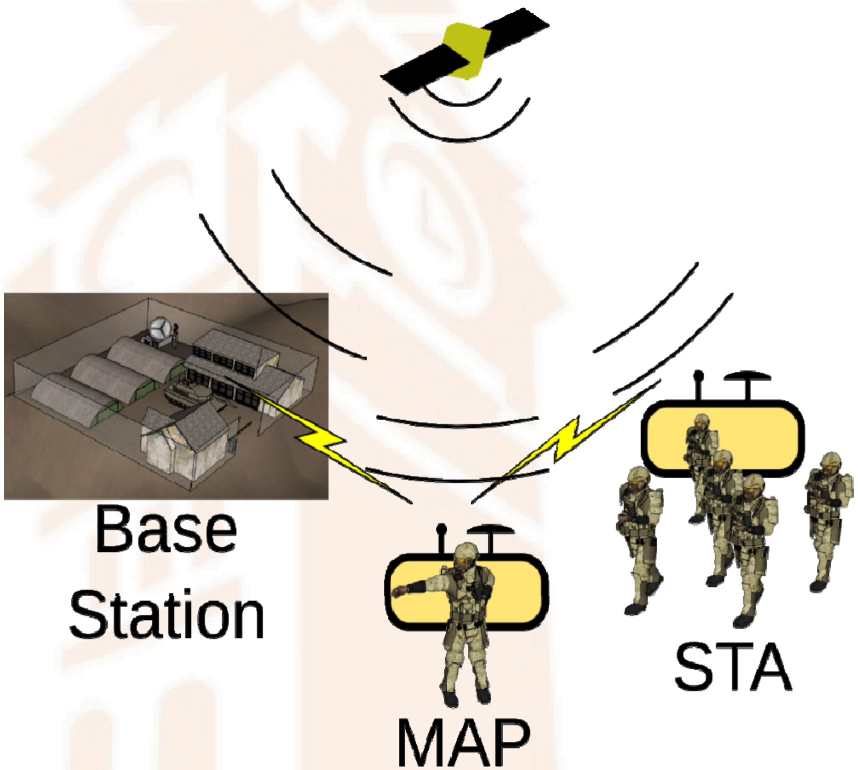
WiFi/GPS Integration

SBIR with IS4S (lead), Auburn, SAIC, and Rockwell Collins

Wi-Fi/GPS Concept Overview

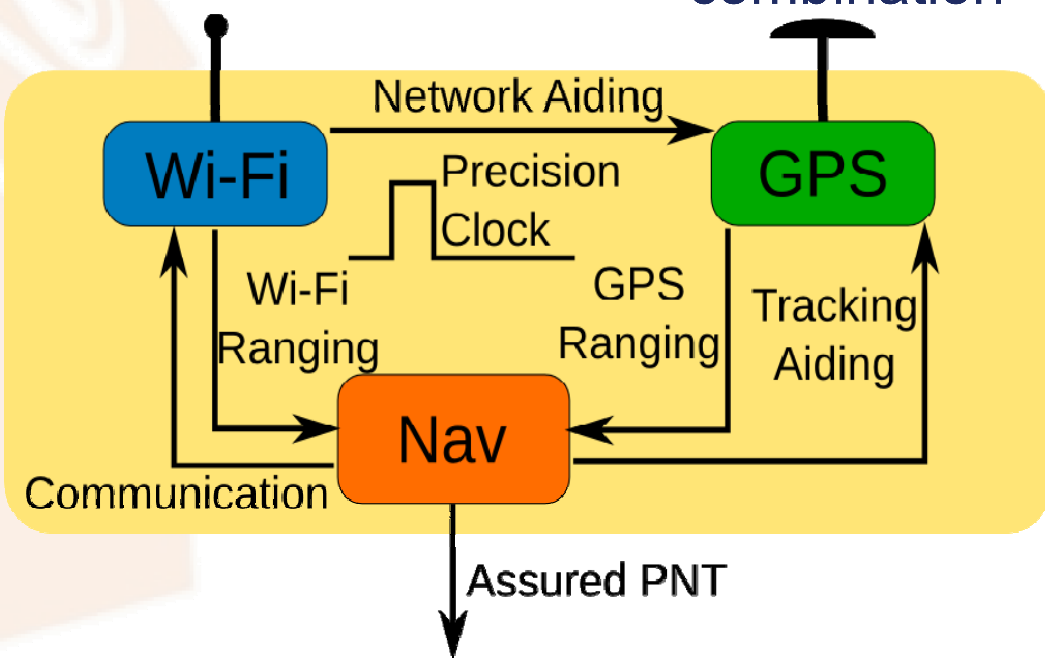
- Ad-hoc networking
  - Assured availability



- Base Station
  - Semi-permanent, surveyed
  - Authentication/GPS servers
- Mobile Access Point (MAP)
  - Squad leader, vehicle, temporary structure
  - Wi-Fi/GPS module
  - Quality Clock
- Stations (STA)
  - Soldiers/tactical equipment
  - Wi-Fi/GPS module

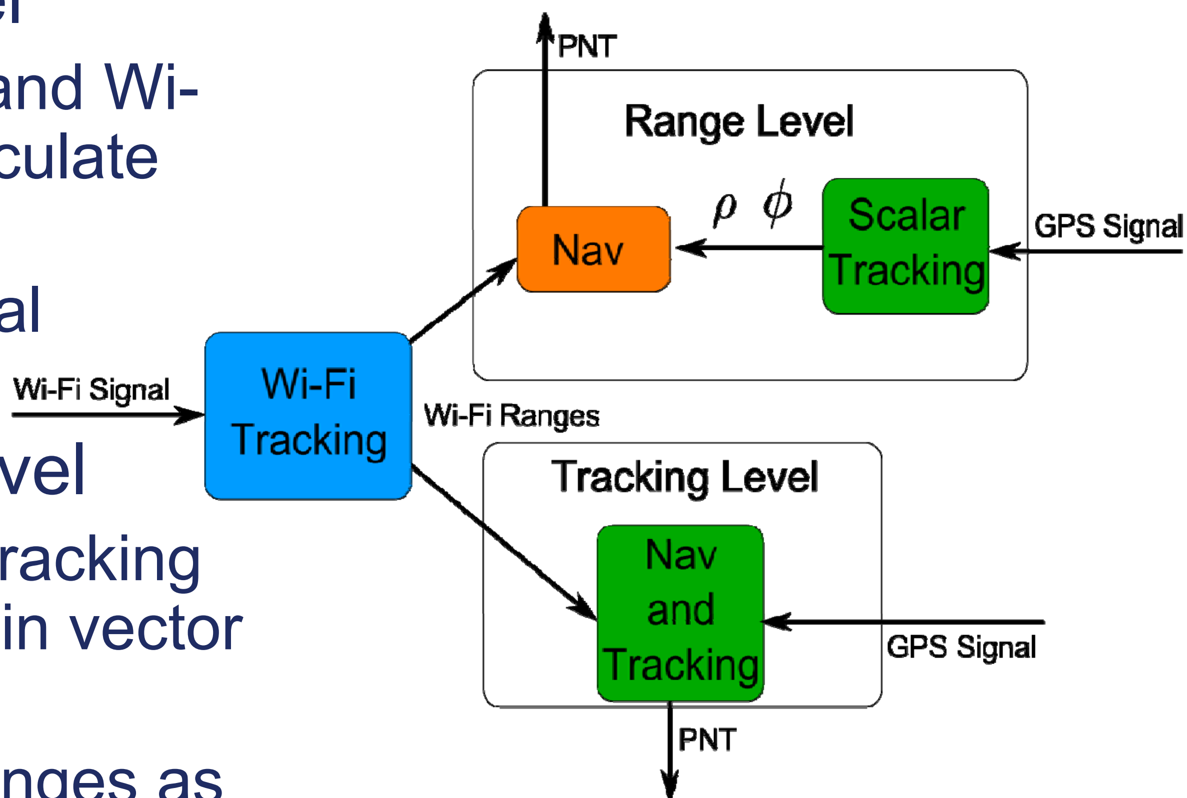
Wi-Fi/GPS Architecture

- Phase II commercial hardware approach (S1)
  - Wi-Fi driver modification
  - Wi-Fi/GPS range level combination
- Phase II custom hardware approach (S2)
  - FPGA Wi-Fi implementation
  - Wi-Fi/GPS tracking level combination



Wi-Fi/GPS Architectures

- S1 - Range Level
  - Combine GPS and Wi-Fi ranges to calculate PNT
  - Uses commercial receiver
- S2 - Tracking Level
  - Combine GPS tracking and positioning in vector formulation
  - Include Wi-Fi ranges as additional measurement to improve PNT and GPS tracking

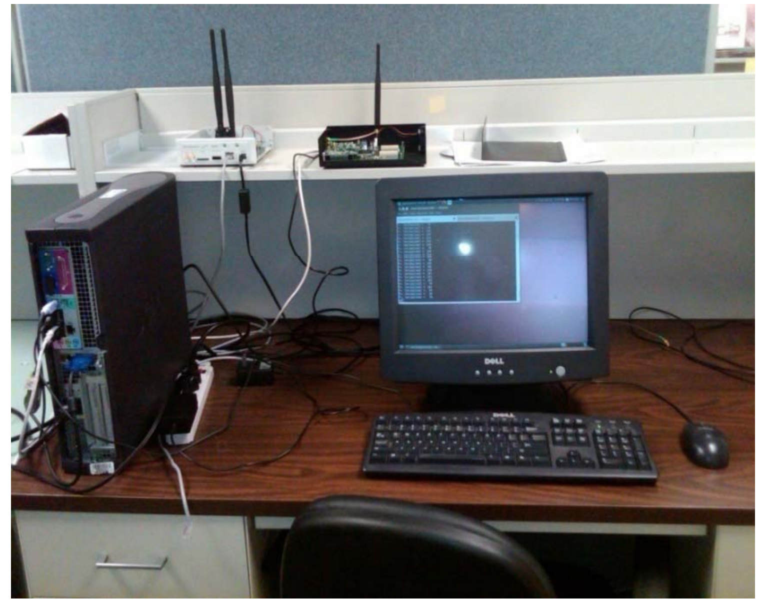


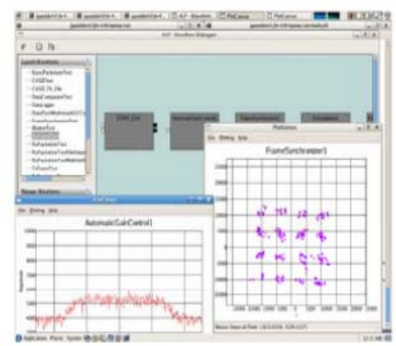
S1 - ToF Variability MAC Driver Conclusions

- Using instrumented Wi-Fi MAC driver by modifying Ath9k drivers, the average ranging error is 25% when computing distances from 50 ft to 250 ft.
- This lower bound error is achieved by averaging a total 10 different runs, each with 100,000 ToF samples
- The benefits of this method is the ability to use standard commercial Wi-Fi hardware
- Possible enhancement to reduce ToF variability is measurement through FPGA and Wi-Fi transceiver hardware monitoring
- Improve results using CSAC (Chip-scale atomic clock) precision timestamps on data and ack packets to compute precise two-way time of flight

S2 - ToF Variability Study w/ GNU Radio/USRP

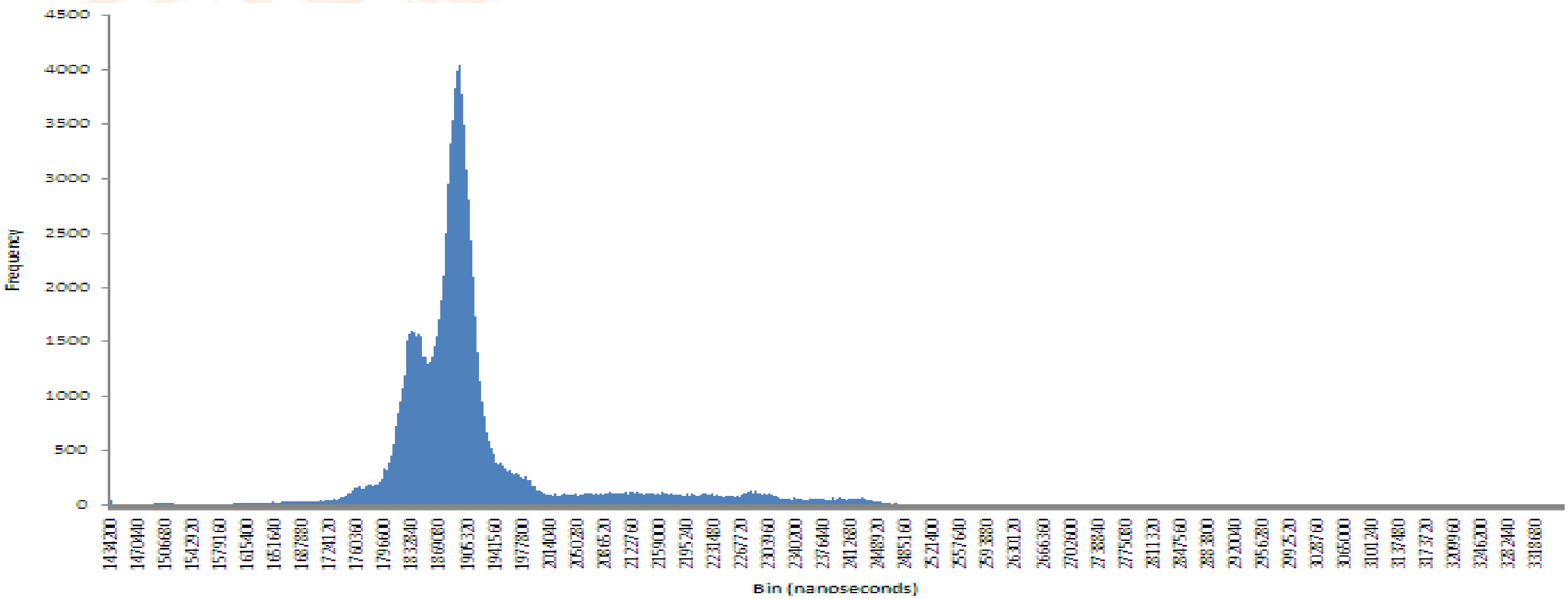
- Improve time-stamping precision per message leveraging the SDR FPGA
- Easily adaptable to alternate spectrum
- Integrate multi-path rejection using per-packet time-of-arrival monitoring
- Integrate navigation & routing in the SDR
- Develop a network publish and subscribe message passing capability
  - For example multicast message sharing
- Use network connectivity to aid GPS receiver initialization
- Integrate Wi-Fi ranges into software GPS receiver to aid PNT solution formulation and increase tracking performance





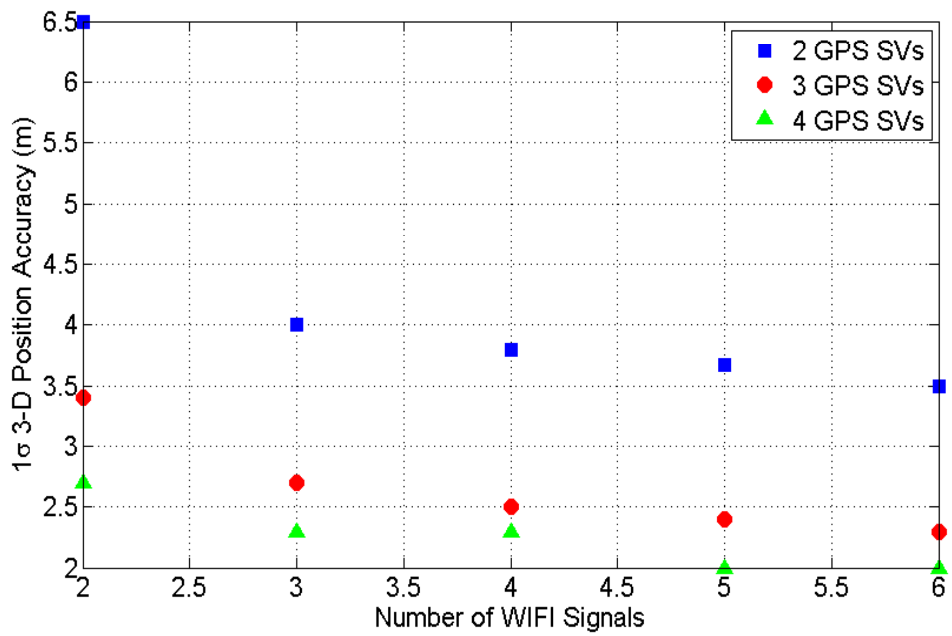
S2 - USRP1 Delay Conclusions

- Multiple packet reception, for two USRP1’s in a lab environment
  - 20 feet apart and 0 foot apart
- Delays measured at the USB port, histogram with bin size 60 ns
- Measured over 1 million packet transmissions ➔ error is 10.9 m
- Acquired two USRP2 with large FGPA space, to implement timestamping and TOF measurement in FPGAs

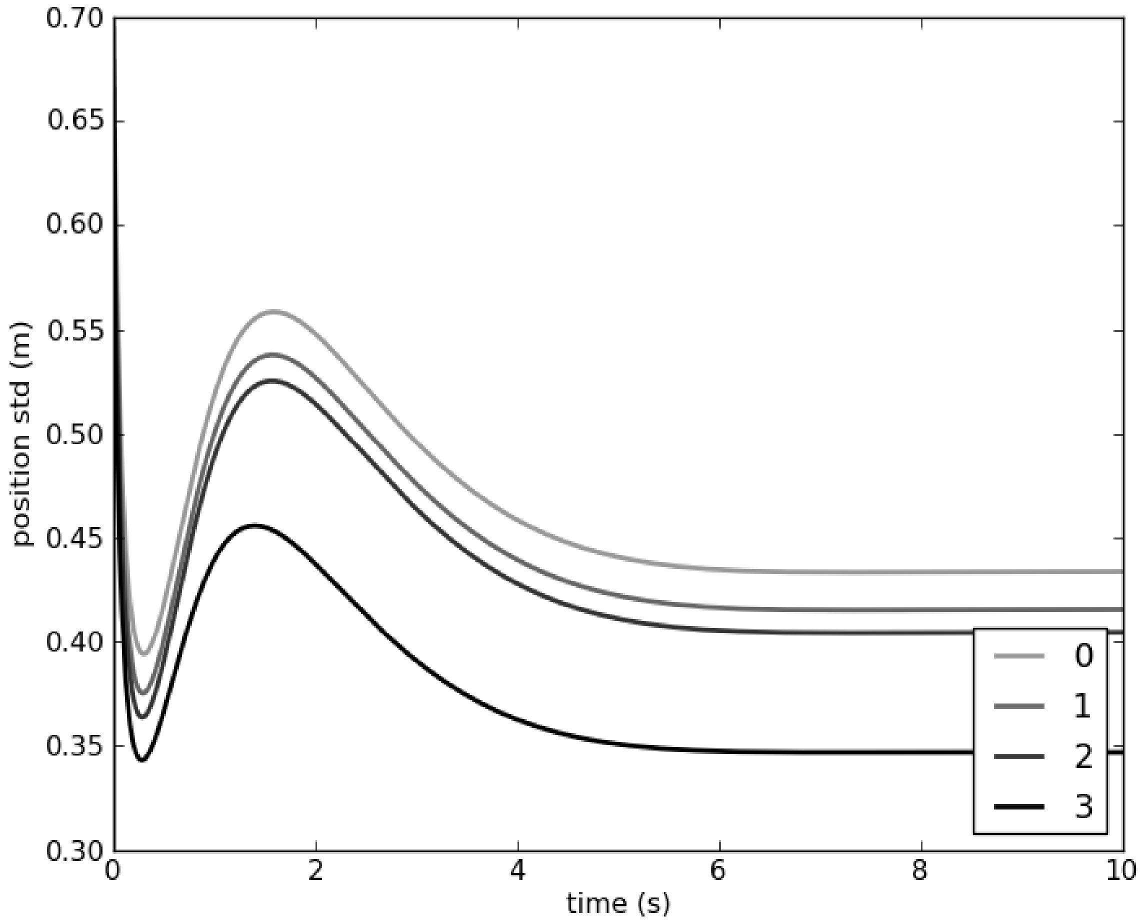


S1 Range Level Performance

- Expected performance shown from simulation
  - GPS 1σ error of 1 m
  - Wi-Fi 1σ error or 5 m
  - Note as more GPS satellites are available, the accuracy depends less on the number of Wi-Fi signals
- GPS Simulator simulated GPS and Wi-Fi range errors
  - Simulator will be modified in Phase 2 to integrate the signals



S2 Simulated Performance



Positioning accuracy increases with more Wi-Fi nodes

- Plot shows number of Wi-Fi nodes and expected variance
- Improves positioning and GPS tracking
- Benefit from additional measurements and improved geometry

Wi-Fi/GPS Future Work

- Real-time implementation
  - GPS software receiver with additional range measurements
  - Modified Wi-Fi driver testbed
  - Custom Wi-Fi radio system
- Error and benefit analysis for both proposed systems
- Demonstration of integrity with both data and measurement errors
- Extend to additional ranging sources
  - Signals of opportunity