Auburn's Next Generation Vehicle Positioning

Principal Investigator
David M. Bevly
dmbevly@eng.auburn.edu

Researchers
Jordan Britt, Scott Martin, Chris Rose

GPS and Vehicle Dynamics Lab
Auburn University

Project Overview

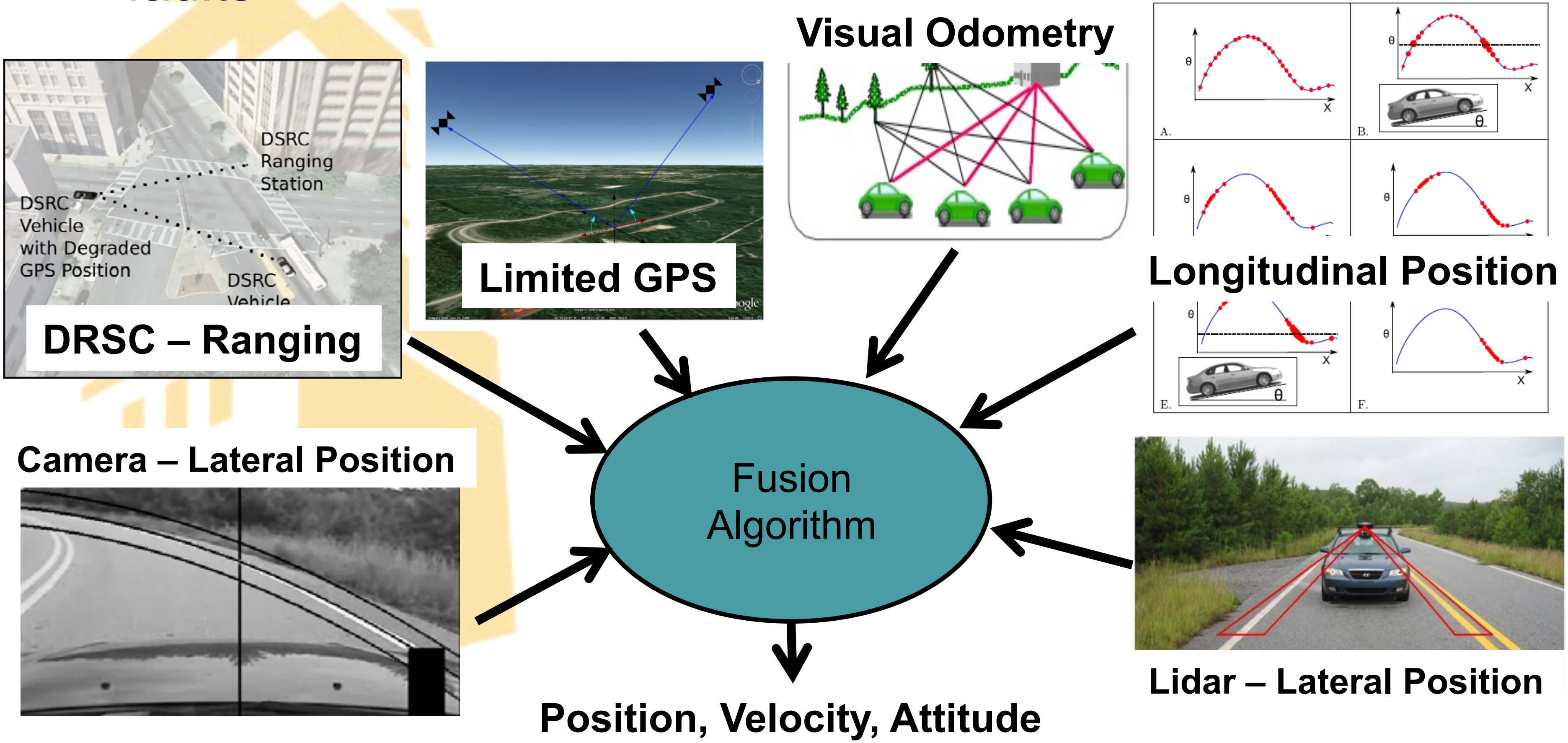
- Objective – Provide ubiquitous precise positioning supporting vehicle safety and automation in presence of GPS degradation
- Partners – Auburn University, Kapsch TrafficCom, Penn State University, Stanford Research Institute
  - Automotive Advisory Panel
- Project Scope – Assess diverse positioning and data-fusion techniques, characterize achievable accuracy and robustness, test and demonstrate capabilities on test track and roadway scenarios

Presentation Overview

- Technical Approach
- Subsystem Overview & Evaluation
- Integration Overview
- Testing Results: Detroit
- Testing Results: NCAT
- Testing Results: Turner Fairbank
- Conclusions & Future Work

Technical Approach

- Technical Approach – Fuse outputs of various positioning technologies in an extended Kalman filter exploiting accuracy/uncertainty and mitigating subsystem faults

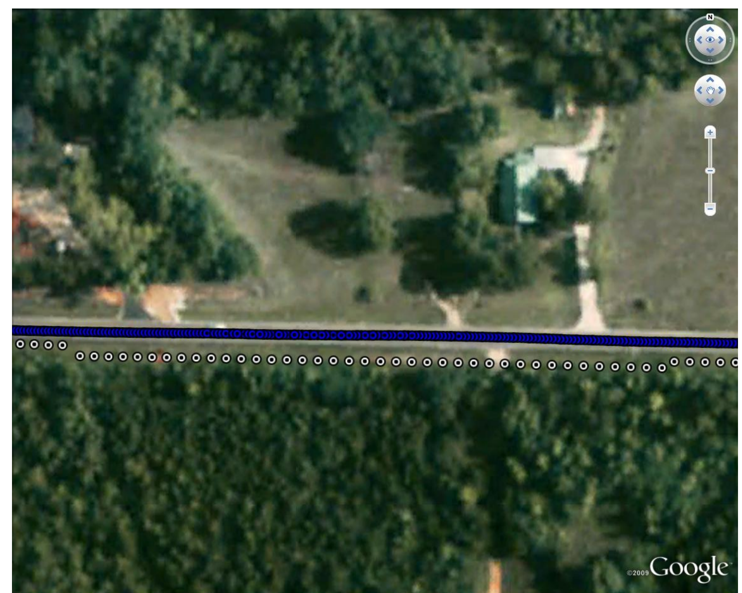


Subsystem Analysis Criteria

- Cost
- Availability
  - Near term
  - Long term
- Six DOF Position
- Three DOF Position
- Drifting Solution
- Infrastructure Requirement
- Map Requirement
- CPU Requirement
  - Minimal
  - Intensive
- Environmental Influences
  - Foliage
  - Urban Canyons
  - Weather
  - Lighting

GPS / INS Navigation

- GPS provides global position solution anywhere there is clear line of sight to four or more SV
- IMUs output at high rates
- Inertial measurements are used to smooth jumps in GPS positions
- IMUs can be used to dead reckon during a GPS outage
- INS solution degrade with time but are corrected by GPS
- GPS fault detection improved by INS solution



GPS / INS Limitations

- Achievable standalone positioning accuracy limited to standard deviation on the order of meters
- INS solution drifts unbounded in GPS denied environments (heavy foliage, urban canyons)

Subsystem Capability Analysis Matrix

		Cost	Current Availability	Six DOF Position	Three DOF Position	Drifting Solution	Infrastructure Requirement	Map Requirement	CPU Requirement	Environmental Influences
GPS		✓ (yellow)	✓ (green)	✗ (red)	✓ (green)	✓ (green)	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)
INS		✓ (green)	✓ (yellow)	✓ (green)	✓ (green)	✗ (red)	✓ (green)	✓ (green)	✓ (green)	✓ (green)
Wheel Speed		✓ (green)	✓ (green)	✗ (red)	✓ (yellow)	✗ (red)	✓ (green)	✓ (green)	✓ (green)	✓ (green)
PSU-Road Fingerprinting										
AU-LDW	Lidar									
	Camera									
SRI-Visual Odometry										
Kapsch-Gantry										

✓ (green)	No concern, current system capabilities not affected by criterion
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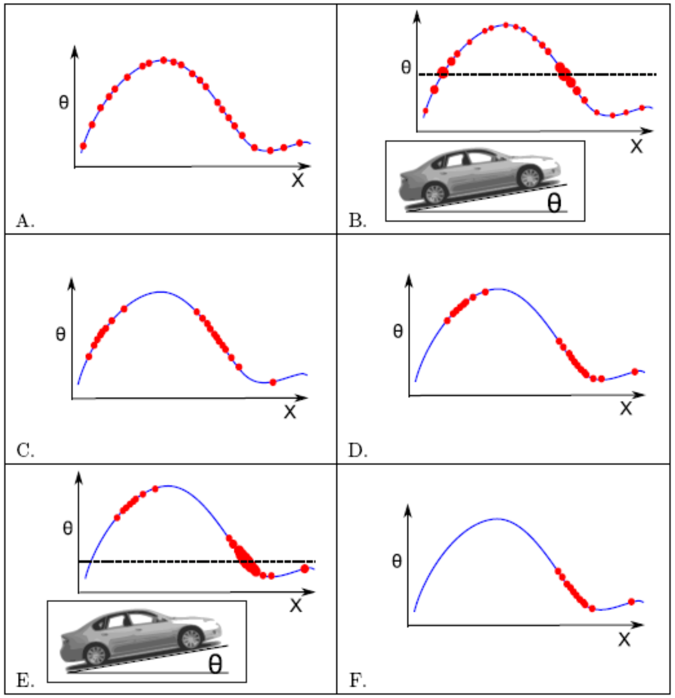
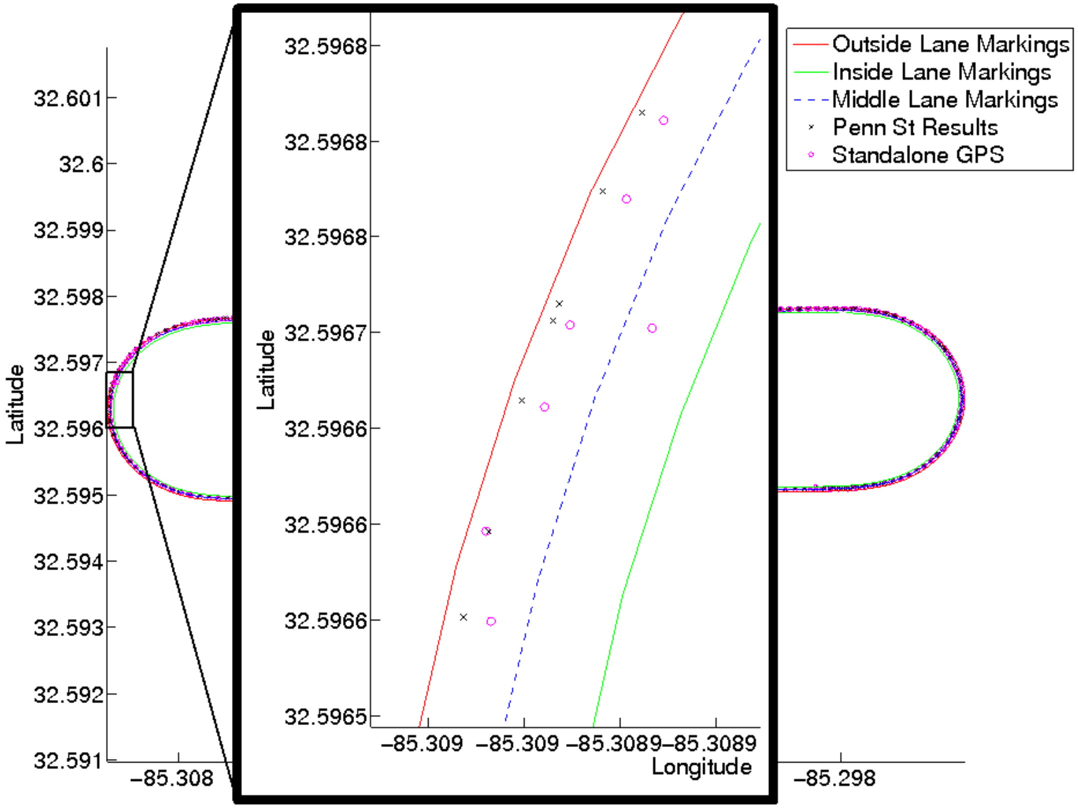
PSU – Road Fingerprinting

- Concept – Use pitch gyro, wheel odometry, and map of pitch signal from previous road survey for positioning.
  - Map created by driving with high grade IMU and RTK GPS
- Hardware – Pitch gyro, wheel encoders
  - Mostly on current automobiles
- Incentive: Continuous availability (provided road is mapped)
- Disadvantages arduous survey process (large amounts of data)

PSU – Road Fingerprinting

- Results – Average error compared to RTK GPS approximately 0.75 - 1m
- Lane level accuracy (horizontal error < 1.5m) over 80% of time on average
- Lack Road Network





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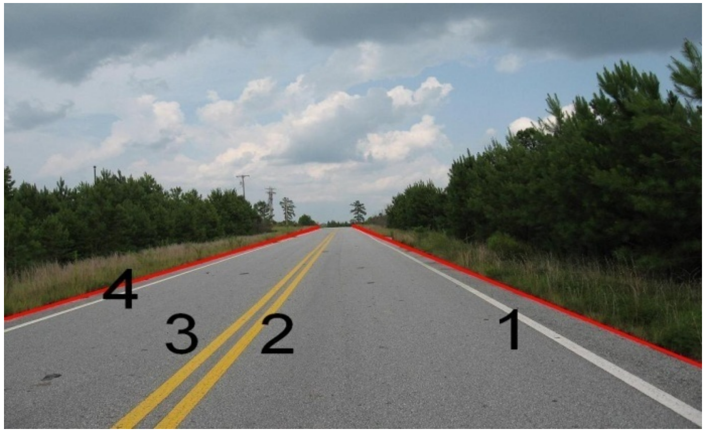
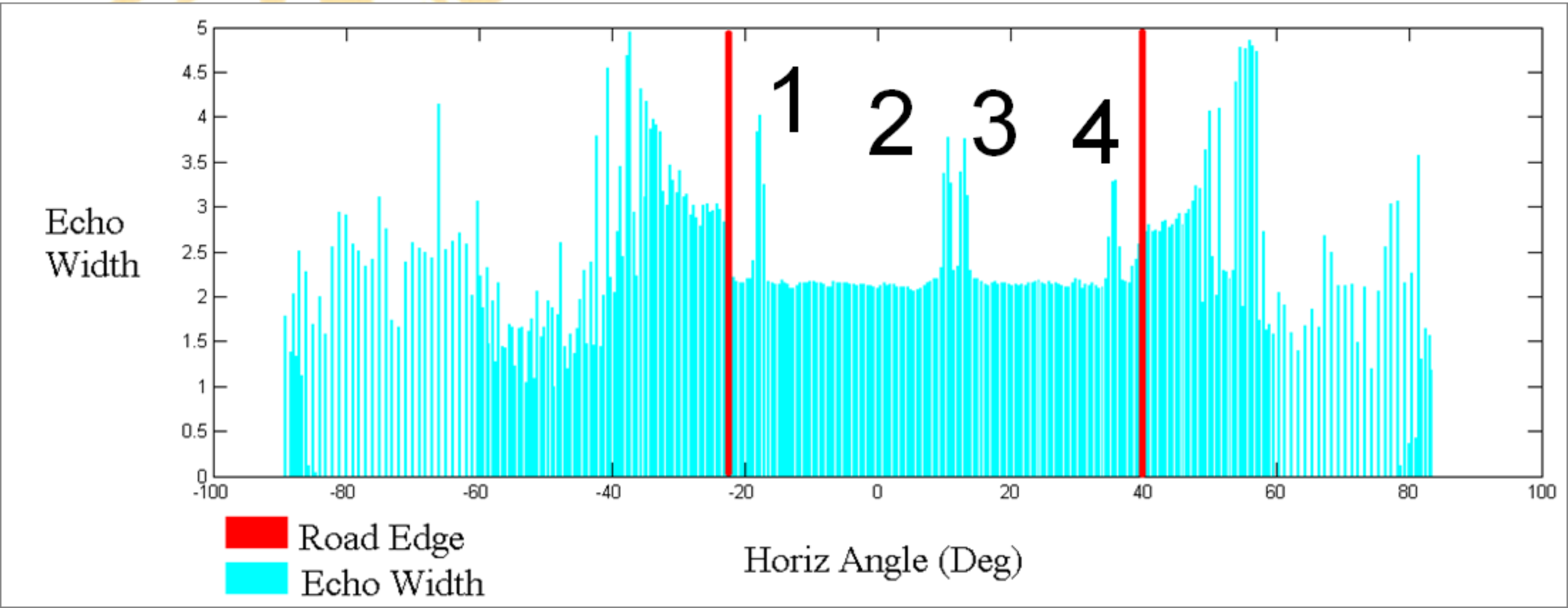
Why Lane Detection?

- If combined with map, it will provide additional lateral position accuracy.
  - Increases lane level positioning
  - Need to know which lane vehicle is in
- Sensor already on some vehicles
- Typically provide high coverage for low cost
- Wanted to compare different types of LDW sensors

Lidar Base Lane Detection Premise

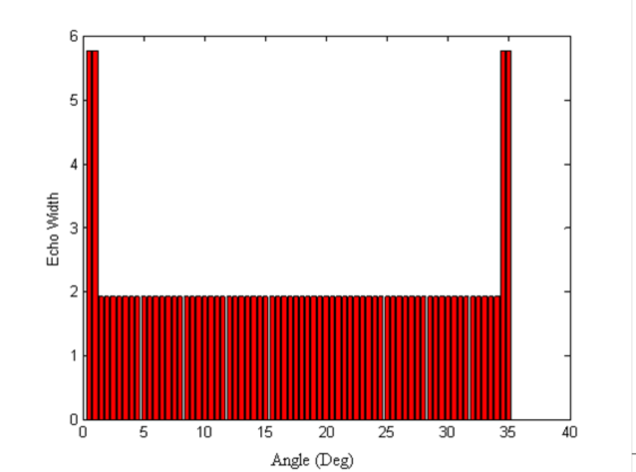
- Lane Markings are more reflective than road surface
- Detect Peaks in reflectivity
- Analyze results for various weather and road conditions

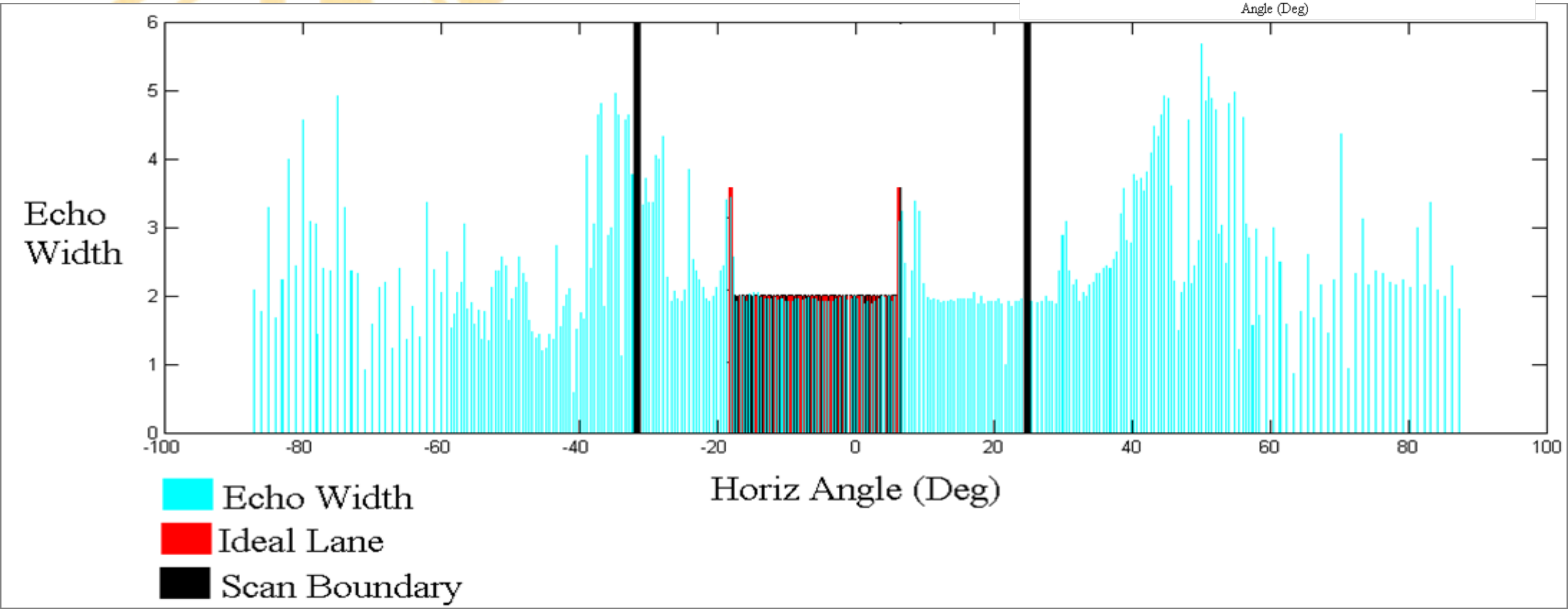




Lidar Base Lane Detection Overview

- Bound Scan Data
- Find minimum RMS error to model
- Check for false positive
- Filter data and weighted averaging
- Final Position

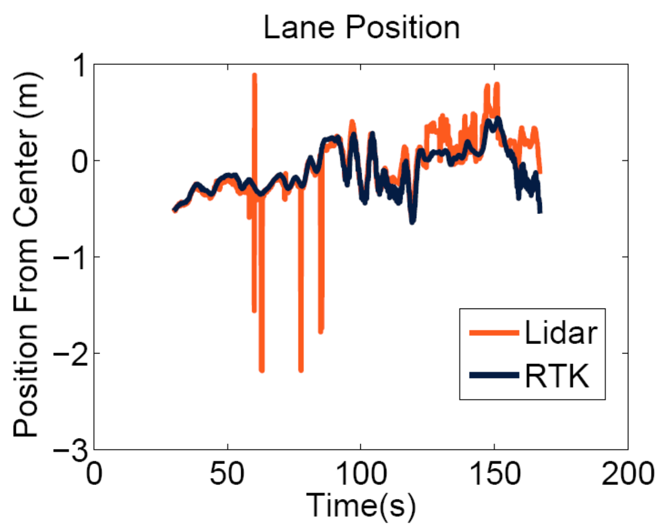




Lidar Base Lane Detection Results

Scenario	MAE (m)	MSE(m)	σ_{error} (m)	%Det
Noon Weaving	0.1818	0.1108	0.3076	98
Dusk 45mph	0.0967	0.0176	0.1245	100
Rain (Medium)	0.1046	0.0177	0.1314	65
Low beam Night	0.0966	0.0159	0.1215	99

	Avg. Lane Width Error (m)	Std of Error (m)	Detection (%)
Highway	0.075	0.233	94.7
Yellow & White	0.042	0.272	81.7
Gravel on Surface	0.129	0.215	97.4
Grass Bordering	0.169	0.329	76.86



Lidar Based Road Edge Detection

- Utilize both distance and reflectivity estimation
- Use a derivative filter to accentuate changes in height or reflectivity
- Select peaks based on a dynamic threshold based on the current road
- Bound, filter, and compare height and reflectivity results before reporting a result

Road Edge Detection Results

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- Tested on County Roads with no outside lane markings
- Day and Night testing
- Data was Post Processed
- Errors are derived from estimating lane width

	Average Error	Std of Error	% Detection
Day	7.6cm / 3in	16.1cm / 6.3in	88.5%
Night	6.7cm / 2.6in	0.13.8cm / 5.5in	91.5%

Subsystem Capability Analysis Matrix

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AU-LDW: Lidar	✓ (yellow)	✓ (yellow)	✗	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (yellow)
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SRI-Visual Odometry									
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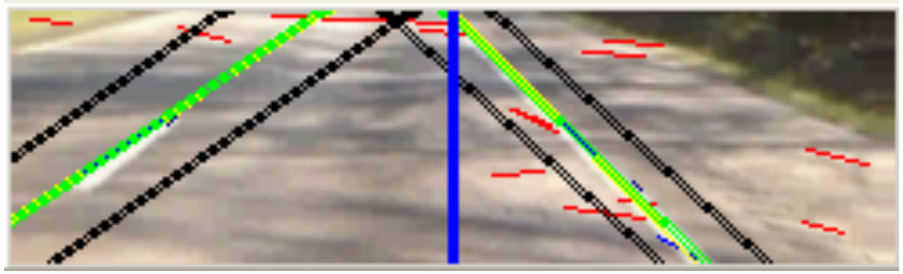
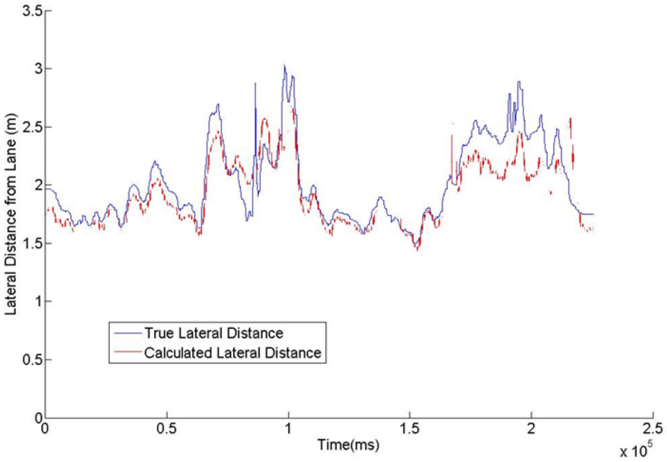
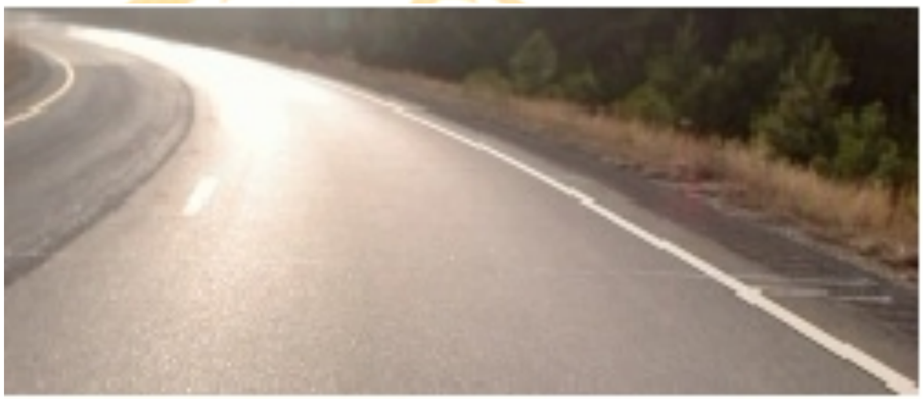
Camera Lane Detection



- 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
  - Lane line checking



Performance in Difficult Environments

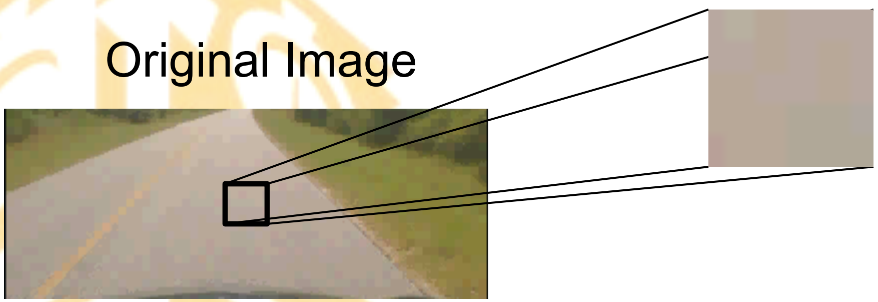


	Dusk	Night	Rain Dusk	Rain Night
Average Absolute Error (m)	0.2379	0.0307	0.0327	0.0512
RMS Error(m)	0.4214	0.0401	0.094	0.1253
std of Error	0.3526	0.0402	0.0887	0.1149
var of Error	0.1243	0.0016	0.0079	0.0132
% Detection	0.4801	0.9	0.1808	0.1947

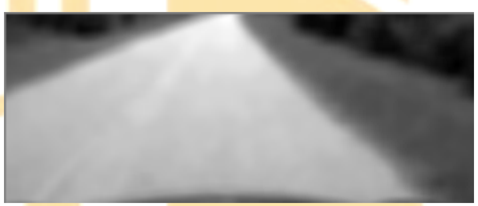
Camera Road Edge Detection

- How do humans determine drivable regions?
  - Color (asphalt vs. grass)
- With a sample of current road surface, the road in the image can be found
- Correlation matching with a sliding window is used to determine a metric for how similar a point in the image is compared with the template

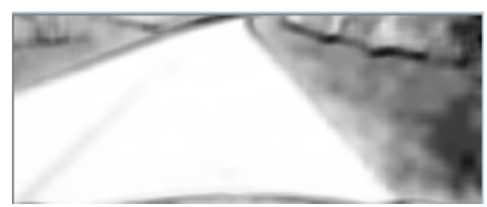
Original Image



Sample (or template) of road



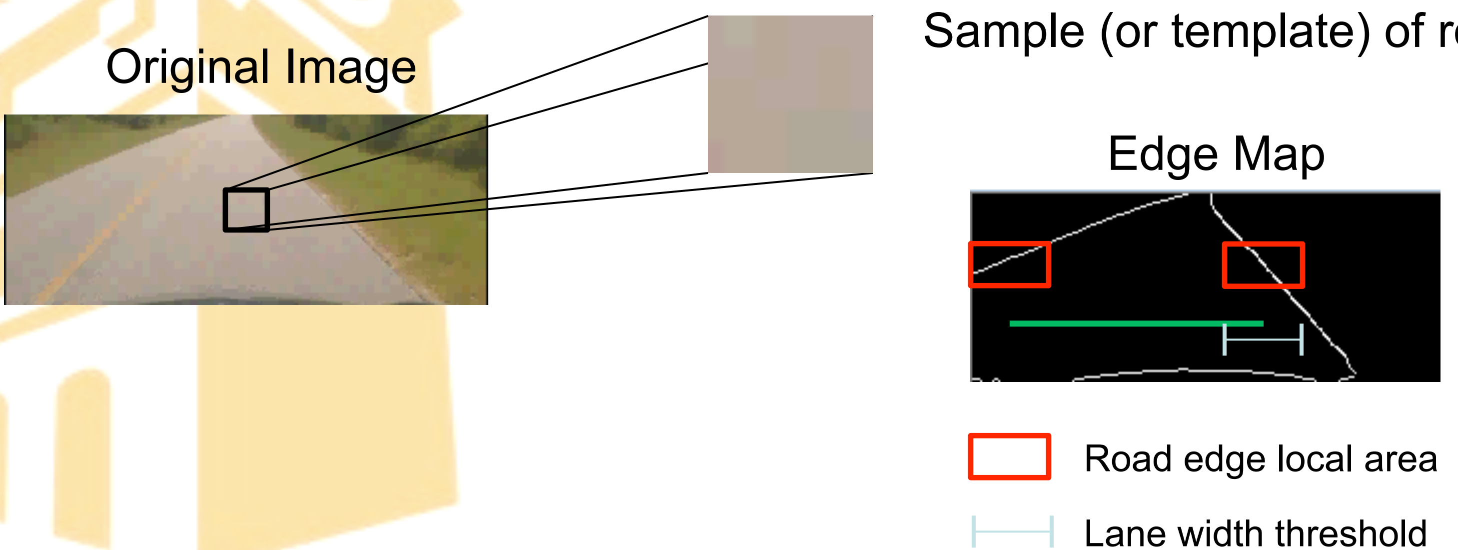
Correlation matching (Unnormalized)



Correlation matching (Normalized) – handles varying lighting

Camera Road Edge Detection

- Thresholding and Canny edge detection
  - Extract the road edges
- Pick out road edges with conditions to reduce erroneous detections
  - Local area
    - Reduces impact of branching roads, driveways, etc.
  - Distance (in pixels) between road edges must be within a threshold of expected lane width
    - Reduces impact of consistent erroneous measurements



Camera Road Edge Detection

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- Kalman Filter
  - 2 states: left and right road edge column location
  - Further reduces impact of erroneous lane measurements from shadows, vehicles, degraded road edge, etc.
  - Actual lane width calculated using precalibrated scale factor

Marked Ideal Image

Marked Unideal Image
Dusk with Heavy Shadows

Red: road surface
Green dot: road edge measurement
Red dot: no measurement
Black circle: road edge estimate (from filter)
Blue rectangle: template (5x5)

Camera Road Edge Detection

- Testing
  - Webcam at low resolution: 240x100 pixels
  - Road width measurement taken far down the road
  - Day and Night
  - Error Sources
    - Tree Shadows (especially at dusk)
    - Headlights (template match problems due to headlight illuminating the road ahead)
    - Driveways, road intersections
- Mean estimates over the course of the run were compared with a physical measurement at the start of the test run

Error	County Road 84	County Road 188	Miss James Road
Day- Average Error	.0706 m	.1043 m	.1704 m
Day- Std. Dev.	.2191 m	.1638 m	.2972 m
Night- Average Error	.0720 m	.1384 m	.0667 m
Night- Std. Dev.	.2780 m	.2253 m	.1574 m

Subsystem Capability Analysis Matrix

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Wheel Speed		✓ (green)	✓ (green)	✗	✓ (yellow)	✗	✓ (green)	✓ (green)	✓ (green)	✓ (green)
PSU-Road Fingerprinting		✓ (green)	✓ (green)	✗	✓ (green)	✓ (yellow)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (green)
AU-LDW	Lidar	✓ (yellow)	✓ (yellow)	✗	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (yellow)
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SRI-Visual Odometry										
Kapsch-Gantry										

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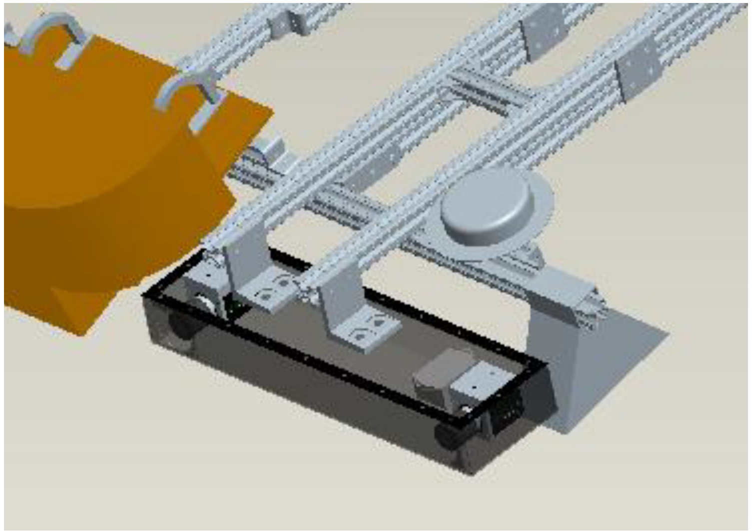
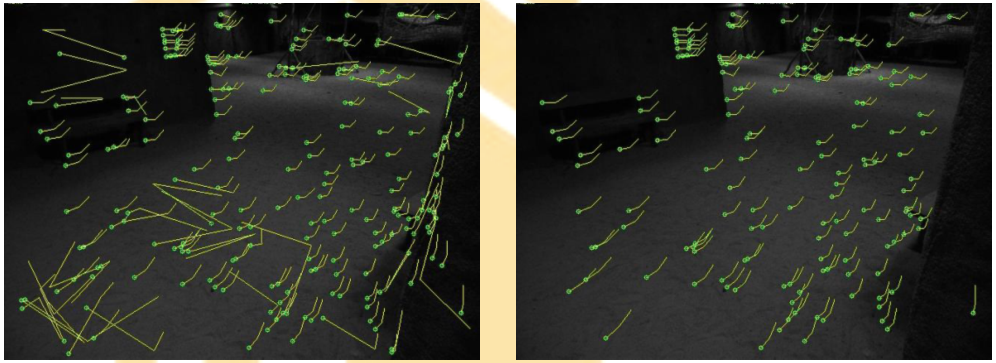
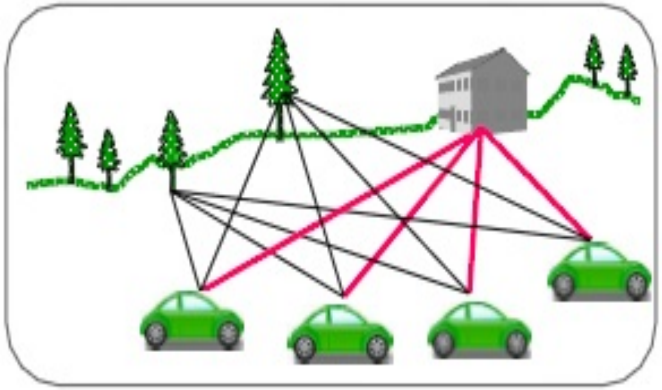
SRI – Visual Odometry

- Concept – Track features image to image and extract ego motion
- Provides local odometry without GPS initialization





Tracking features over 3 frames before and after pruning and outlier rejection



Visual odometry concept

SRI – Sensor Mount

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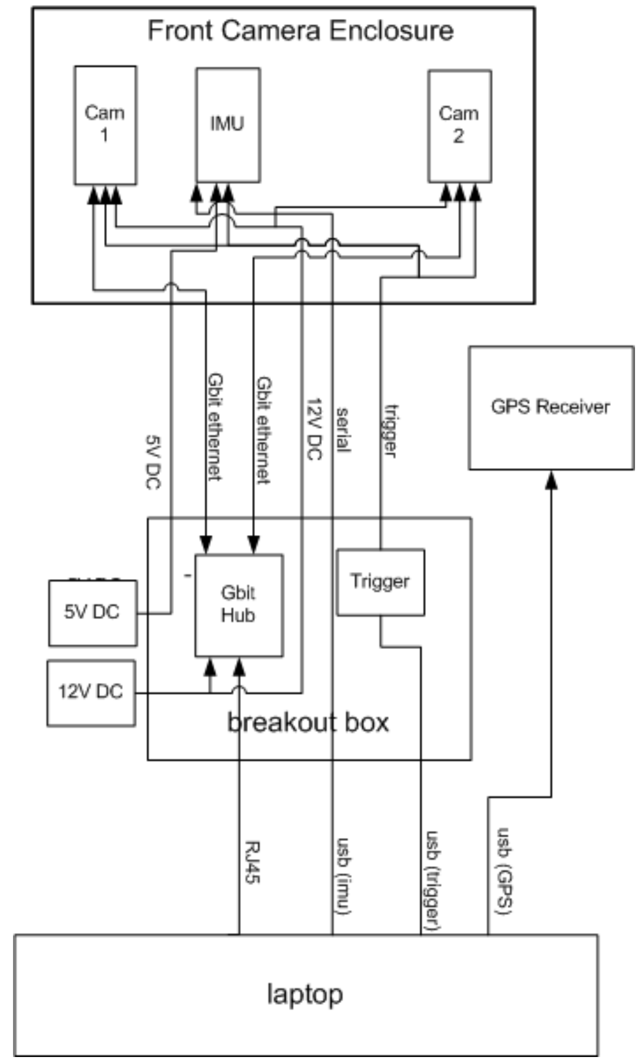
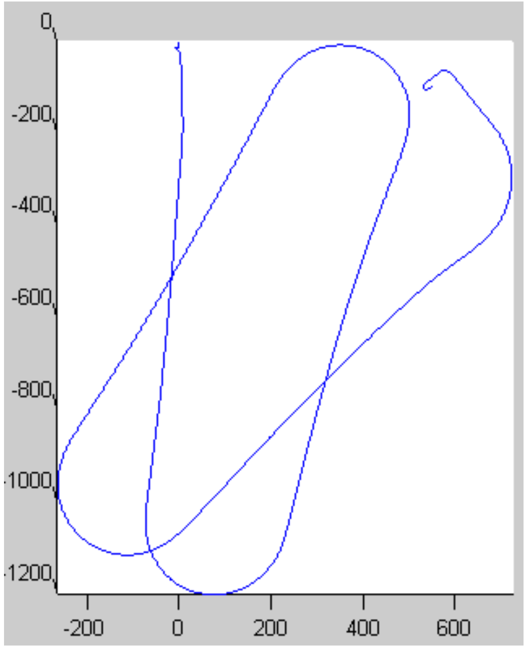
Components:

- Cameras (2) - Allied Vision Prosilica GC1380
  - GigaBit Ethernet interface
  - 640x480 (after 2x2 binning) x 30 fps,
  - Sony ICX285 CCD, monochrome
- Lenses (2) - Kowa LM6JC
  - 6.0 mm/F1.4
- IMU (1) – CloudCap Crista
  - 100 Hz operation, 10x oversampling
- Ethernet hub (1) – Netgear GS105NA
  - 5 RJ45 ports
  - Jumbo frame support to 9720 bytes
- Cabling and connectors
  - Weather proof RJ45 connectors
  - Shielded CAT6 cable
  - Mil-style 10 pin connectors
- Computer (1) – AVA Direct Clevo D900F
  - Intel quadcore i7, 3.33 GHz



Results in Inclement Weather

- Data collection in the rain (1/17) showed expected effect – lenses covered with water droplets.
- Feature tracking and positioning remained functional
- Droplets were cleared by moving air once vehicle reached higher speeds (over 30mph)
- Hoods overhanging the lenses may be sufficient for reducing the effects of both water and sun glare.



Results with GPS Degradation at 50 mph

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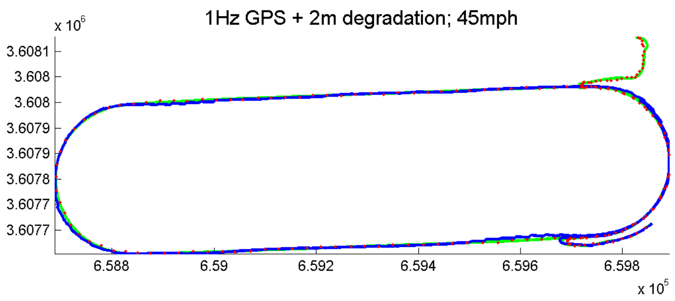
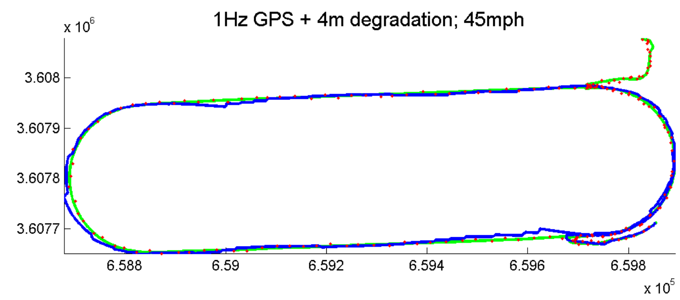
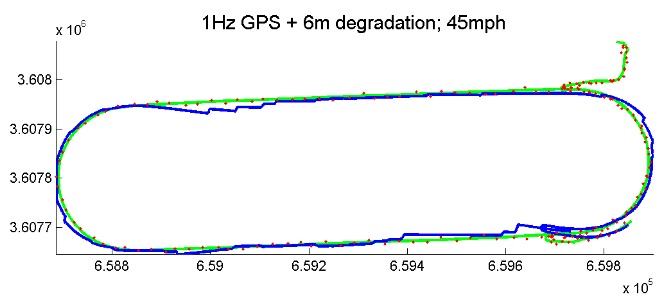


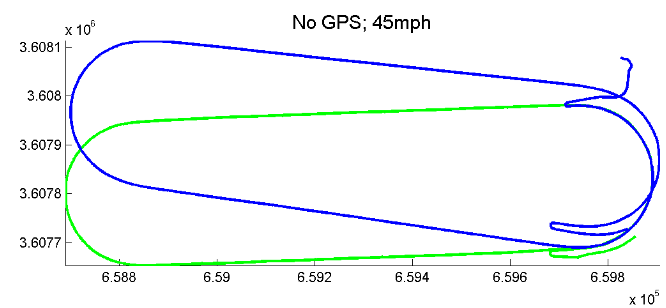
drift: total 1.415m, mean 2.857m
(over 4305 m traveled distance)



drift: total 2.419m, mean 4.981m
(over 4305 m traveled distance)



drift: total 9.629m, mean 9.258m
(over 4305 m traveled distance)



drift: total 21.83m, mean 60.56m
(over 4305 m traveled distance)

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Kapsch-Gantry									

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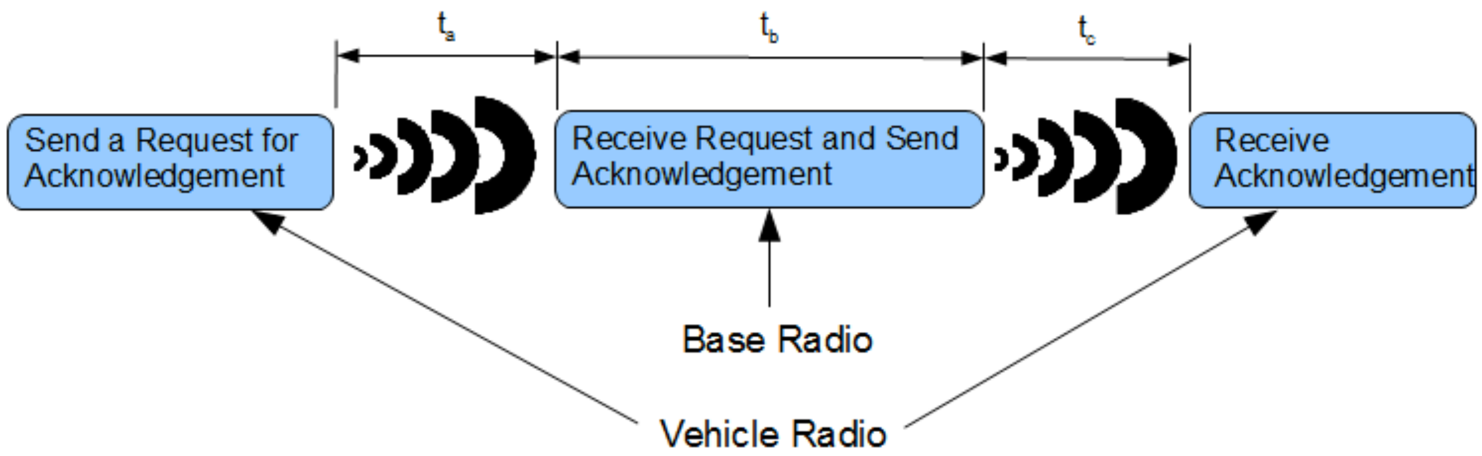
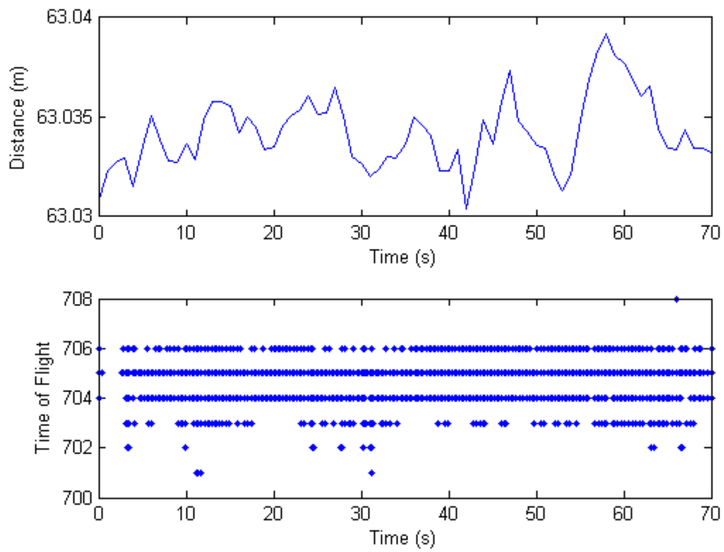
Kapsch TrafficCom – DSRC ranging

- Initial plan: estimate range based on turnaround time for unsynchronized clocks
  - 1 microsecond error-> 300 meters of range error: for 1 foot range error, 1 nanosecond precision is required
- Project hardware was not capable of lane level precision
- Sensor may still provide some information if nothing else is available

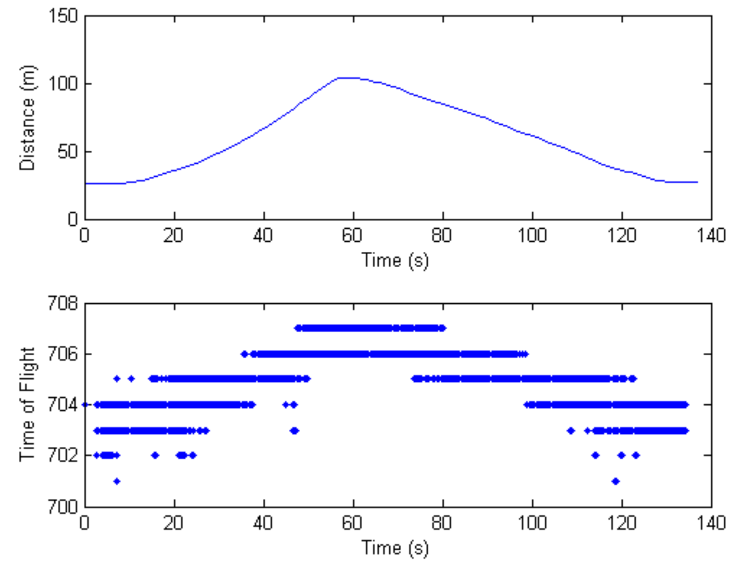


Kapsch TrafficCom – DSRC ranging

- Data was collected at the NCAT test track to collect time of flight between:
  - Kapsch radio base station
  - Auburn vehicle
- Variation in time of flight measurements was not sufficient for lane level measurements



Static testing at 63 meters



Dynamic testing at 35-100 meters

Kapsch – TrafficCom

- Gantry based transceiver communicates with on-board transponder
- Vehicle position estimated in lane while vehicle in communication zone

Kapsch TrafficCom Lane Level Localization*

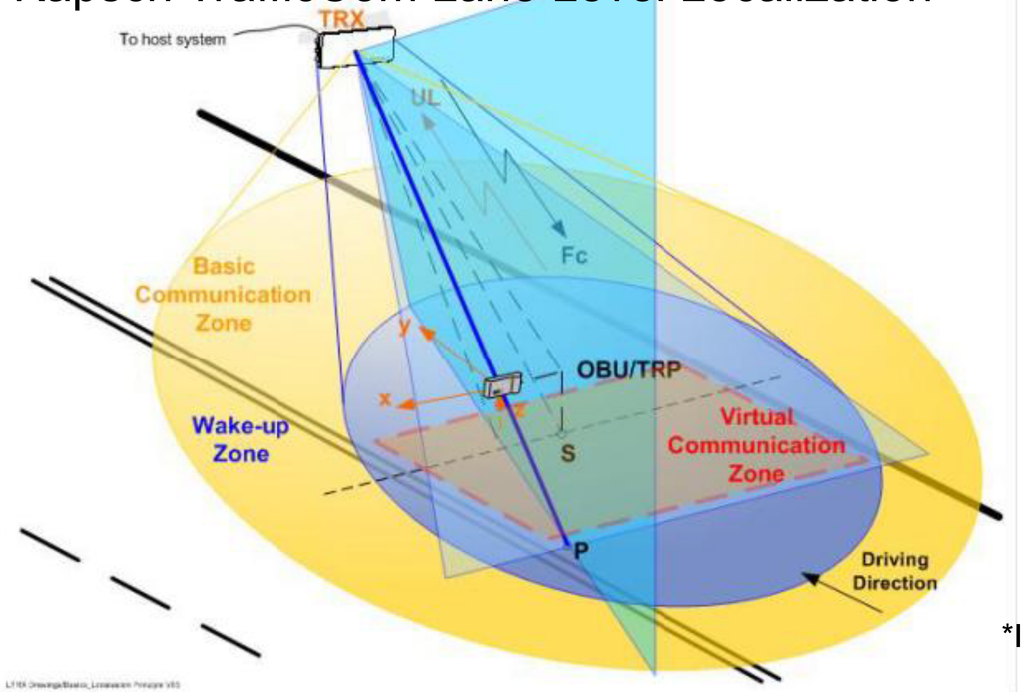


*Image From Kapsch TrafficCom

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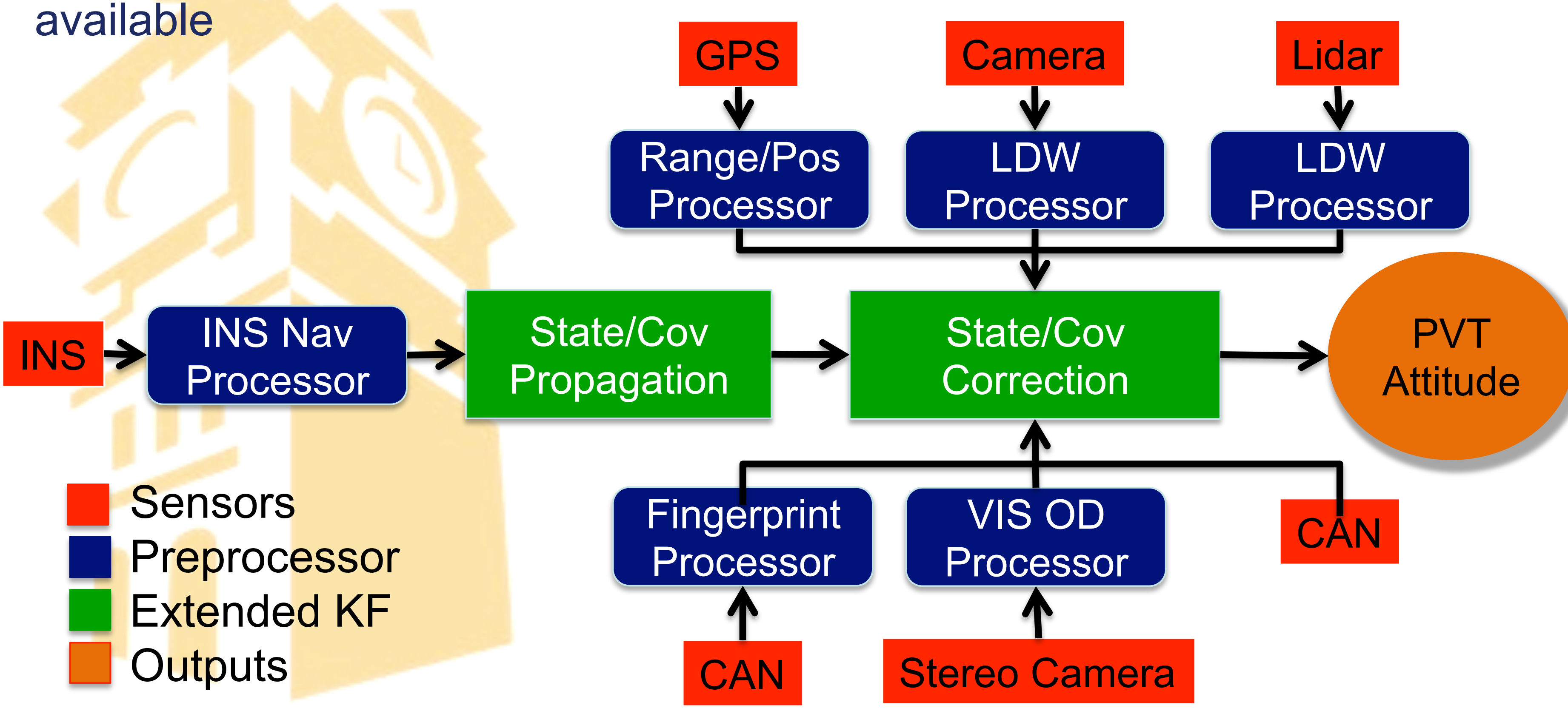
INS		✓ (green)	✓ (yellow)	✓ (green)	✓ (green)	✗	✓ (green)	✓ (green)	✓ (green)	✓ (green)
Wheel Speed		✓ (green)	✓ (green)	✗	✓ (yellow)	✗	✓ (green)	✓ (green)	✓ (green)	✓ (green)
PSU-Road Fingerprinting		✓ (green)	✓ (green)	✗	✓ (green)	✓ (yellow)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (green)
AU-LDW	Lidar	✓ (yellow)	✓ (yellow)	✗	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (yellow)
	Camera	✓ (green)	✓ (green)	✗	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)	✓ (yellow)	✓ (yellow)
SRI-Visual Odometry		✓ (yellow)	✓ (yellow)	✓ (yellow)	✓ (green)	✓ (yellow)	✓ (green)	✓ (green)	✓ (yellow)	✓ (yellow)
Kapsch-Gantry		✓ (yellow)	✓ (yellow)	✗	✓ (green)	✓ (green)	✓ (yellow)	✓ (green)	✓ (green)	✓ (green)

✓ (green)	No concern, current system capabilities not affected by criterion
✓ (yellow)	Some concern, criterion may limit implementation or capability
✗	Criterion cannot be overcome without additional subsystems

Data Fusion Block Diagram

- Subsystems are currently fused in extended Kalman Filter implementation
- 18 states are propagated using nonlinear dynamic relationship and IMU measurements
- Additional subsystems correct INS solution as measurements become available



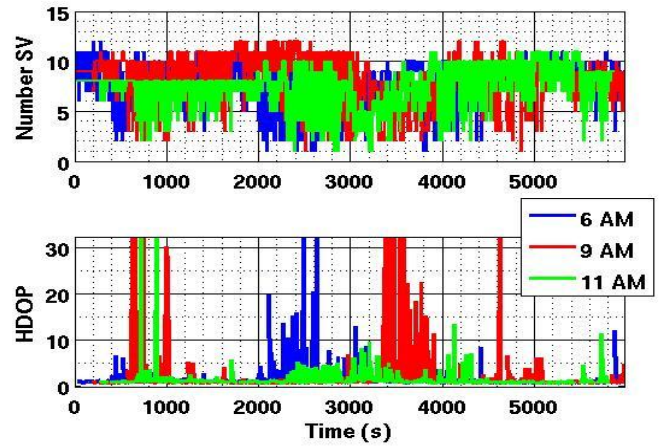
Data Fusion

- Subsystems provide positioning information in load or global navigation frames as well as estimates of output uncertainties

Subsystems	Inputs	Outputs
INS navigation processor	Body frame accelerations and angular rates	Navigation frame accelerations and angular rates (bias corrected)
GPS processor	RF signals for SV	Range/Range Rates Positions/Velocities
Camera LDW processor	Raw image	Lateral lane position
Lidar LDW processor	Distance and reflectivity	Lateral lane position
Fingerprint processor	Pitch rate and wheel speed	Navigation frame position
Visual Odometry processor	Raw image from two cameras, internal IMU, and GPS positions	Navigation frame position

Integration Testing (Detroit)

- Test route developed by Honda to meet road-use class proportioning found by FHWA
- Environments included trees, tree canopies, overpasses, buildings, urban canyons, and tunnels



Environment		Features				
		Terrain	Vegetation	Buildings	Overpasses	Tunnels
	Open	flat or mildly undulating; mask ≤ 5°	almost none	almost none	none	none
Rural	Sparse		scattered trees	rare, low, far	none	none
Rural	Moderate	mountains masking 5-20°	some tree canopies	some low	maybe but rare	
Rural	Dense	mountains mask 20-60°	dominant tree canopies	negligible compared to natural obstructions although there could be a long tunnel		
Urban	Sparse	usually flat or mildly undulating with mask ≤ 5	scattered trees	some, low or far	none	none
Urban	Moderate		moderate number, some short canopies	multi-story, rare high-rises	some	rare
Urban	Dense			dominant high-rise canyons	frequent	long

Methodology (Detroit)

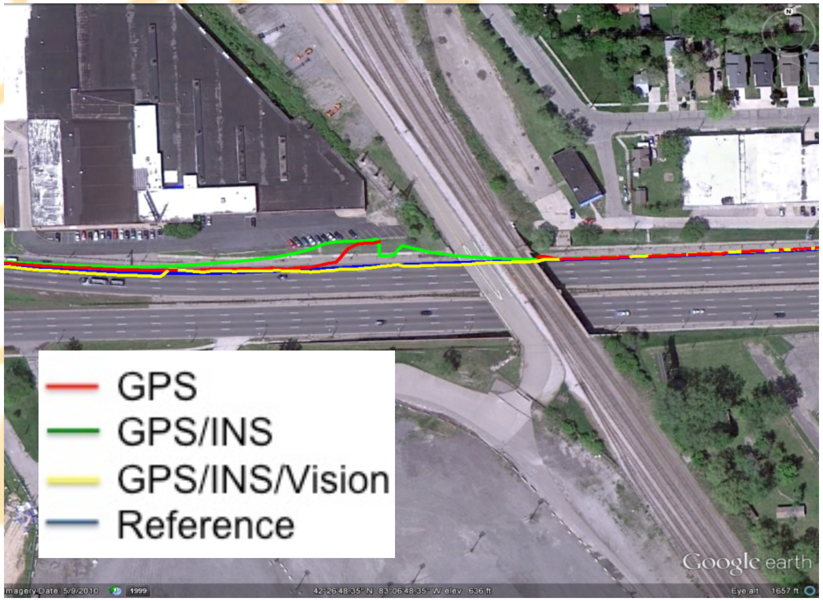
- Sensor combinations
  - Reduced inertial system, L1 GPS, wheel speeds
  - 6 DOF MEMS IMU, L1/L2 GPS, wheel speeds
  - 6 DOF MEMS IMU, L1/L2 GPS, wheel speeds, vision and map based lateral positions
- Extended Kalman filter implementation
- Estimated position, velocity, and attitude of vehicle
- Integrated vision information using low resolution map developed using Google Earth

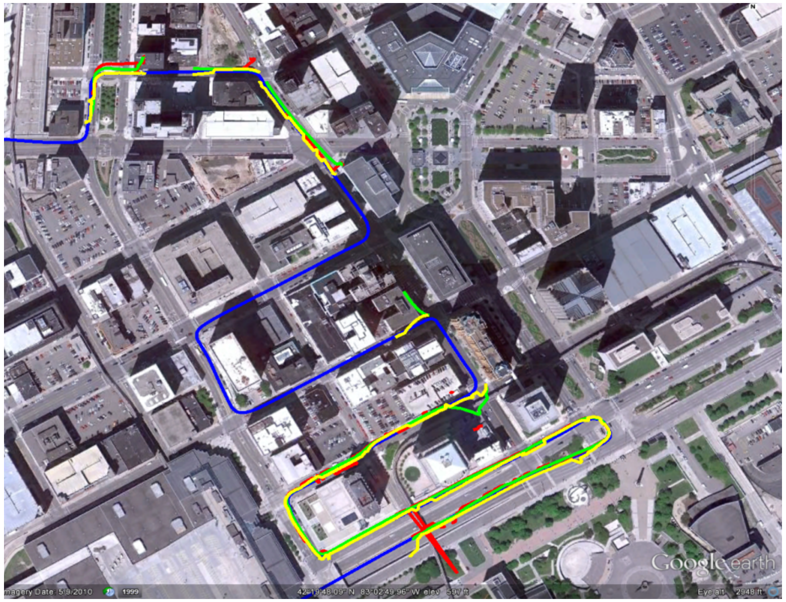
Production or Near-Production Grade			Beyond Production Grade			Reference System		
Type	Model	Rate (Hz)	Type	Model	Rate (Hz)	Type	Model	Rate (Hz)
GPS	Novatel Propak V3 (L1 only)	5	GPS	Novatel Propak V3 (L1 and L2)	5	GPS	NovAtel SPAN-SE	5
Wheel Speed	From in vehicle CAN network	50	IMU	Crossbow IMU 440, full	100	IMU	Honeywell HG1700 AG58	100
RISS	Crossbow IMU 440, reduced	100	Lidar	Ibeo Alasca XT	10	External encoder	Peiseler MT1000	Speed dependent
Camera	Logitech Quickcam 9000	10				DGPS	Differential GPS solution was calculated post-process	

Results (Detroit)

- GPS/INS provided improved results over standalone GPS particularly in heavy foliage and urban canyon environments
- Vision updates provided improvements where the lane of travel was assumed to be known (4 and 2 percentage point improvement in availability of lane level accuracy)

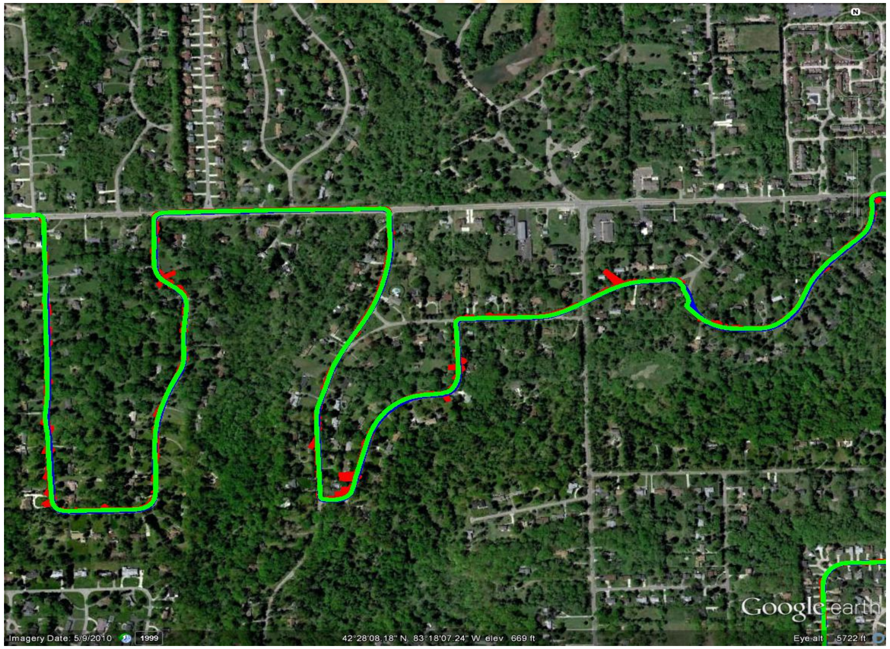
Device	Horizontal Error (m)		% < 1.5 m		% < 5 m
Propak_R3	2.9		46.7		88.8
GPS_INS_R3	2		59.8		95.5
Propak Overall	2.6		41.8		88.4
GPS_INS Overall	2.2		49.2		94.3
Device	Environment				
	Open	Ok	Trees	Canyon	All
Propak All Runs (%<1.5m)	67	49	33	14	42
GPS_INS All Runs (%<1.5m)	74	56	40	18	49
Precentage of Test Route	4	54	15	8	100

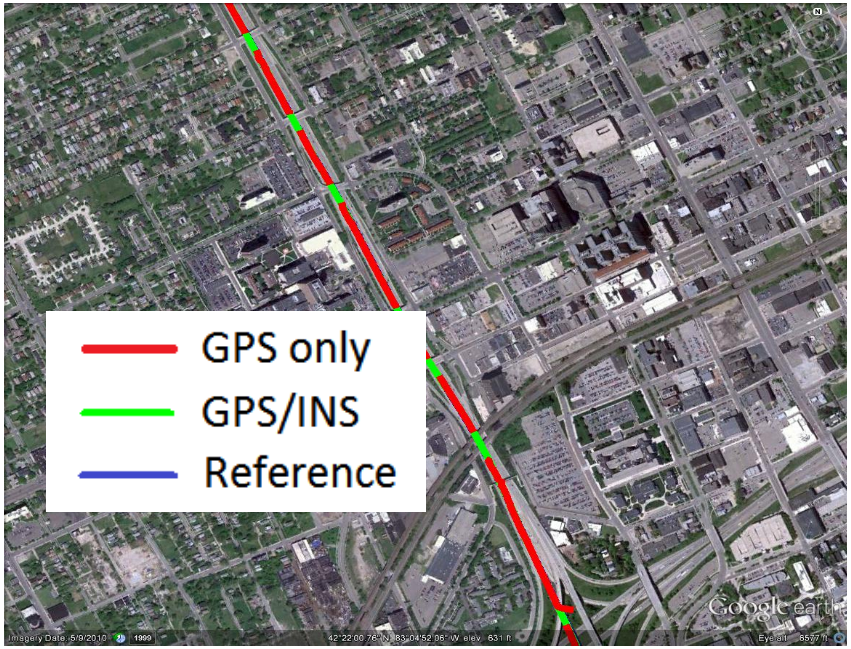




Observations (Detroit)

- Subsystem integration improved positioning accuracy as expected but limited by map/survey accuracy/availability
- Identified limitation of road fingerprinting and visual odometry systems
- Need lane detection algorithm leveraging new road edge detection methods and/or inertial information





Integration Testing (NCAT)

- Nation Center for Asphalt Technology
  - 1.7 mile oval
  - RTK GPS Survey of lane markings and lane centers
  - Fingerprint Survey
- RTK Base Station
  - Wireless comm.

Methodology (NCAT)

- Subsystems Operational
  - 6 DOF MEMS IMU
  - L1/L2 GPS
  - Vehicle CAN
  - AU-LDW (Camera, Lidar)
  - PSU Fingerprinting
- Estimated position, velocity, and attitude of vehicle
- Integrated vision/fingerprinting information using high accuracy map/survey of test track
- Four data sets of several laps over three days
- Speeds ranging from 5 to 55 mph

Results (NCAT)

AUBURN UNIVERSITY

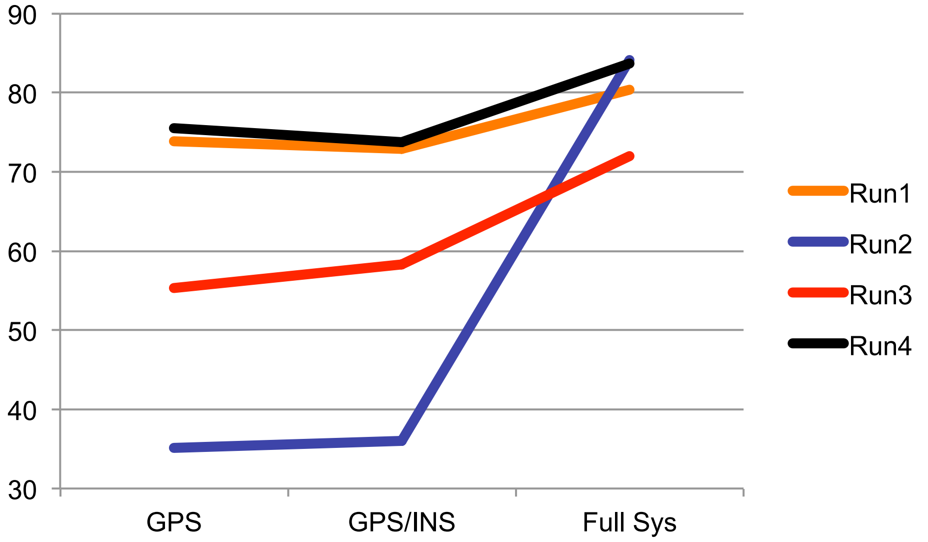
- GPS/INS accuracy dependent on GPS
- Vision and Fingerprinting integration results in consistent improvement in horizontal errors

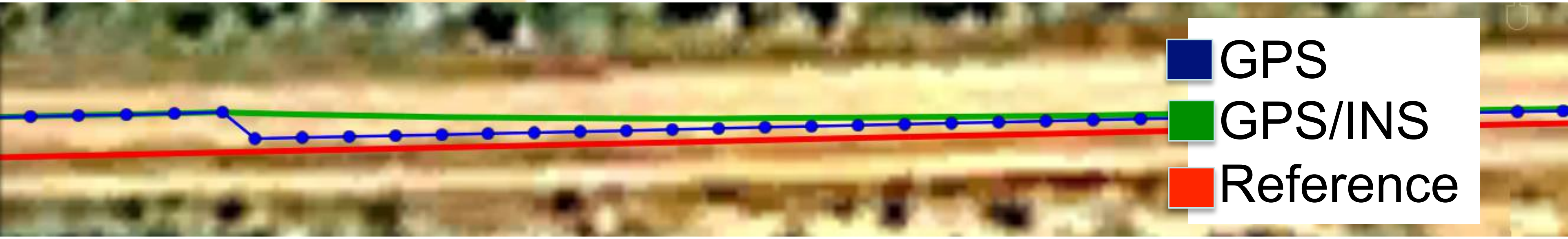
Horizontal Error (m)					
	Run 1	Run 2	Run 3	Run 4	Average
GPS	1.61	1.98	1.79	1.60	1.75
GPS/INS	1.60	1.96	1.70	1.61	1.72
Full Sys	1.10	1.07	1.00	0.93	1.03

Results (NCAT)

- Lane level accuracy improves significantly with vision and fingerprint aiding
- Filter memory limits affects GPS/INS solution

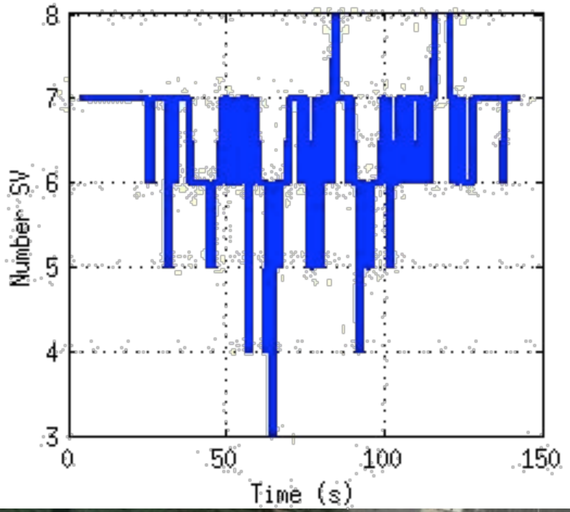
Horizontal Error < 1.5 meters (%)				
GPS	73.9	35.1	52.4	75.5
GPS/INS	72.9	36.0	58.3	73.7
Full Sys	80.4	84.1	72.0	83.7

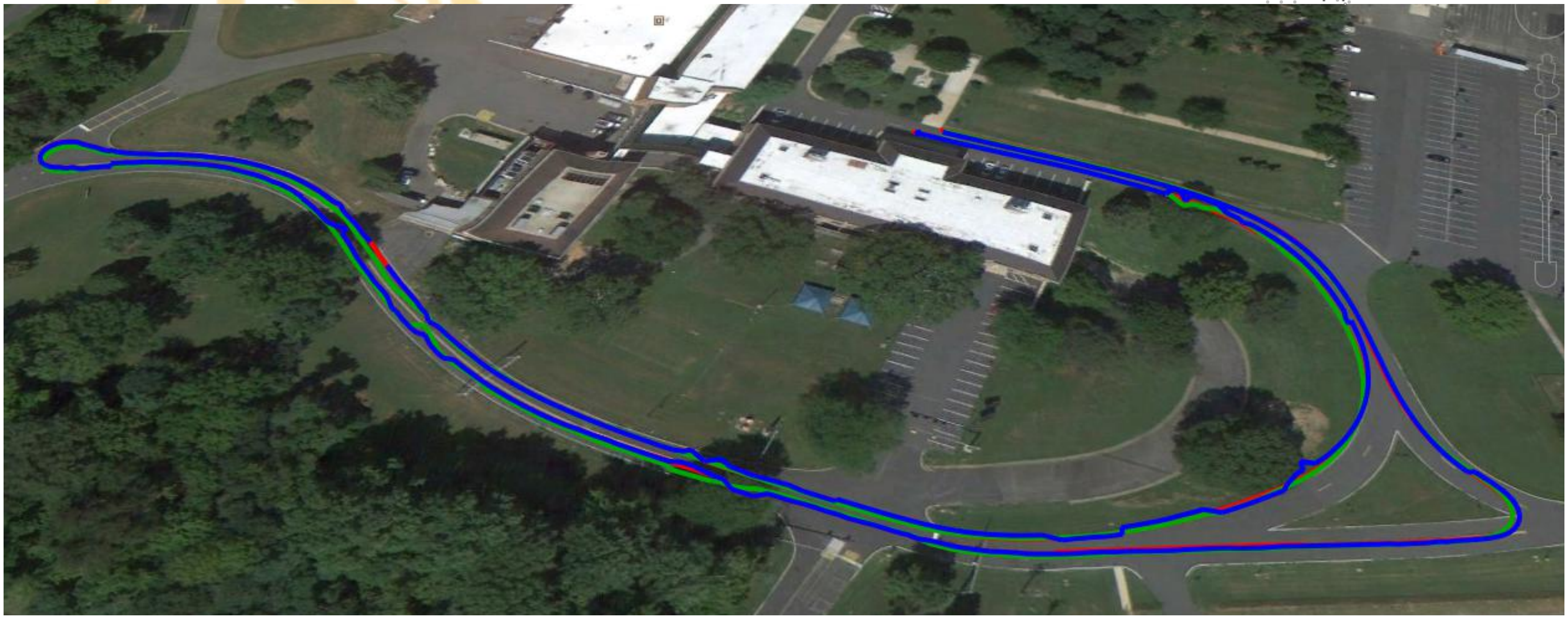




Testing (Turner/Fairbank)

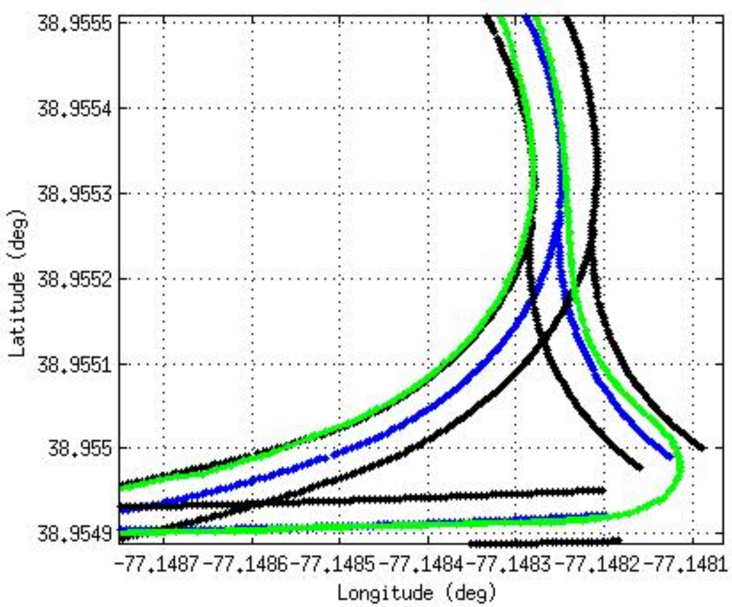
- Data was collected in the Turner/ Fairbank driveways
- Novatel base station provided RTK corrections
- Satellite visibility degraded in some areas

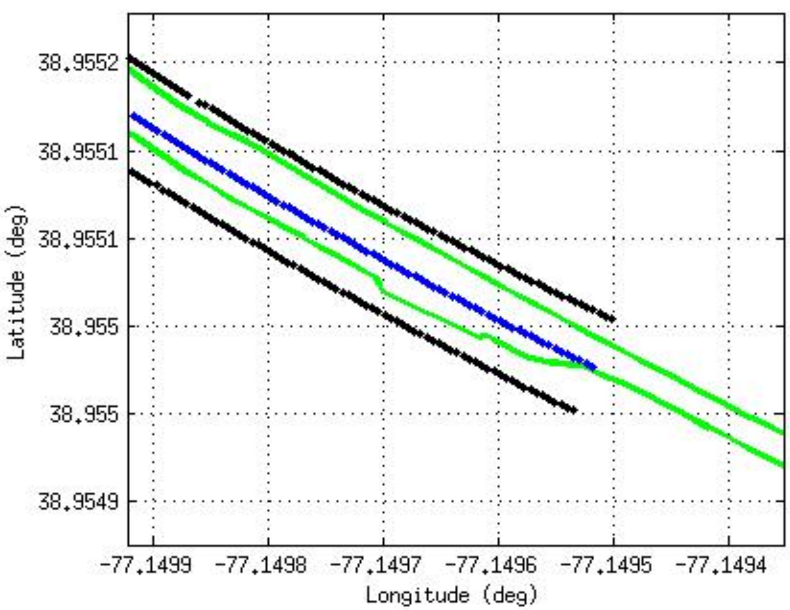




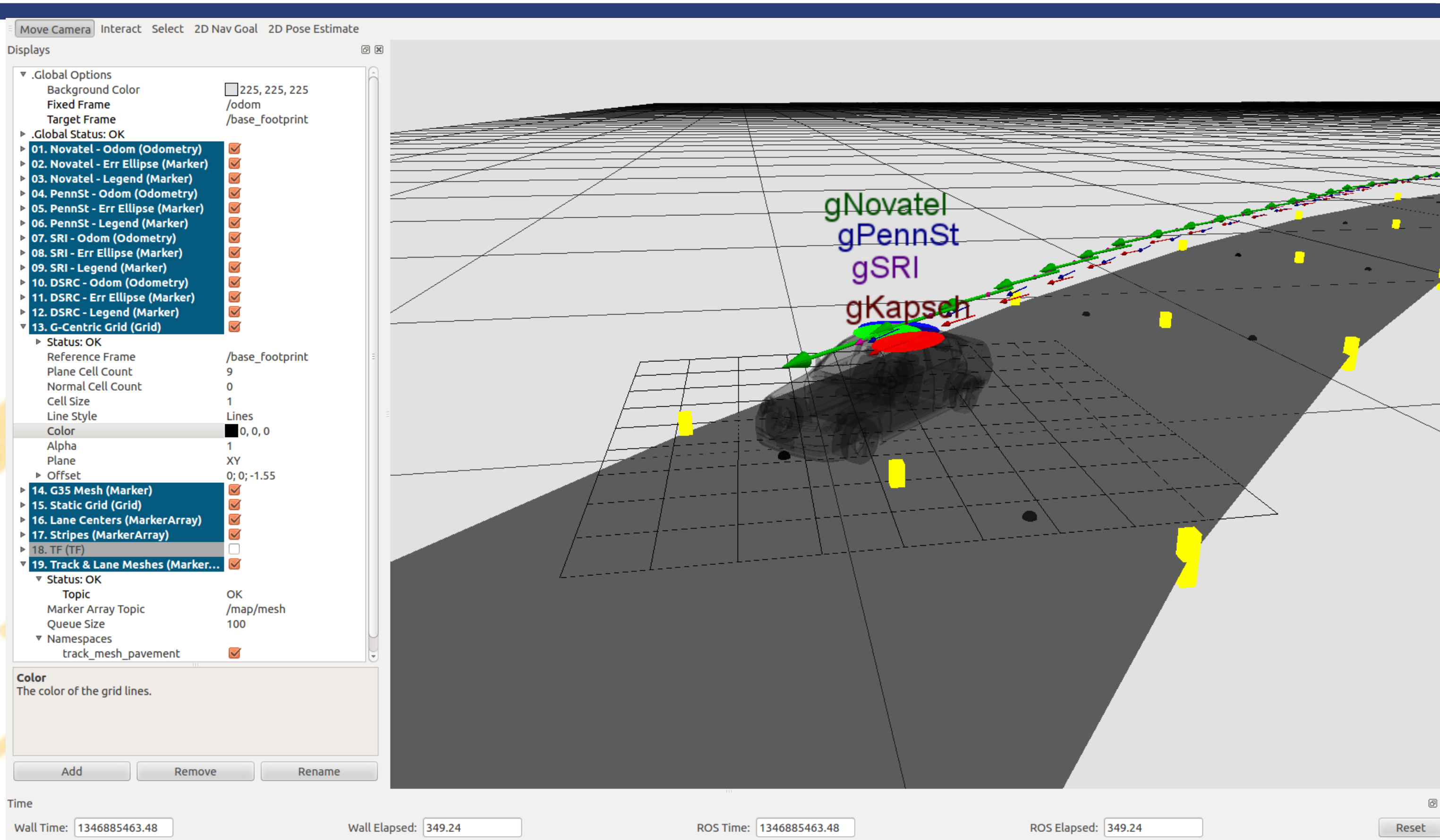
Results (Turner/Fairbank)

- RTK accuracy for reference solution was intermittent (55 % of run on average)
- Limited precision of fingerprinting survey
- Lane level accuracy best with GPS/INS due to error correlation





Positioning Visualization



- Real time display of positions from multiple sensors
- Error ellipse & pose history
- Easily import map data points

Positioning Visualization

- See Videos

Conclusions & Beyond

- Addition of Subsystems help improve lane level accuracy
- Continued testing needed to assess system robustness

- Onsite Demo Dec 10
- Automotive Panel invited
  - VW, Trimble, Volvo truck confirmed.