

Next Generation Vehicle Positioning in GPS-Degraded Environments for Vehicle Safety and Automation Systems



Auburn University
Penn State University
SRI International
Kapsch TrafficCom

Automotive Review Panel

- External review panel has been assembled to monitor progress and provide direction and feedback
- Current list of participants:
 - Ford Motor Company (Tom Piluti)
 - Mercedes-Benz (Michael Maile)
 - Honda (Jim Keller)
 - Volkswagen (Dirk Langer)
 - Volvo (Paul Schmitt)
 - Nissan (Hiroshi Tsuda)
 - Bosch (Kyle Williams)
 - Eaton Corporation (Ben Saltsman)
 - GM (Chaminda Basnayake)
 - Richard Bishop

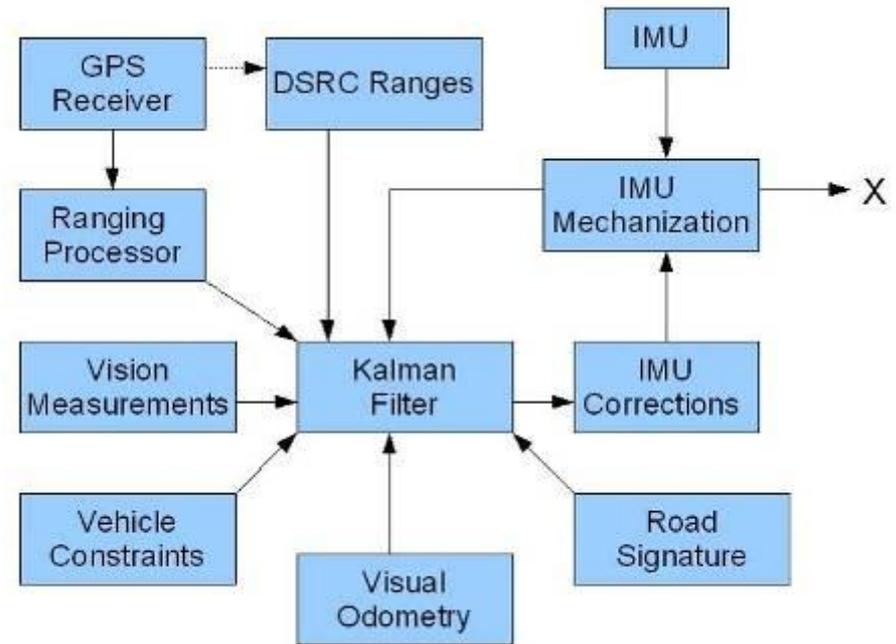
System Overview

Sensors include:

- cameras
- lidar
- DSRC
- GPS
- IMUs
- wheel odometry

Maps?

- Navteq – no longer on project



Initial Concept for Including Additional Inputs

Team Overview

- Auburn (David Bevly, dmbevly@eng.auburn.edu)
 - Lead Systems Integrators
 - Overall Team Management
 - Sensor Integration
- Kapsch (Steve Sprouffske & Dmitri Khijniak, Dmitri.Khijniak@kapsch.net)
 - DSRC Ranging
- Penn State University (Sean Brennan, sbrennan@psu.edu)
 - Road signature based positioning
- SRI International – Sarnoff (Supun Samarasekera & Chetna Bindra, raia.hadsell@sri.com)
 - Visual Odometry

EXPLORATORY ADVANCED RESEARCH PROGRAM

DSRC-based localization

Automotive workshop

Dmitri Khijniak



Agenda

1. Scope of Work
2. RSSI-based ranging
3. “Packet Time-of-Flight” ranging
4. Future work – “Angle of Arrival” ranging



Work scope

- Year 1 :
 - DSRC Ranging
 - Utilize 5.9 GHz DSRC for next generation non-GPS localization services.
 - Evaluate signal ranging using Received Signal Strength Indication (RSSI) in-conjunction with other aspects of the DSRC communications channel.
- Year 2
 - Evaluation of Integrated Positioning Solution (IPS) on the Auburn Test track and in an urban environment
 - Use DSRC equipment capable of providing lane level localization using the DSRC communications channel.

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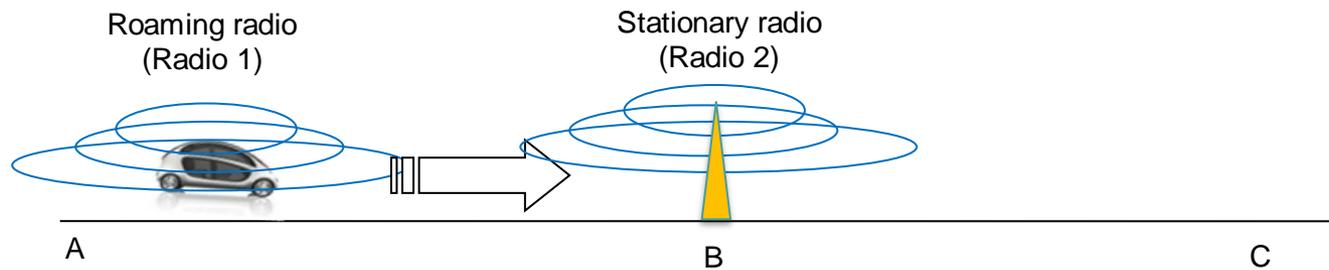


RSSI Range Testing (Led by Auburn University team)

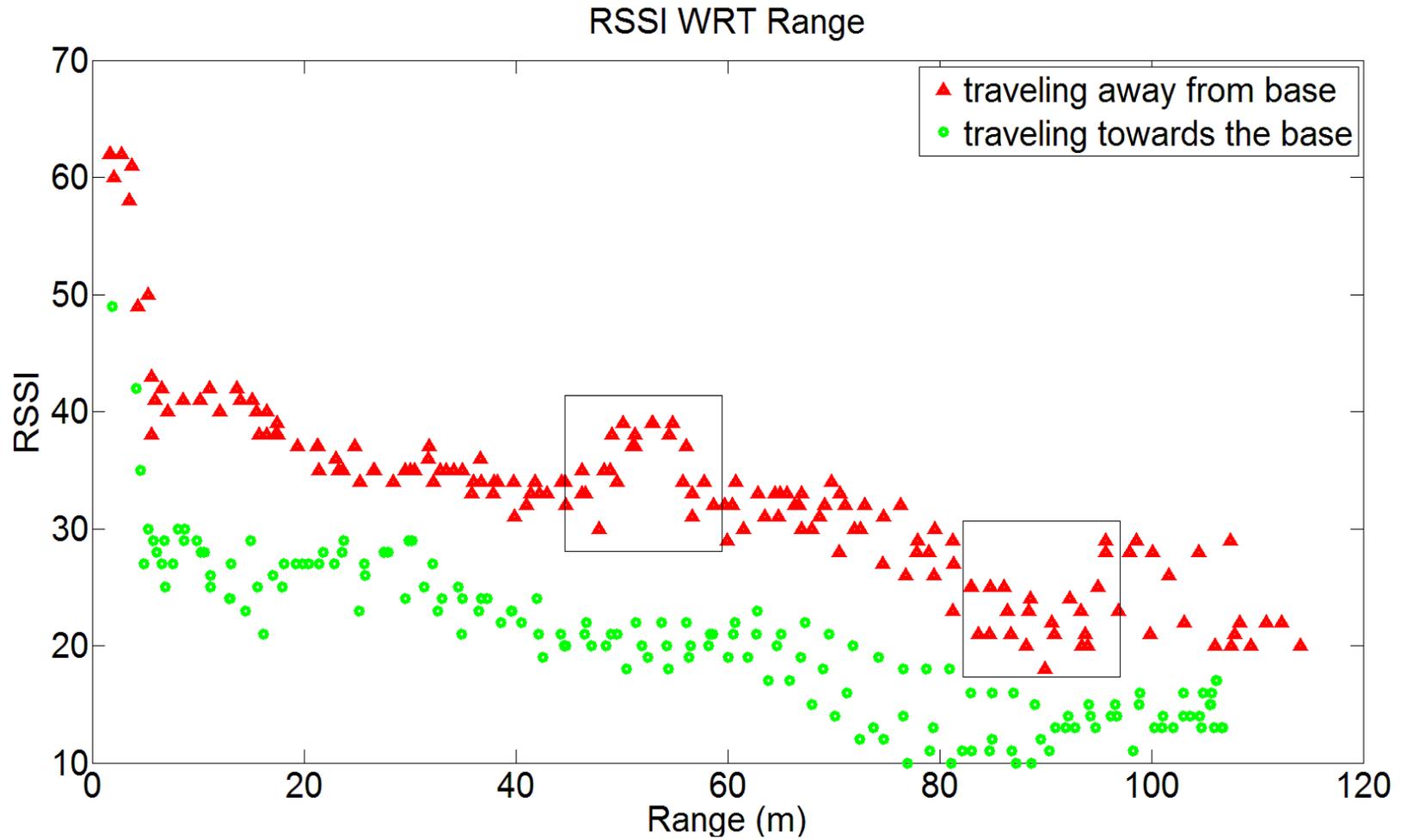
- Measure Received Signal Strength Indicator (RSSI)
 - RSSI is proportional to the power in the received signal
- Find a correlation between RSSI and distance between radios
- Use RSSI to estimate range between radios

Experiment

- Stationary DSRC radio was attached to a pole
 - Placed on one end of the skid pad
- Roaming radio was placed in a test vehicle
- The antenna of the vehicle-based radio was located on the back of the vehicle roof
- Both antennas were placed at approximately the same height above the ground
- RSSI and distance between radios was recorded into a log file



Results



Discussion & Conclusion

- RSSI plots varied when one radio traveled toward and away from another radio
 - Two different sets of 1st and 2nd order curve fits were computed
- The RSSI fluctuates too much to create a strong correlation between range and signal strength
 - Standard Deviation of the error in range is 15 m
- Signal is susceptible to the environment
 - Signal variations may be explained by signal obstructions and signal reflection (i.e. multi-path phenomenon)
- **Conclusion**
 - Signal strength could be used to get a general idea of the range between radios; however, range estimates based of signal strength are not accurate enough to incorporate into the current navigation filter

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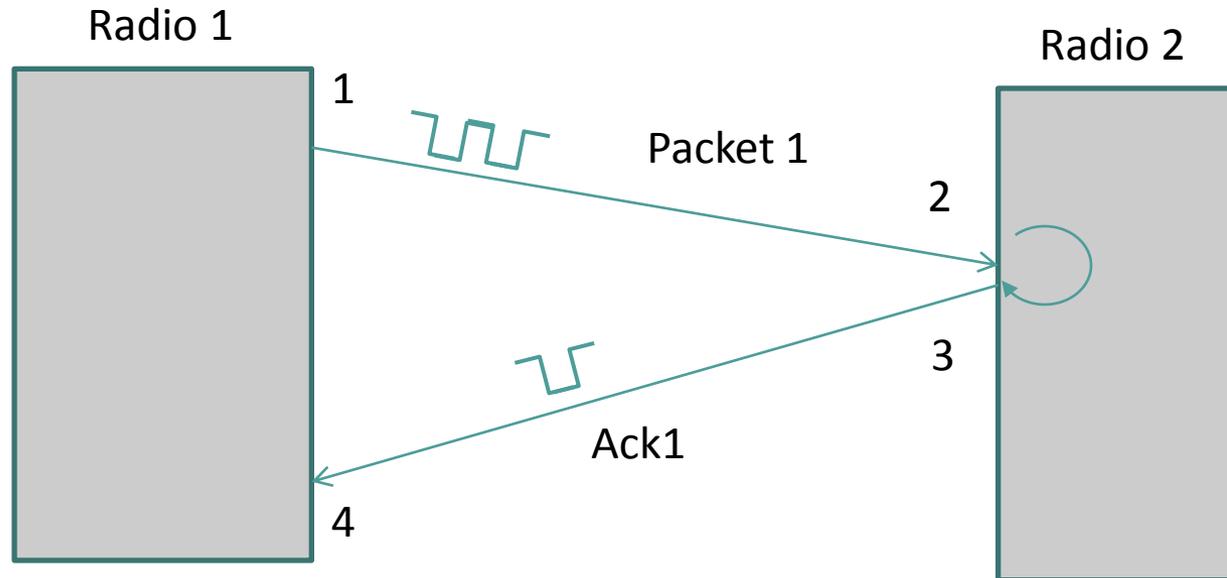


Ranging using packet Time-of-Flight

- Measure Time-of-Flight of packets between two radios
 - Time-of-Flight is proportional to the distance
- Utilize COTS radio chipset

- Ref: “Accurate Positioning Using Short-Range Communications, Yasser Morgan, Software Systems Engineering, University of Regina”

Calculation of time-of-flight

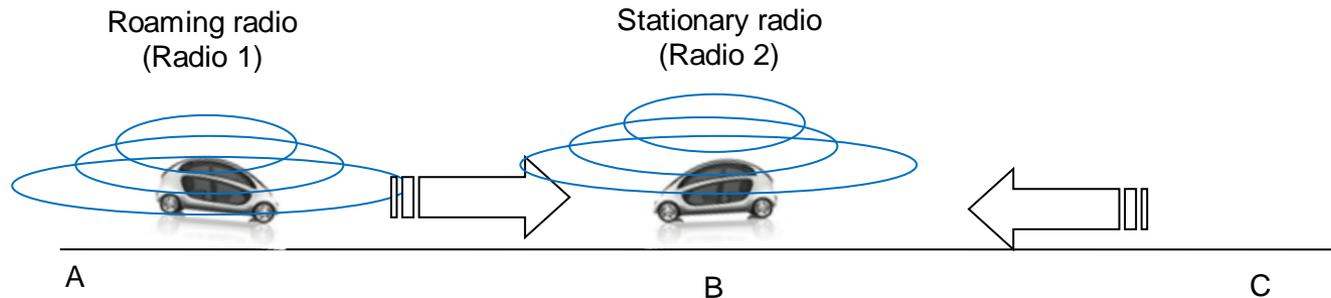


Carrier Sense Multiple Access / Collision Avoidance (CSMA/CA) packet exchange

- Packet 1 = “Unicast” data packet
- Ack1 = Acknowledgement frame sent by receiving radio

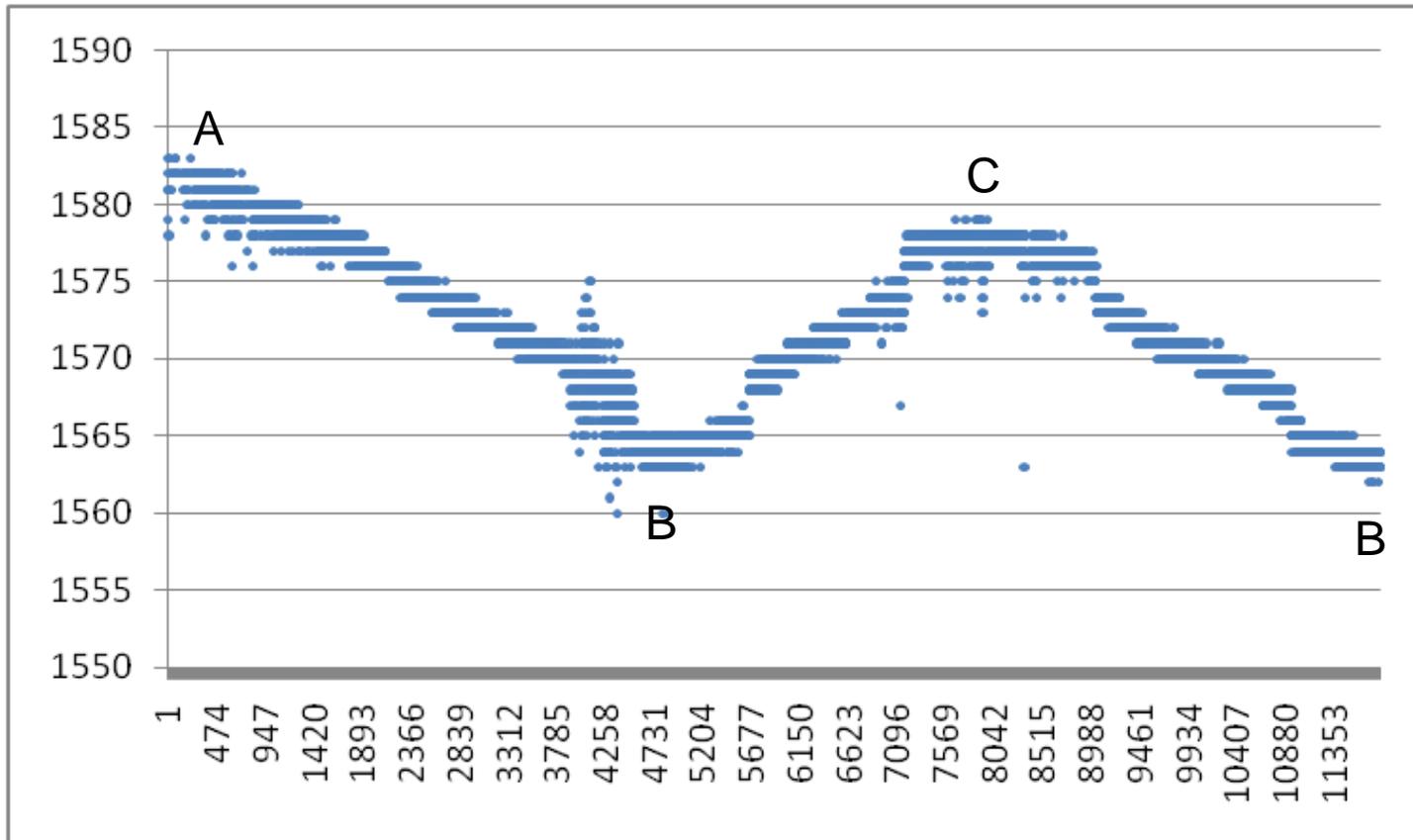
Time of flight $T = t4 - t1$, where $(t2 - t3) \rightarrow 0$

Experiment



Two vehicles equipped with DSRC radios
 Stationary vehicle positioned on the side of two way street (1 lane each direction)
 Roaming radio travels toward and away from the stationary radio $A \rightarrow B \rightarrow C \rightarrow B \rightarrow A$
 Distance is estimated using laser range finder

Results



Vertical axis: value proportional to elapsed time

Horizontal axis: sampling value corresponding to a vehicle position on the road

Results & Next step

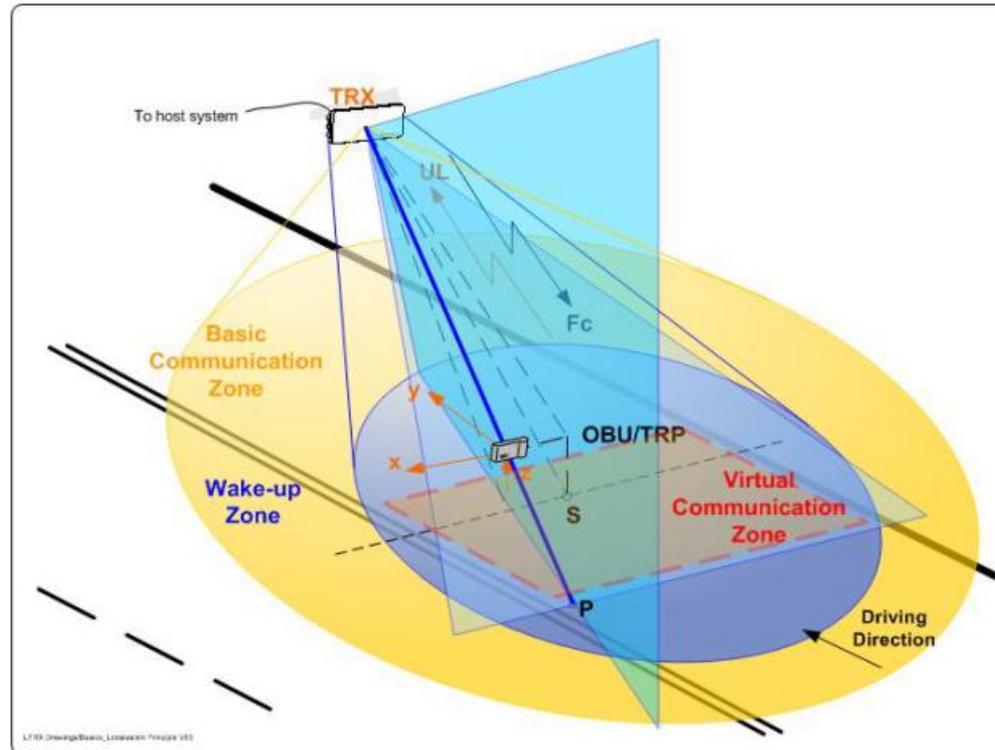
- Results
 - ToF time varies with distance
 - Traveling toward and away from a stationary radio shows similar characteristics
 - Results show repeatability in measurements
- Next Steps
 - Conduct experiment on Auburn test track
 - Validate accuracy and repeatability of the ToF method
 - Compare RSSI and ToF results, identify strength and weaknesses of each method

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Year 2 Localization experiments

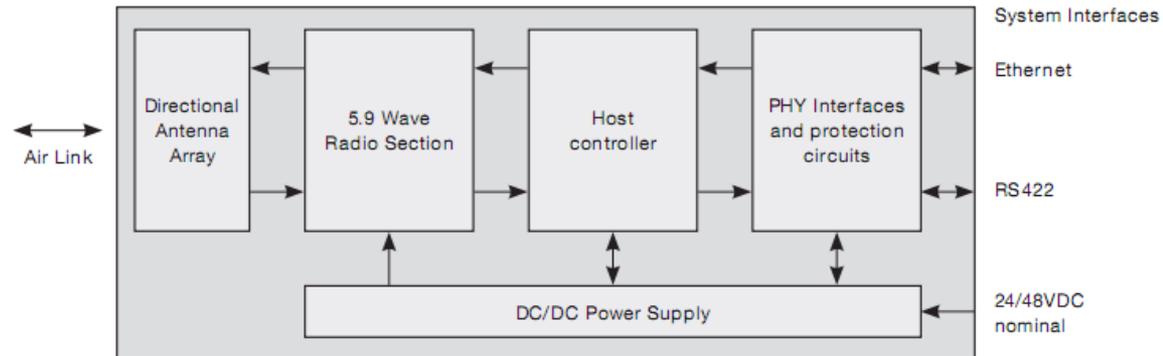


- Transponder position determined relative to the traveling lane
 - Minimize “cross-lane” reads.
 - Distinguishes vehicles in “HOT” lane zone vs non-paid lanes

5.9GHz DSRC transceiver with road localization capabilities



WAVE Transceiver TRX-9450



- 5.9GHz DSRC transceiver for tolling applications
- The radio unit meets the Class C emission spectrum mask
- IEEE 1609 WAVE compliant communication
- Built-in directional antenna arrays
- 2-dimensional localization of radio sources within the communication zone
- Handles authentication and encryption security required for tolling applications

5.9GHz DSRC transponder

- First 5.9GHz DSRC toll transponder
- Supports 1609 WAVE protocols and encrypted transactions
- Battery operated
- Windshield mounted
- Target applications:
 - Open-road tolling
 - HOT lanes
 - Commercial vehicle inspection

First installation of 5.9GHz toll system in Washington State, at Hood River Bridge toll plaza in Sep 2010



DSRC-based RF ranging during Year 2

- Test advanced signal ranging utilized in the next-generation 5.9GHz roadside transceivers
 - Install equipment at the Auburn Test track
 - Test localization obtained from DSRC roadside units
 - Validate accuracy and reliability
- Combine lane-level localization information from RSE and IPS in roadway scenarios
 - Support testing of the IPS localization in roadway conditions



Dmitri Khijniak

Tel. +1 760 650-5880
dmitri.khijniak@kapsch.net

Steve Sprouffske

Tel. +1 760 525-5454
steve.sprouffske@kapsch.net

Kapsch TrafficCom Inc.

System Engineering
2035 Corte del Nogal, Suite 105 | Carlsbad, CA
92011 | USA

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PENNSTATE

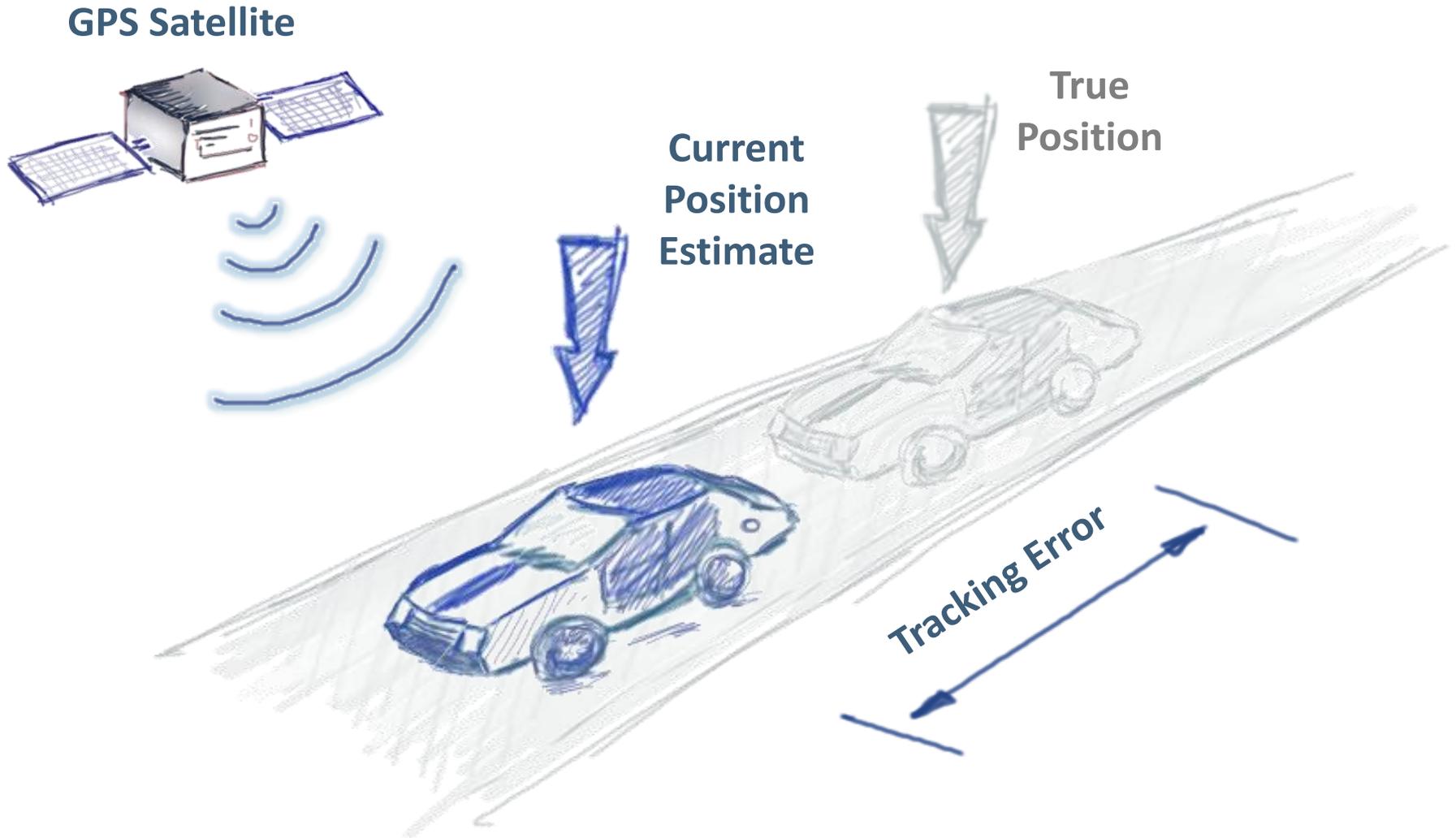


GPS-Free Terrain-based Vehicle Tracking

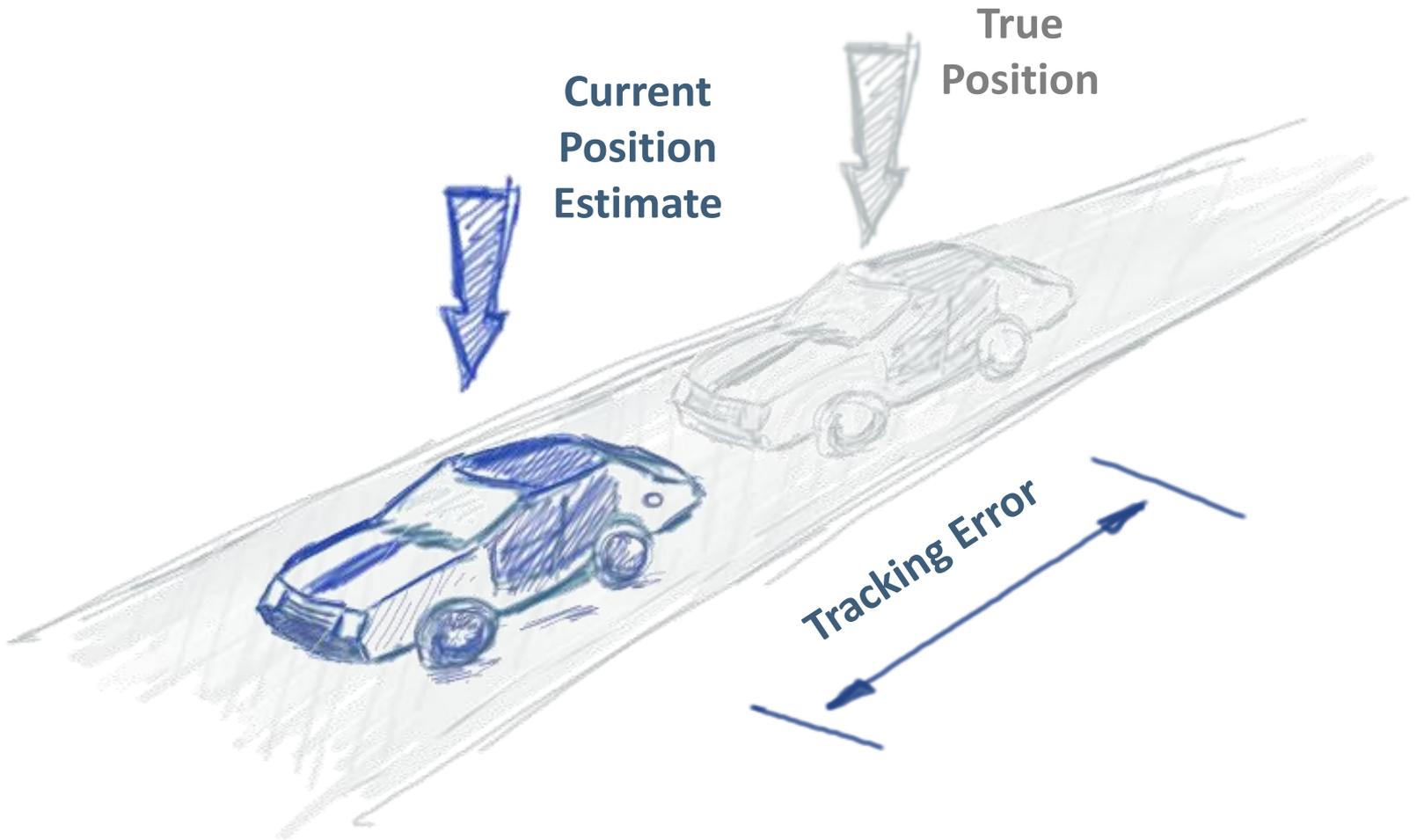
Kshitij Jerath, Sean N. Brennan
April 29, 2011

Department of Mechanical and Nuclear Engineering
The Pennsylvania State University

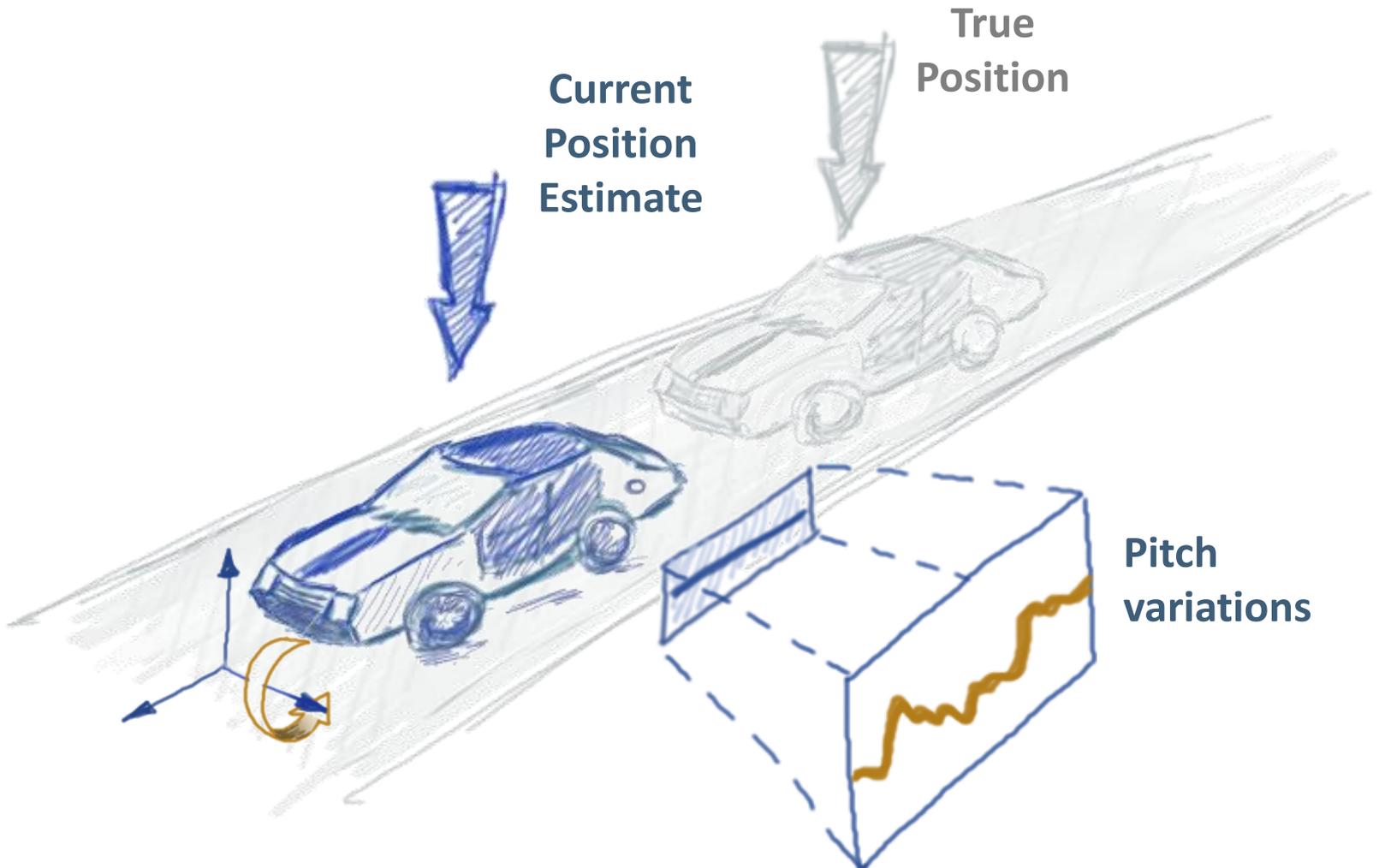
Vehicle Tracking Performance



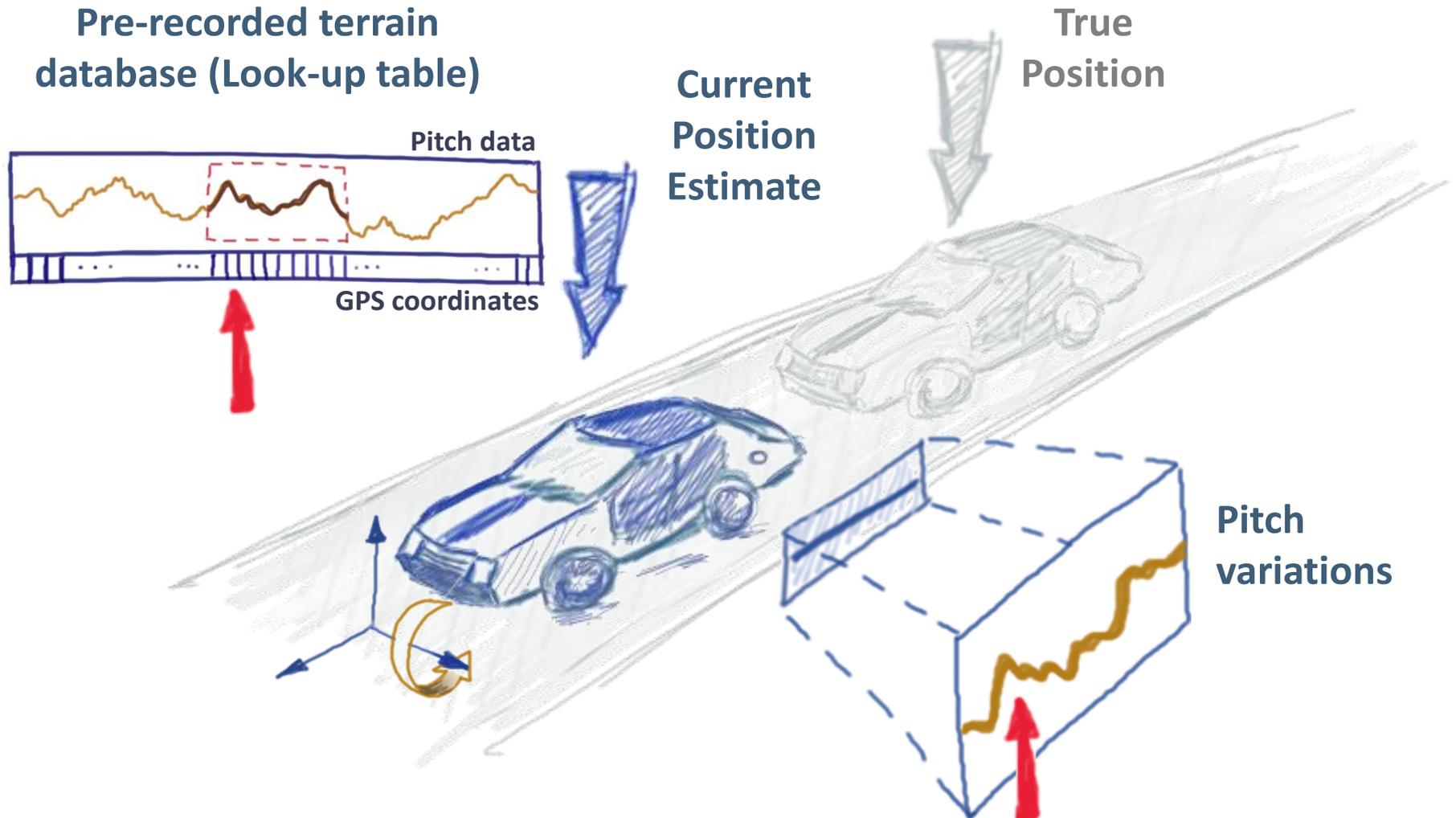
GPS-Free Vehicle Tracking Performance



GPS-Free Terrain-based Vehicle Tracking Performance



GPS-Free Terrain-based Vehicle Tracking Performance



OUTLINE

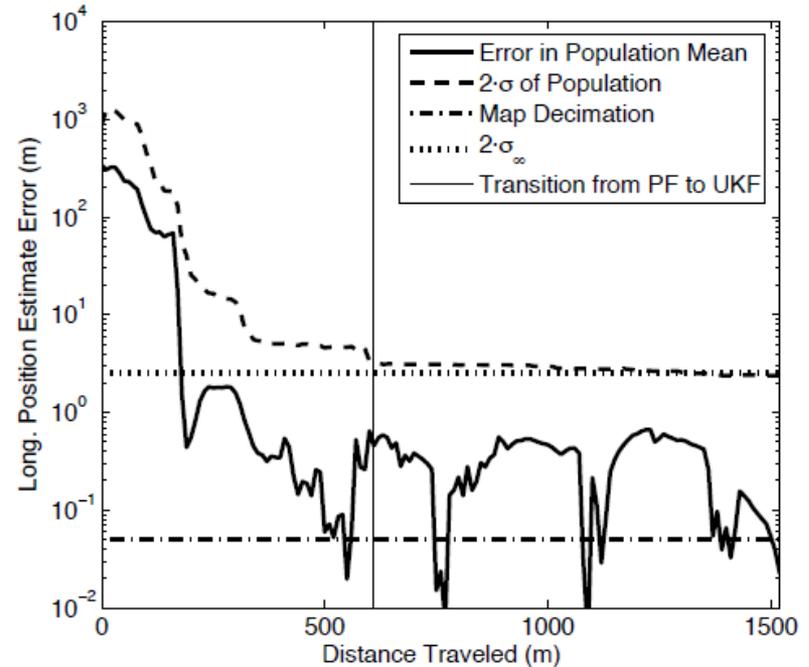
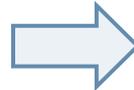
- Prior Research
- Completed work
 - Sensor Modeling, Characterization and Simulation
 - Vehicle Tracking with Low-cost Inertial Sensors
 - Comparison of Available Sensors
- Current work
 - Framework for real-time implementation
 - Real-time implementation results
- Future work
 - Road network implementation
- Summary

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Terrain-based vehicle tracking is promising...

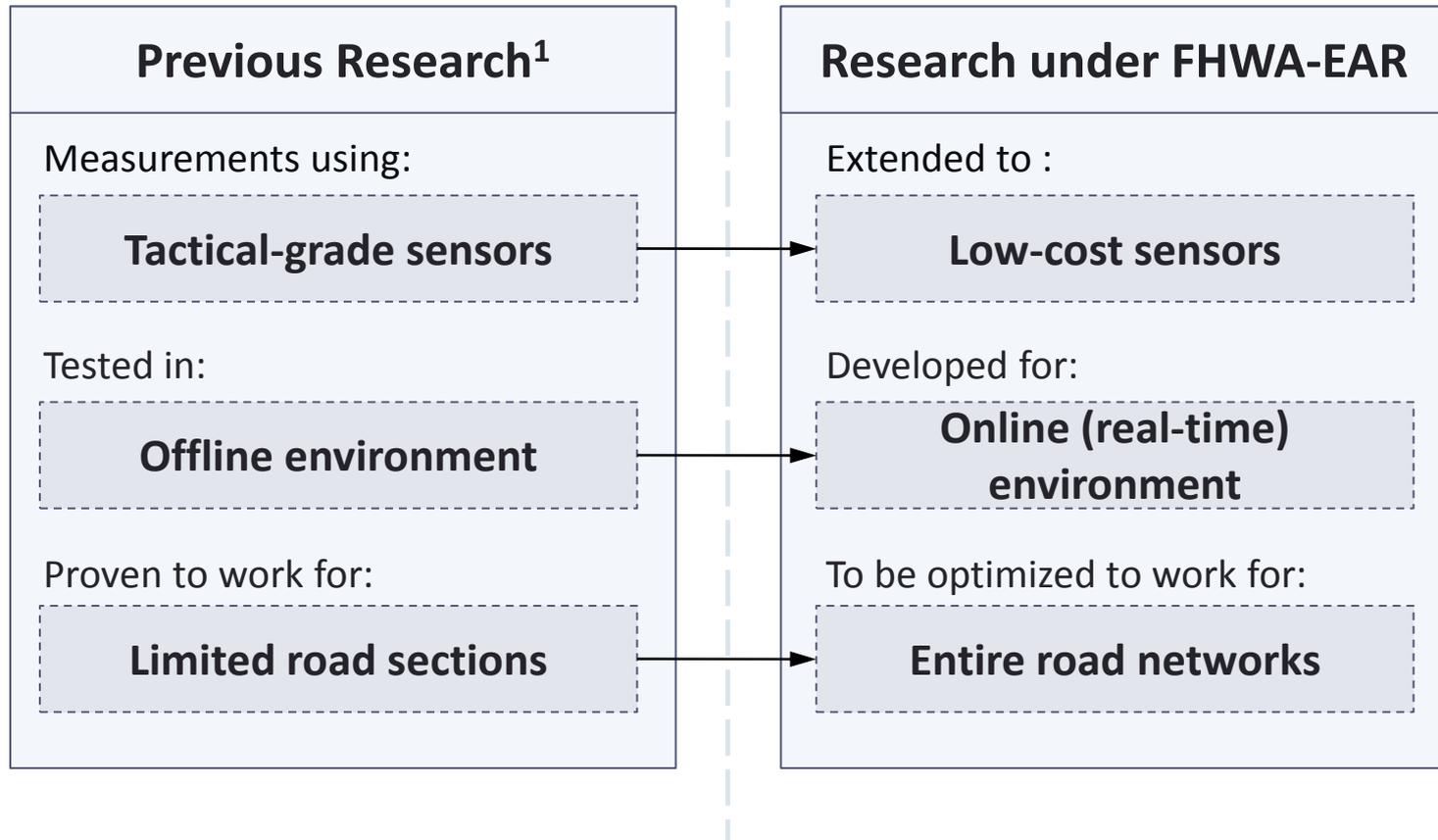
- Prior work^[1] described use of:
 - Particle filters for terrain-based global localization
 - Unscented Kalman Filter (UKF) for terrain-based local tracking



[1] Dean, A J; Langelaan; J W; Brennan, S N; "Improvements in Terrain-based Road Vehicle Localization by Initializing an Unscented Kalman Filter Using Particle Filters", Proceedings of the American Control Conference 2010, Baltimore, MD, June 30-July 02, 2010

However...

- Limitations of prior work



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Noise modeling

- Noise model

$$\omega = \omega_{TRUE} + \eta + b$$

ω = Angular rate

η = White noise (Angle Random Walk)

b = Drift in bias (Bias Instability)

- Primary noise sources in inertial sensor gyroscopes
 - **Angle random walk** with characterizing coefficient N

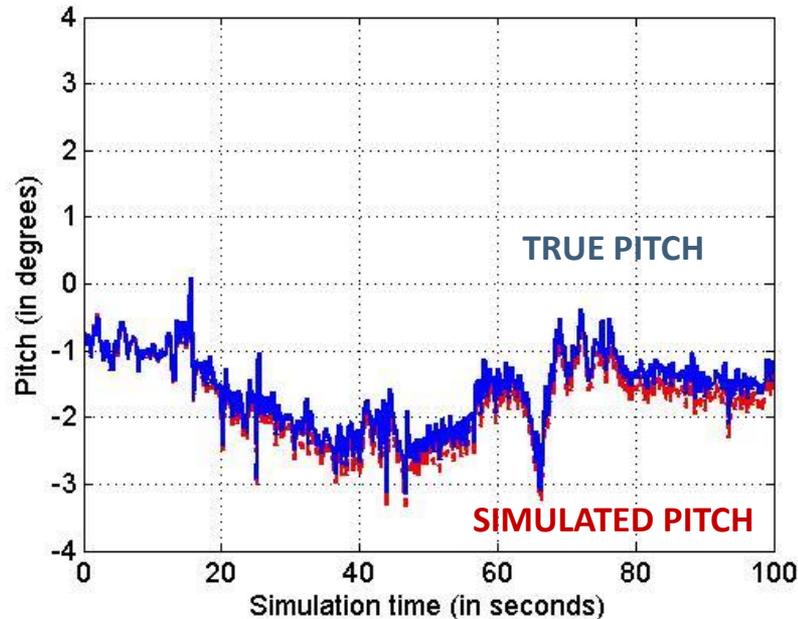
$$E[\eta^2] = N^2$$

- **Bias instability** with characterizing coefficient B

$$\dot{b} = -\beta b + \eta_b$$

Low-cost sensors produce drift in measurement

- Simulating pitch measurements from virtual sensors

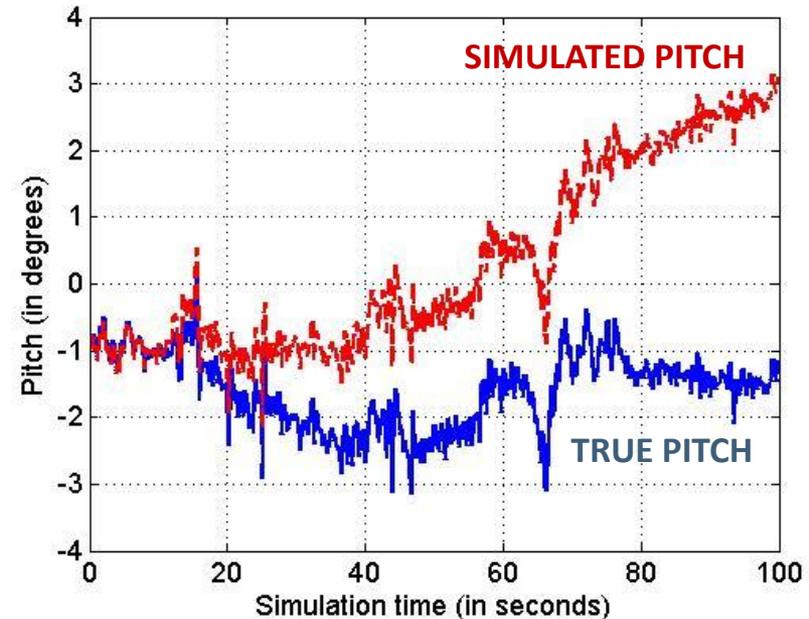


Representative tactical-grade sensor

Noise model parameters

$$N = 0.001^\circ/\sqrt{\text{sec}}$$

$$B = 0.0001^\circ/\text{sec}$$



Representative low-cost MEMS sensor

Noise model parameters

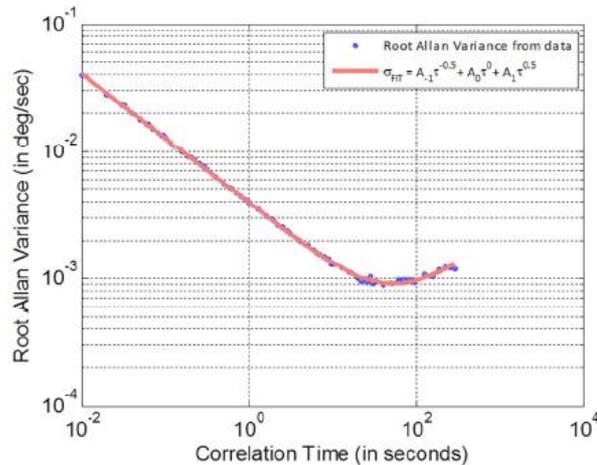
$$N = 0.01^\circ/\sqrt{\text{sec}}$$

$$B = 0.01^\circ/\text{sec}$$

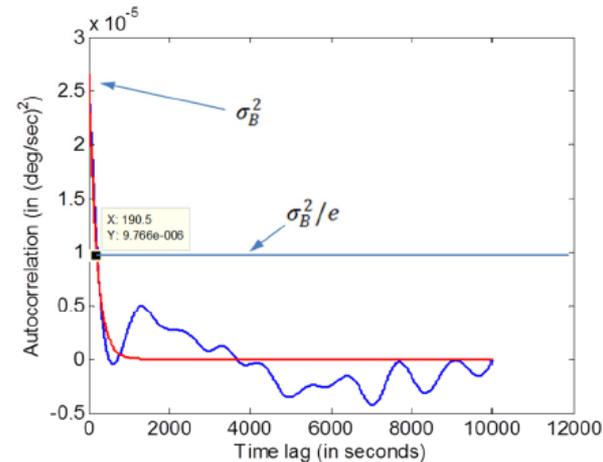
Modeling is validated through sensor characterization

- Using Allan variance and autocorrelation analysis to recover sensor specifications

Parameter	Input	Recovered
Angle random walk coefficient, N ($^{\circ}/\sqrt{sec}$)	0.0040	0.0041
Bias instability coefficient, B ($^{\circ}/sec$)	0.005	0.0047
Correlation time, T_C (sec)	200	190.74



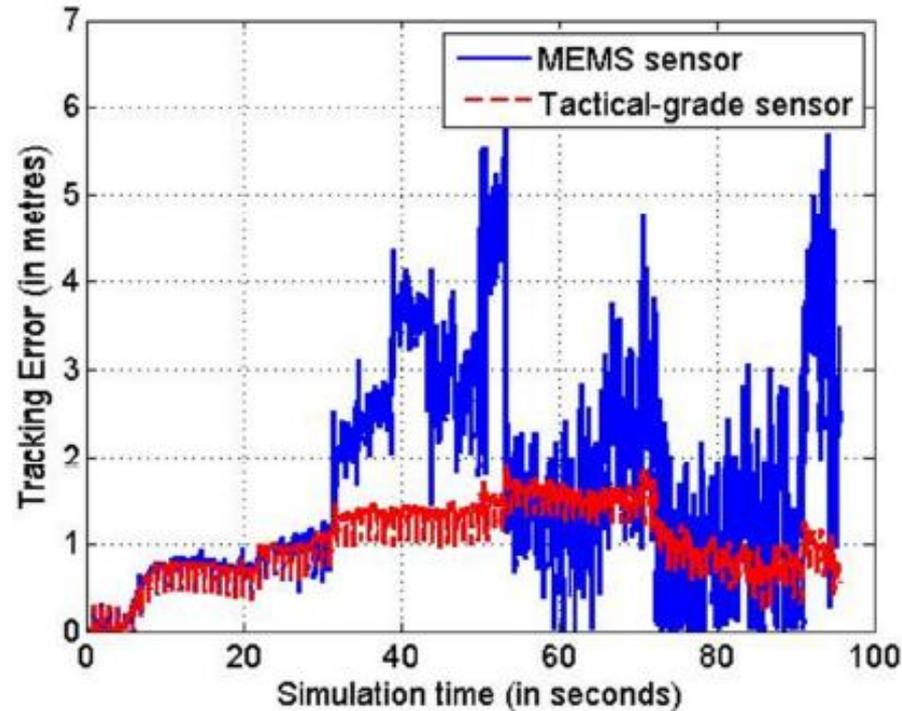
Allan variance analysis



Autocorrelation analysis

Tracking is possible with low-cost sensors

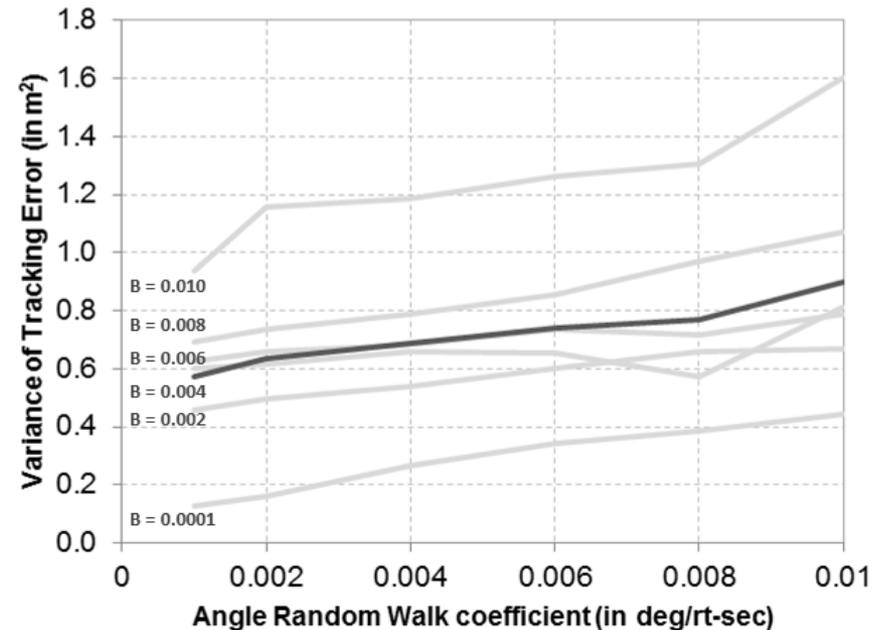
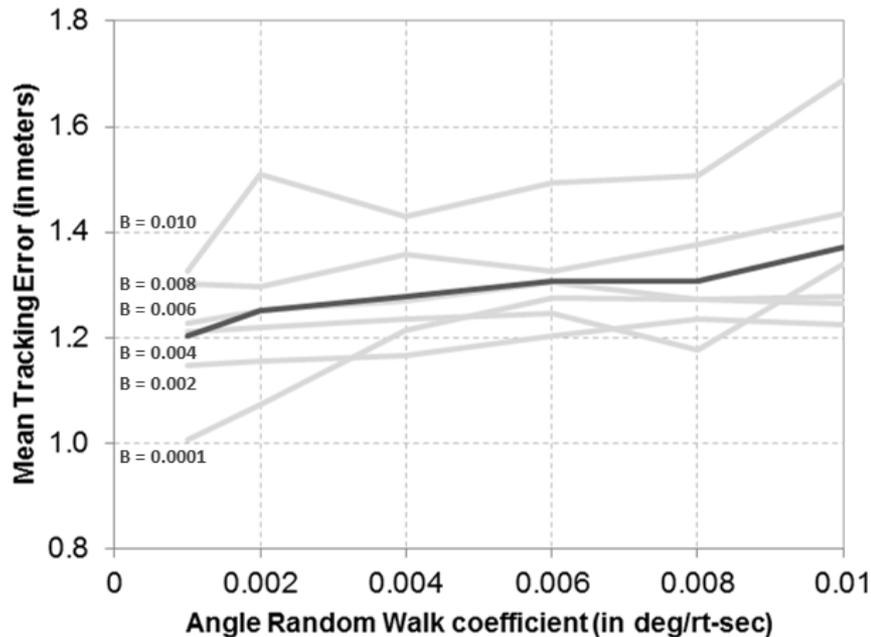
- Vehicle tracking can be achieved even with low-cost inertial sensors



- However, the tracking errors are larger with the low-cost inertial sensors

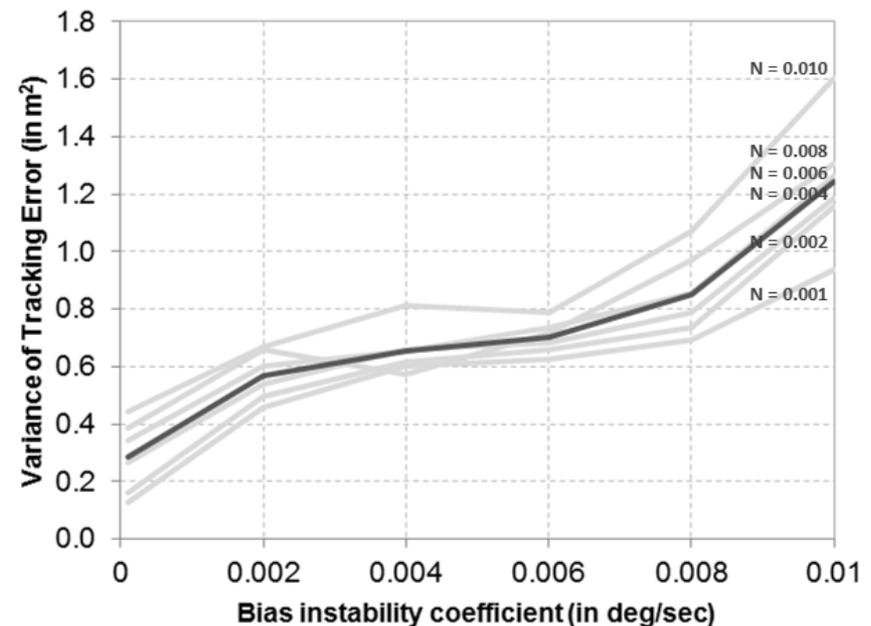
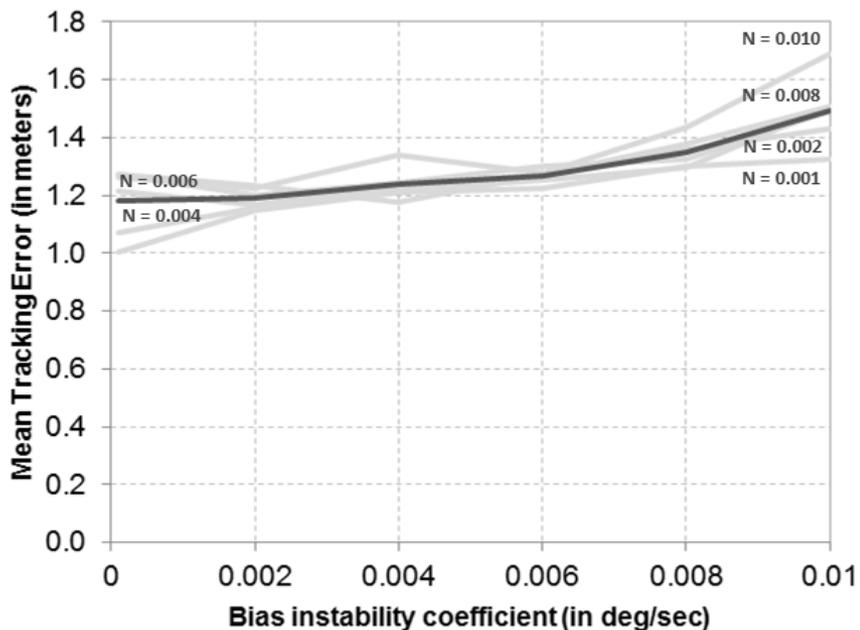
Angle random walk has little impact...

- Relatively constant mean tracking error and tracking precision are observed



But bias instability does...

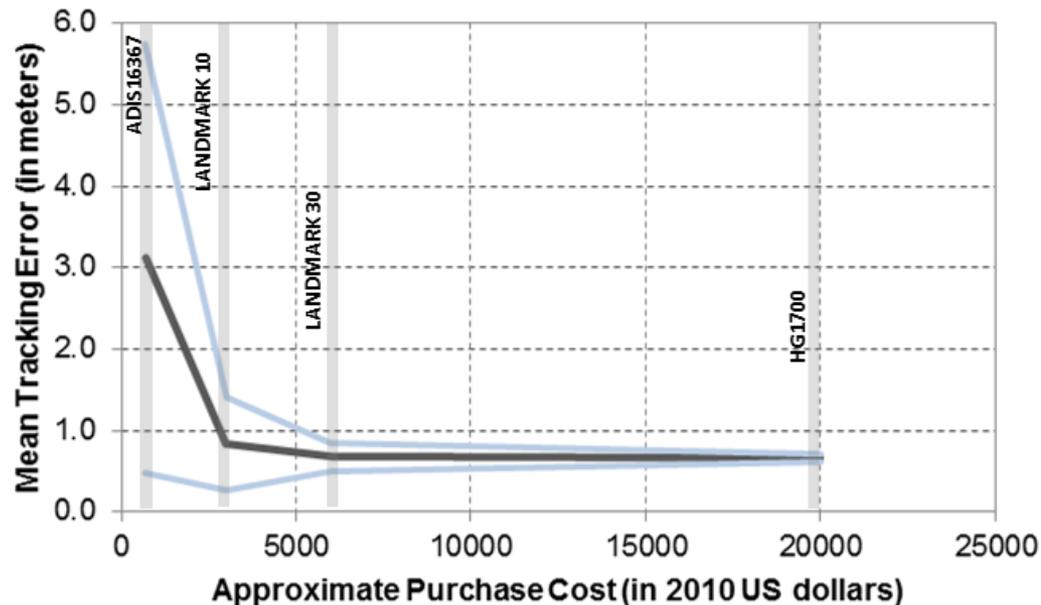
- Variance of tracking error varies approximately linearly with bias instability coefficients
- Mean tracking error remains unaffected



Accuracy and precision increase with cost...

- Sensors considered for analysis

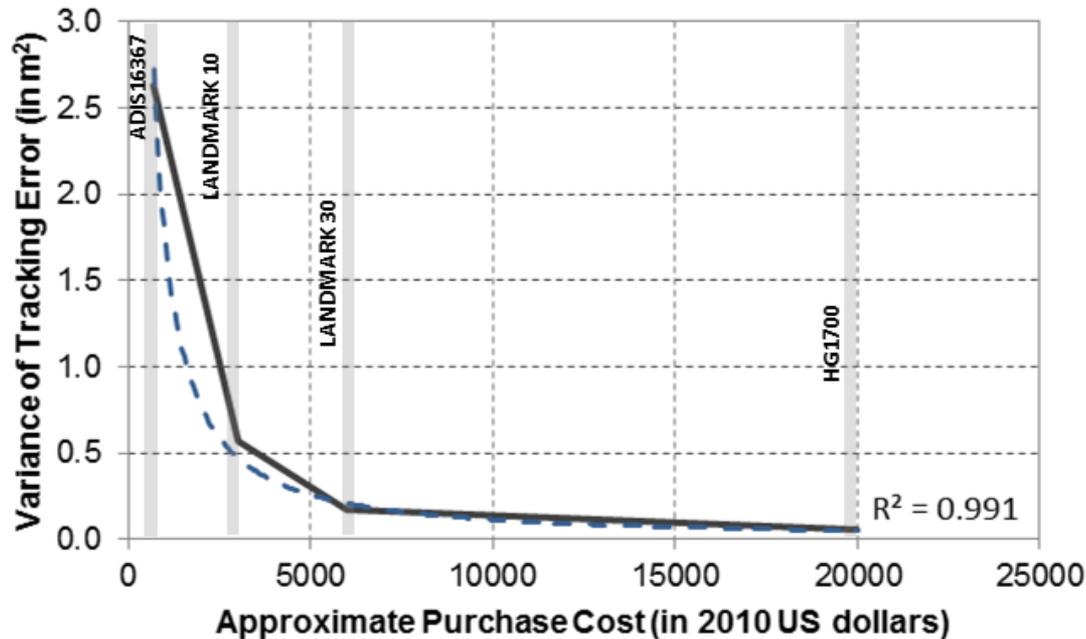
Sensor	Angle Random Walk Coefficient, N ($^{\circ}/\sqrt{sec}$)	Bias Instability Coefficient, B ($^{\circ}/sec$)
Analog Devices ADIS16367	0.033	0.013
Gladiator Technologies Landmark 10	0.014	0.007
Gladiator Technologies Landmark 30	0.01	0.003
Honeywell HG1700	0.0016	0.0003



But the law of diminishing returns kicks in...

- Higher tracking precision comes at an increasingly larger investment
- Tracking error variance is related to sensor cost by a power law:

$$\text{Tracking Error Variance} = 6997.1 (\text{Cost})^{-1.199}$$

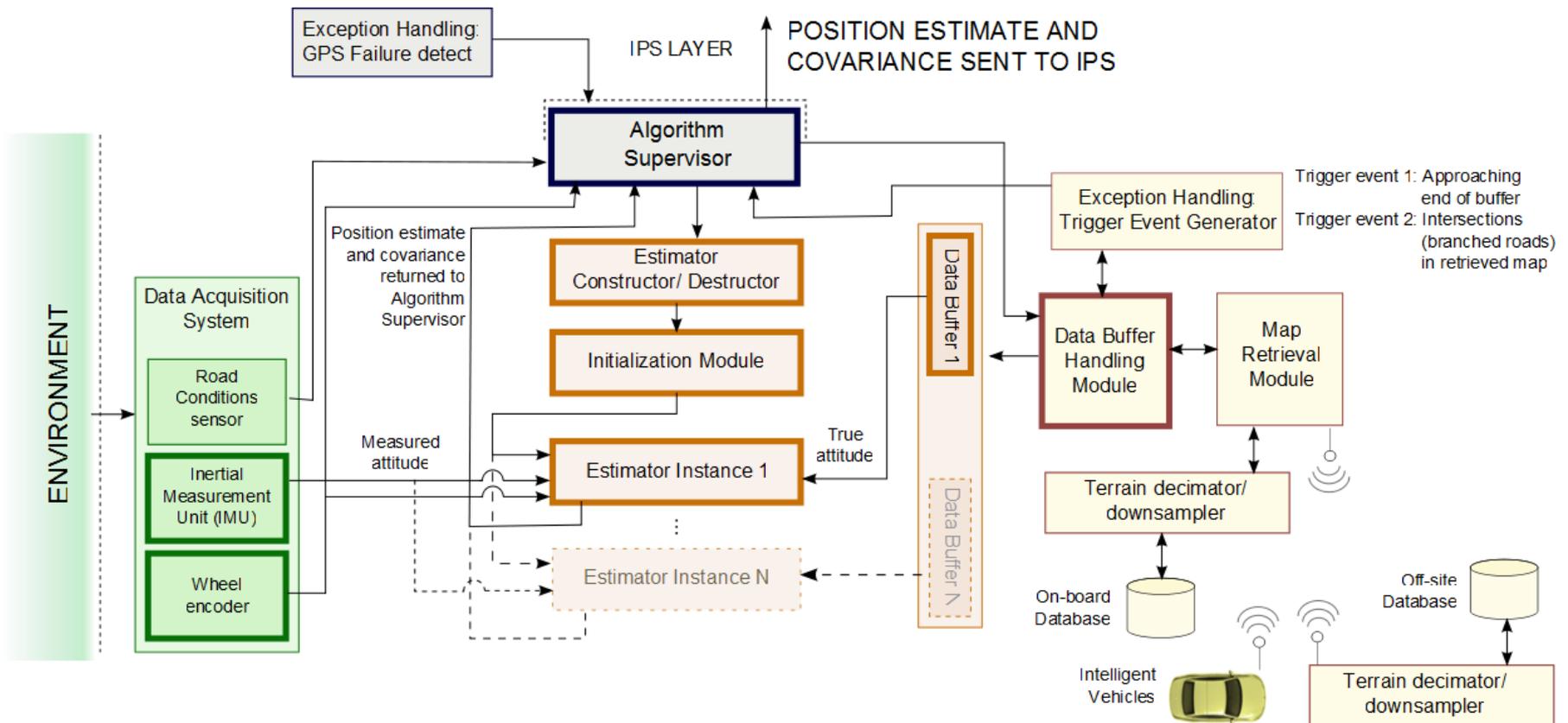


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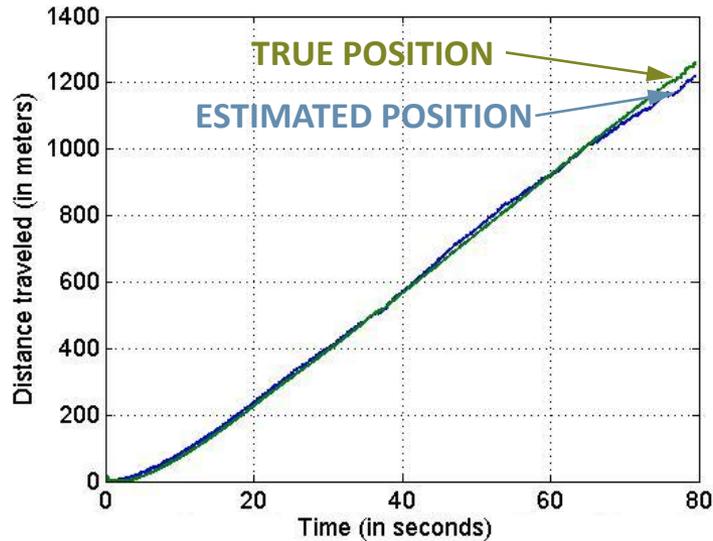
Framework for real-time implementation

- Bold boxes indicate currently operational modules
- Modules not in bold show next steps/improvements or future avenues to explore, once the current system is operationalized

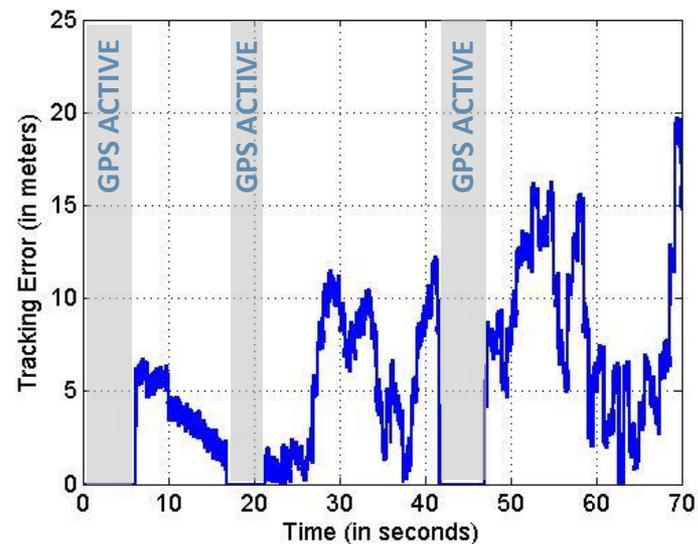
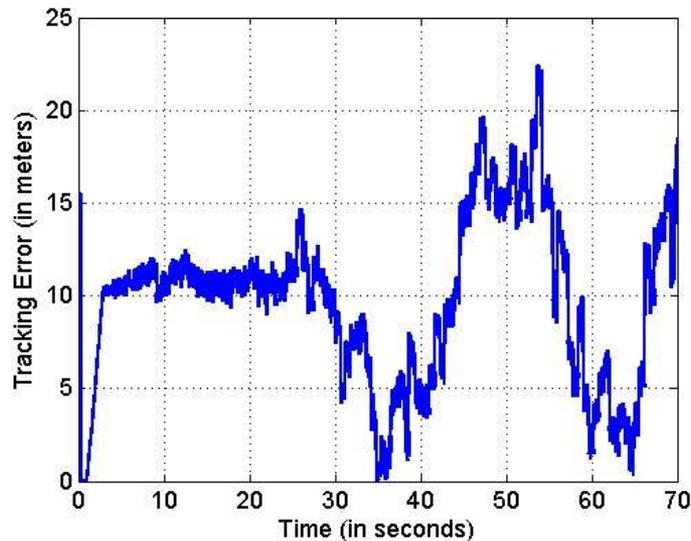
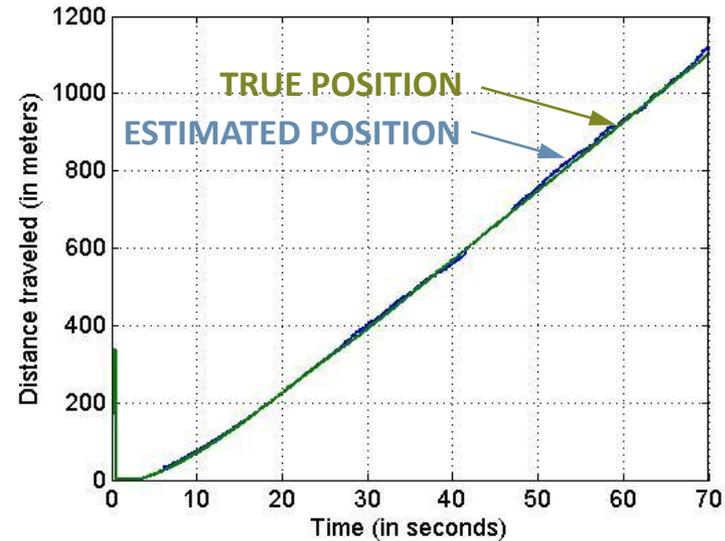


Real-time tracking results with low-cost sensors

No GPS



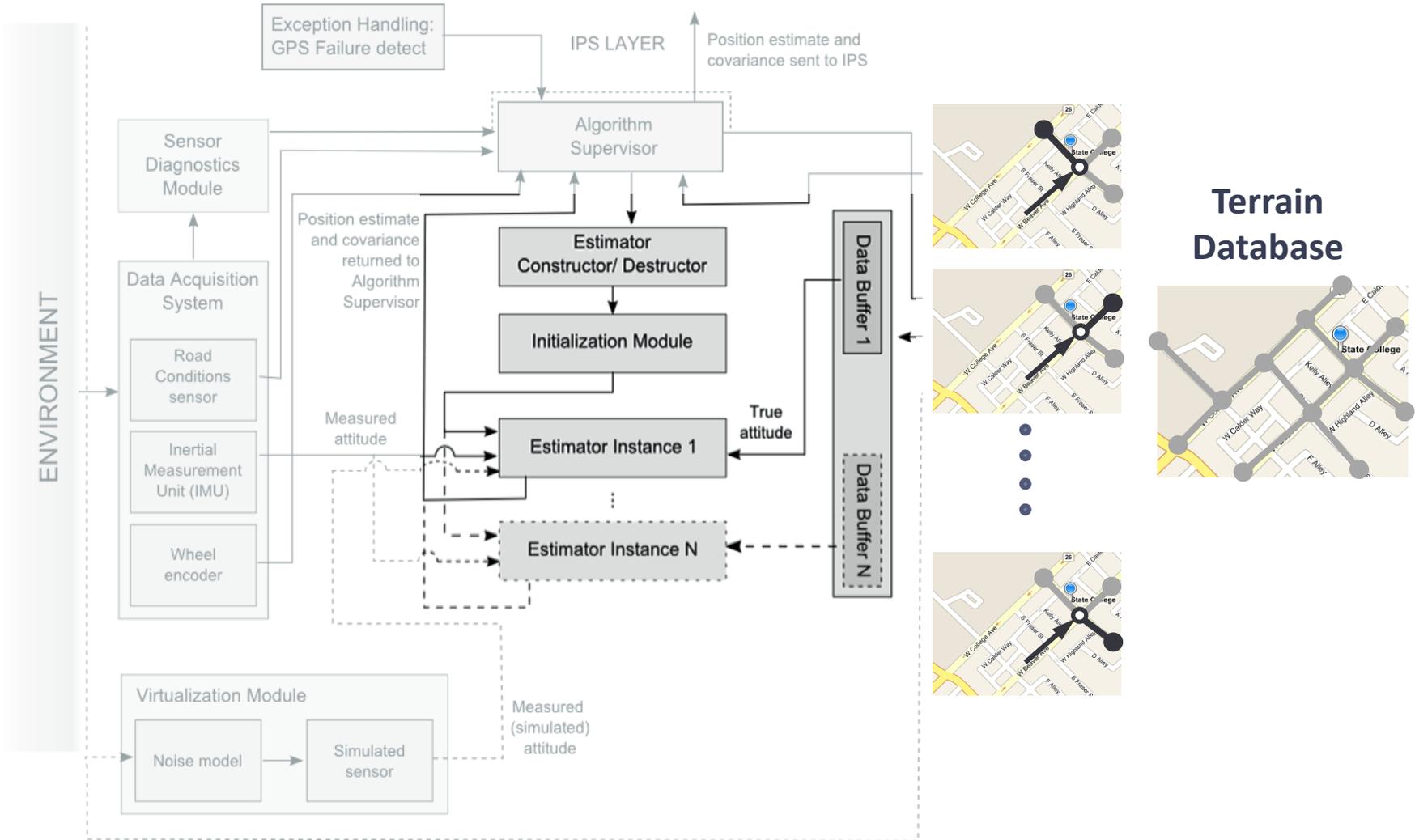
Intermittent GPS



OUTLINE

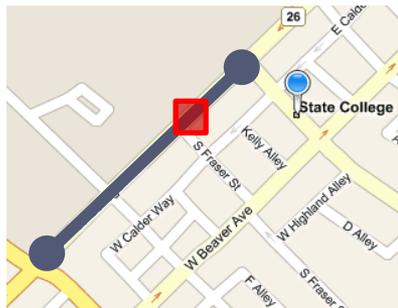
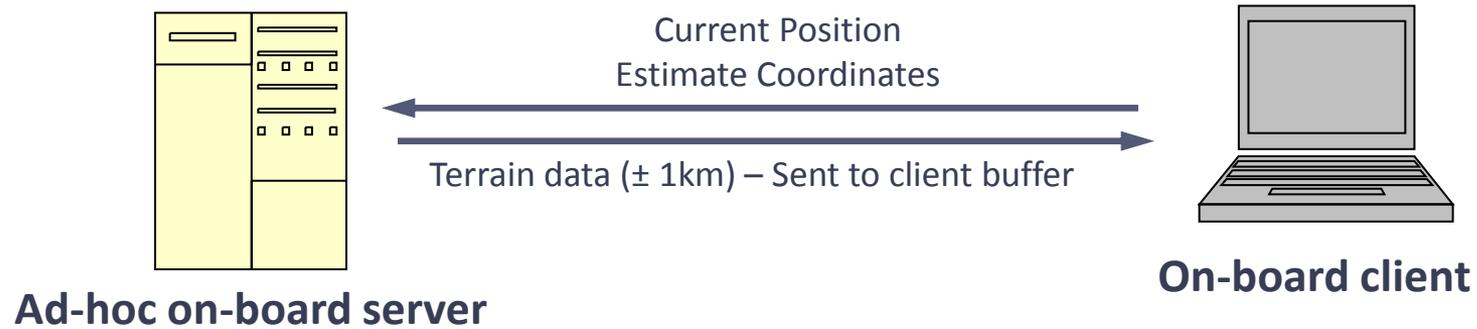
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Vehicle tracking framework



Terrain database management is an issue

- Database size
 - Single computer cannot handle a ‘large’ terrain database
 - Memory allocation errors arise for road segments larger than 5 km
- One possible solution



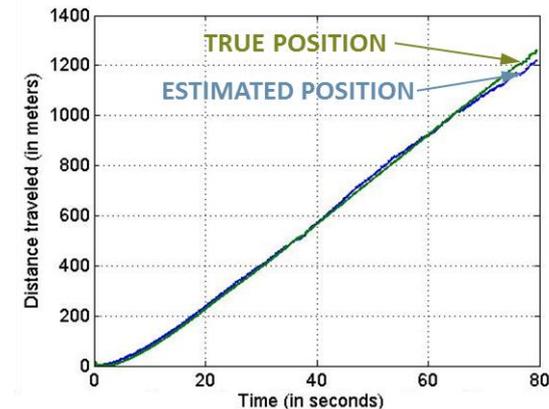
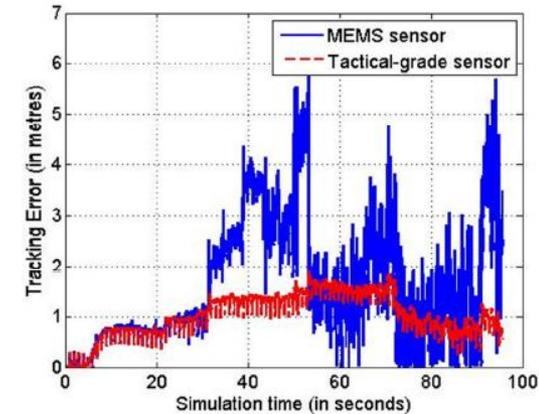
Road ID	Distance								
	Attitude (Pitch)								
	GPS coordinates								
Road ID	Distance	...							
		•							
		•							

OUTLINE

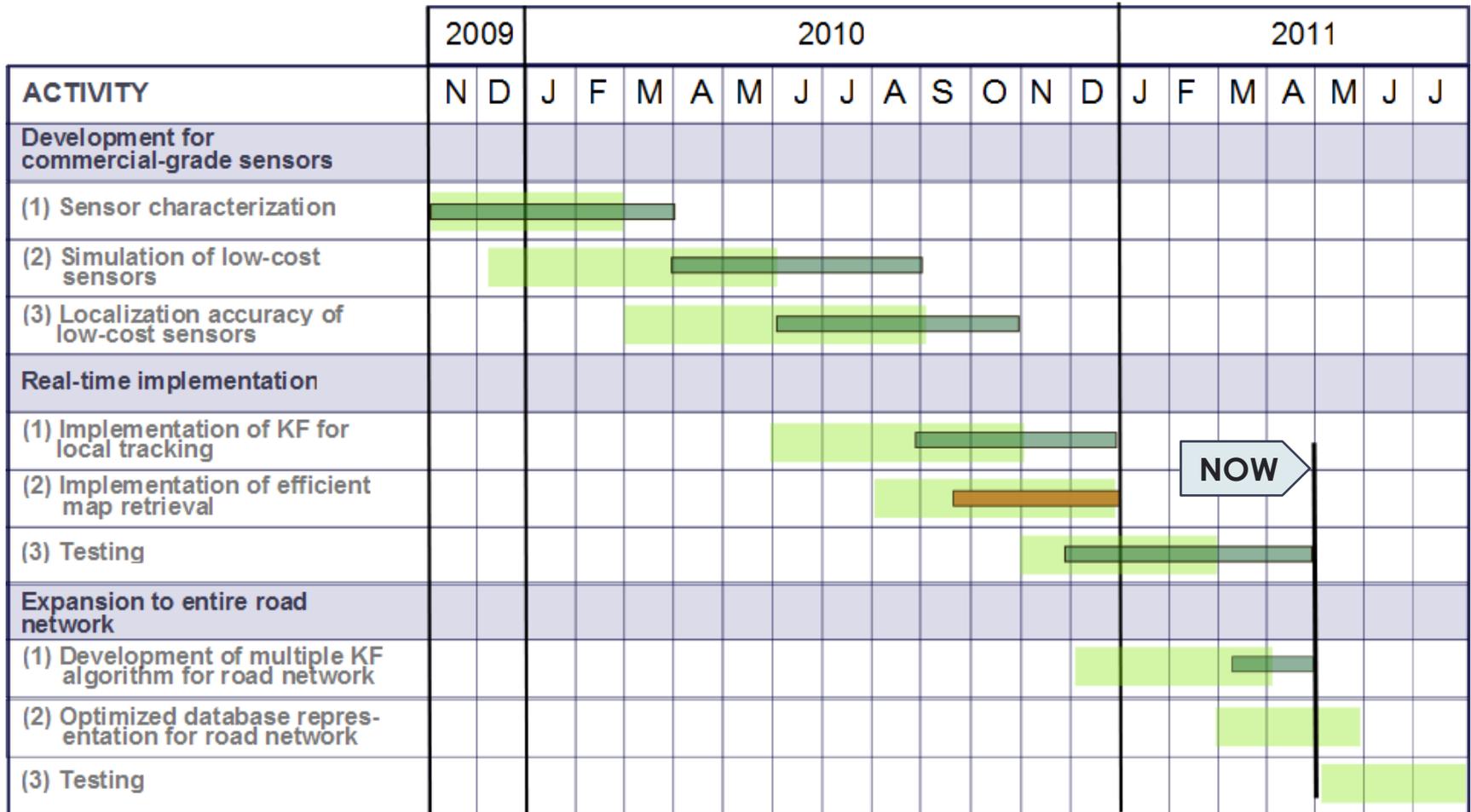
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Summary

- Vehicle tracking can be achieved using low-cost inertial sensors with inferior specifications
- Real-time tracking is currently achievable on small road segments (length < 5 km)
- Work is underway to expand capabilities to handle road networks



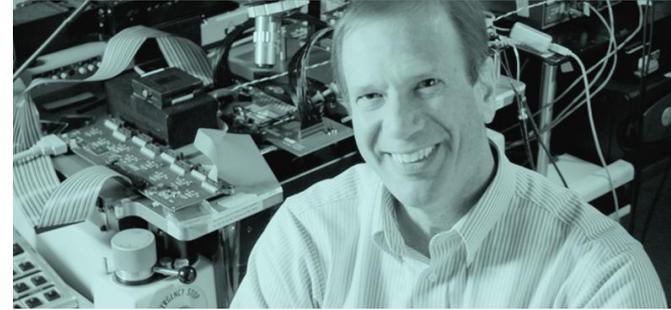
Timeline



Questions?

Kshitij Jerath | kjerath@psu.edu
Sean N. Brennan | sbrennan@psu.edu

Department of Mechanical and Nuclear Engineering
The Pennsylvania State University



Visual Navigation for Robust Localization in GPS-degraded Environments

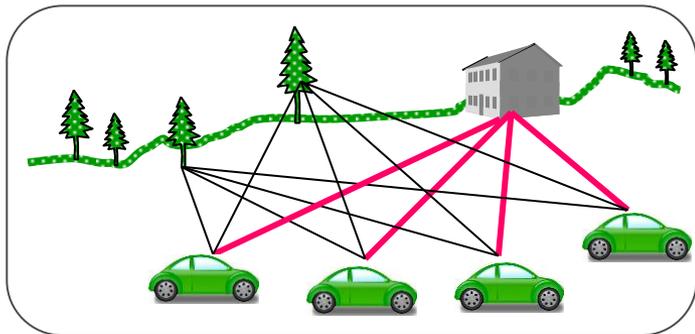
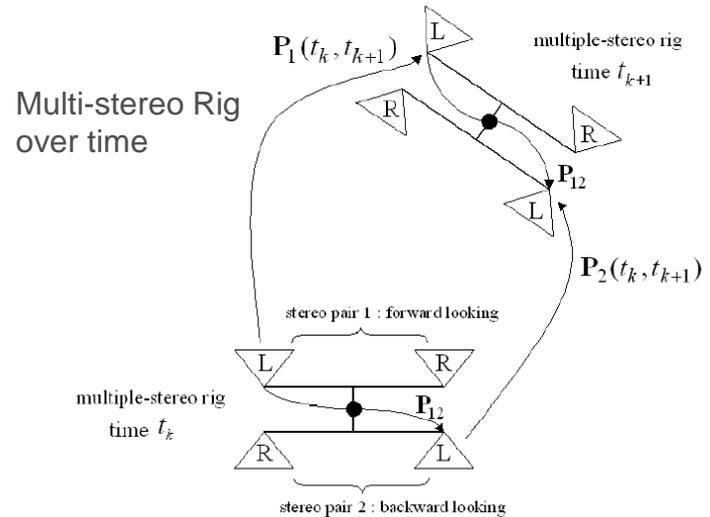
Raia Hadsell, Lu Wang, Supun Samarasekera
Vision Technologies Division

SRI International Sarnoff Princeton, NJ

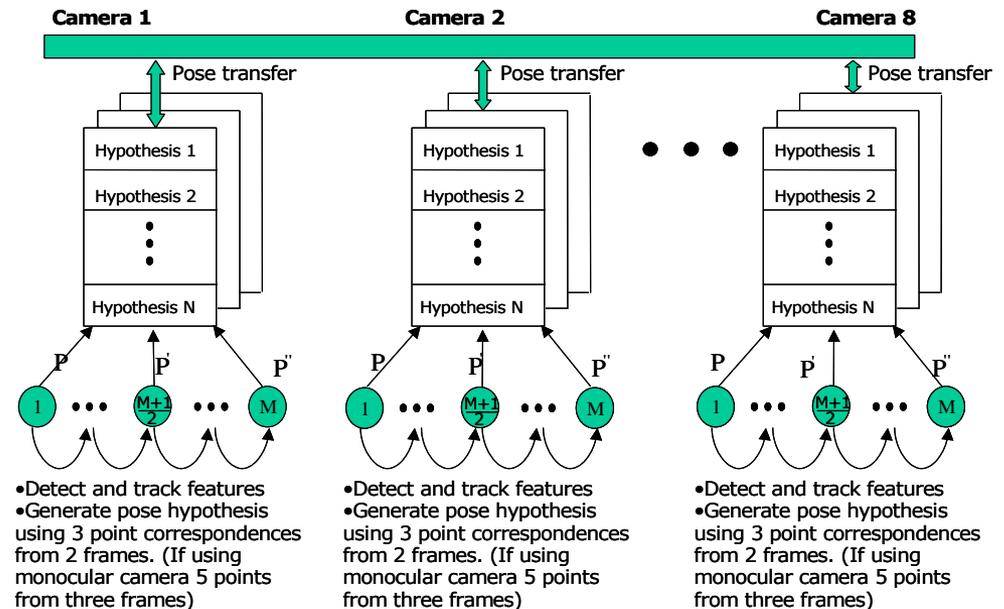
April 29, 2011

Multi-Camera Visual Odometry

- Step 1: Feature Detection and Tracking
 - Harris corner detection (up to 1000/frame)
 - Each feature correspondence creates a feature *track*
 - Feature tracks are maintained over many frames, until lost
- Step 2: Multi-camera Preemptive RANSAC
 - 500 hypotheses per camera set



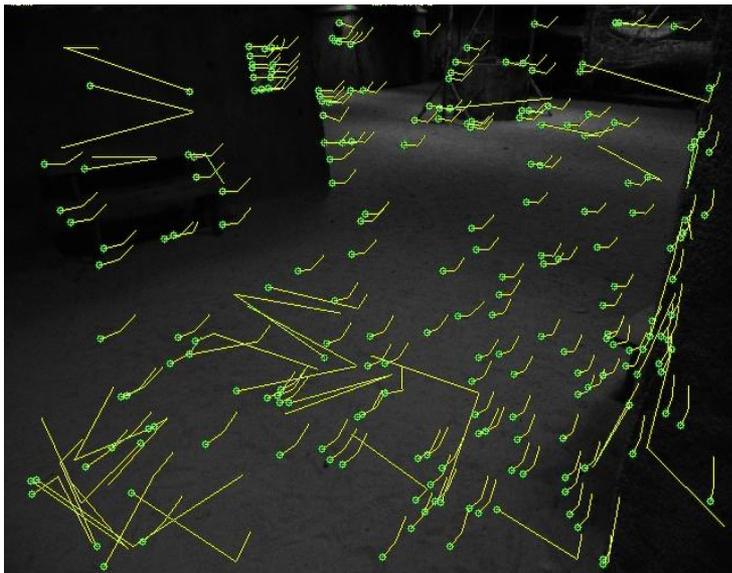
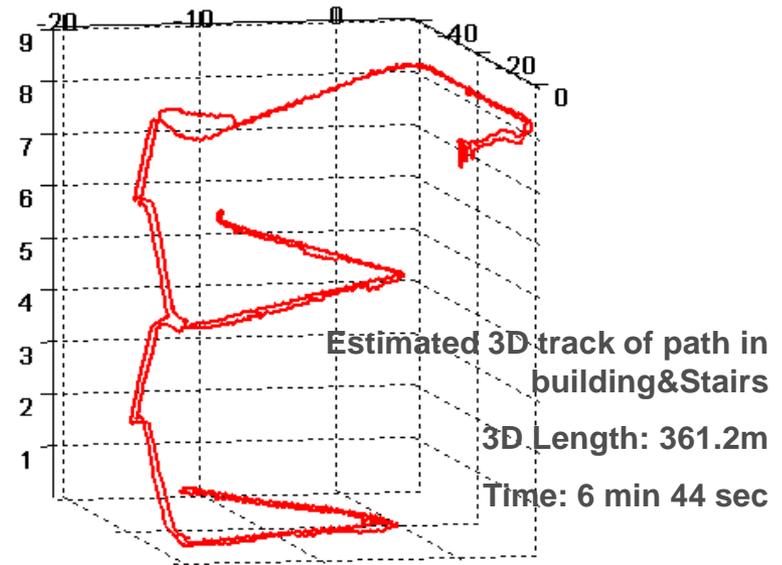
Visual odometry concept



Multi-camera preemptive RANSAC

Multi-Camera Visual Odometry

- Step 3: Multi-camera Pose Refinement
 - Each camera iterative refines its solution
 - Each refined pose is evaluated over all cameras
 - 6DOF pose is output



tracked features over 3 frames

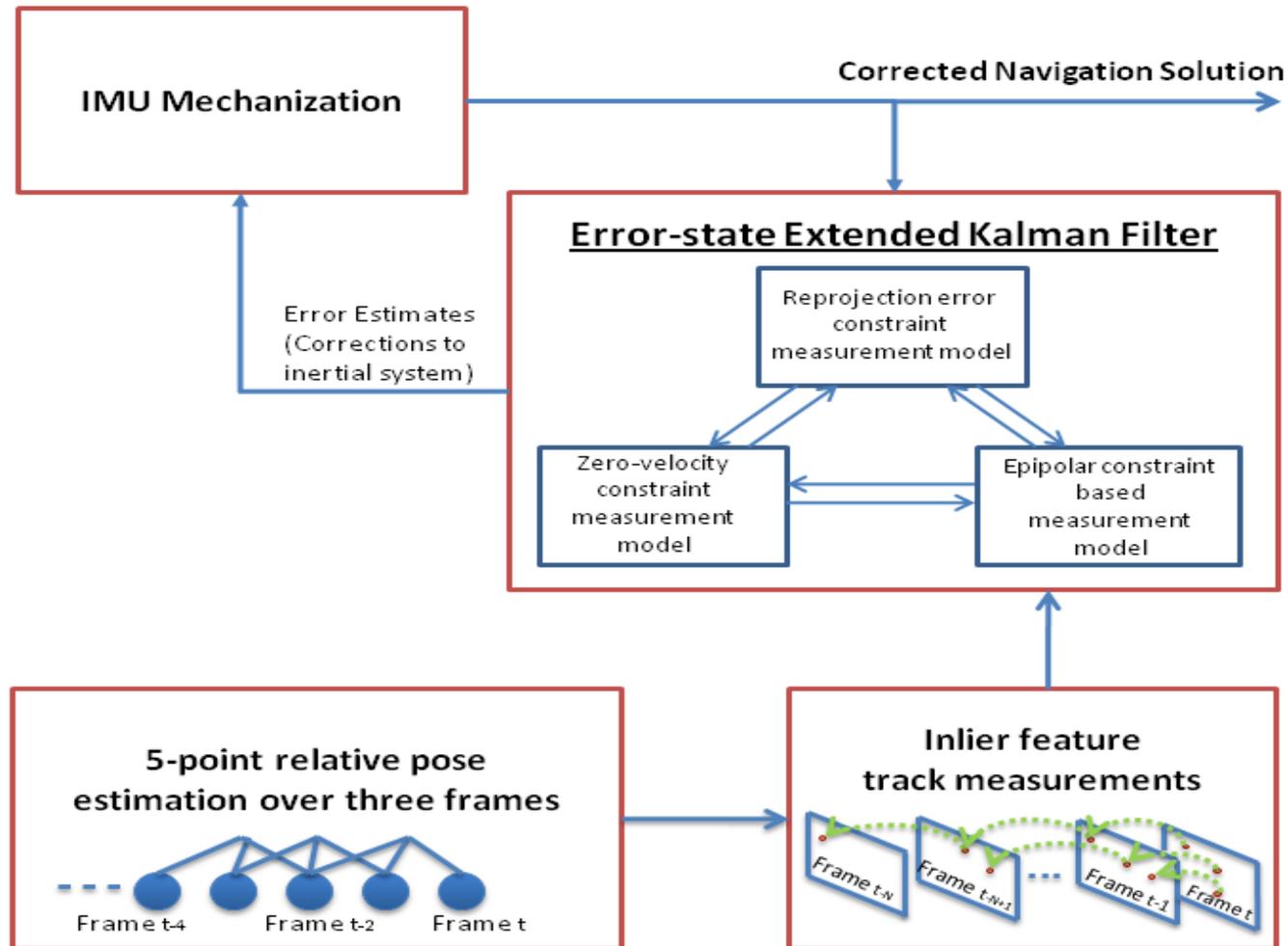


after hypothesis pruning and outlier rejection

Extended Kalman Filter

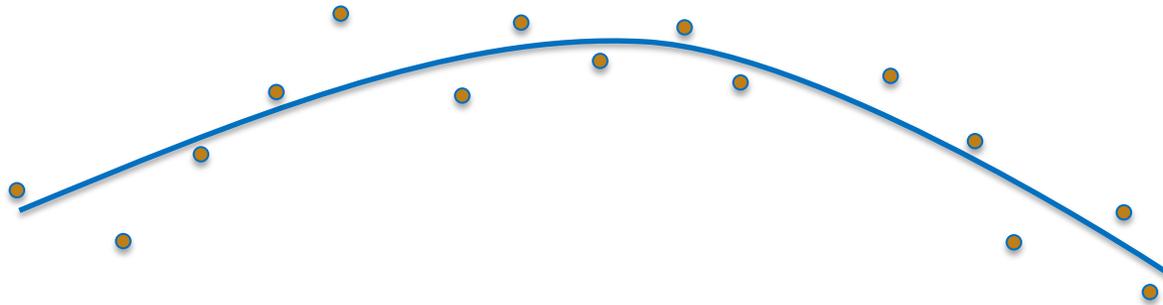
- Multiple constraint measurement model:
 - Re-projection constraint (used most of the time)
 - Each feature track is used independently to form a measurement for the Kalman filter.
 - Directly feeding the low level visual information provides the most natural measurement model to implement tightly coupled IMU and camera integration.
 - Camera pose estimates from vision alone are only used to remove outlier matches in the feature tracks as much as possible.
- Error state (indirect form):
 - Kalman filter estimates errors in the state vector, which are then fed back into the IMU mechanization block to obtain the final corrected navigation solution.
 - Circumvents the need to employ platform specific dynamic process model.

Extended Kalman Filter



Visual Odometry with GPS filtering

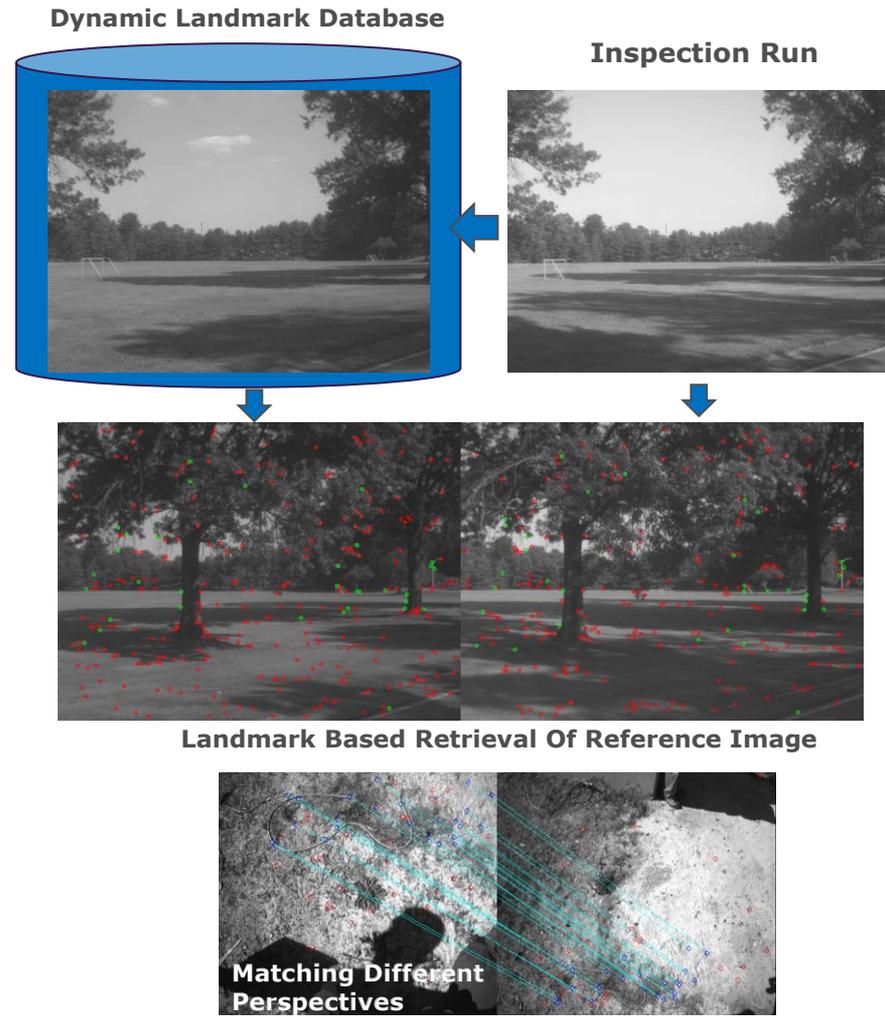
- Our approach:
 - Modify the Kalman filter implementation from a local world reference frame to earth-centered earth-fixed coordinate system
 - Accumulate GPS tracks over short durations and compare against visual-odometry/ IMU based tracks.
 - When there is track consistency accept inlier GPS measurements with weighted confidence.
- Use inlier GPS measurements for global position and heading fix.
- Create explicit heading measurement from short duration GPS tracks that have passed consistency checks to initialize global heading direction



Visual Odometry with Landmark Matching

Visual landmarking gives absolute 3D positioning from landmark databases recorded and augmented on the fly.

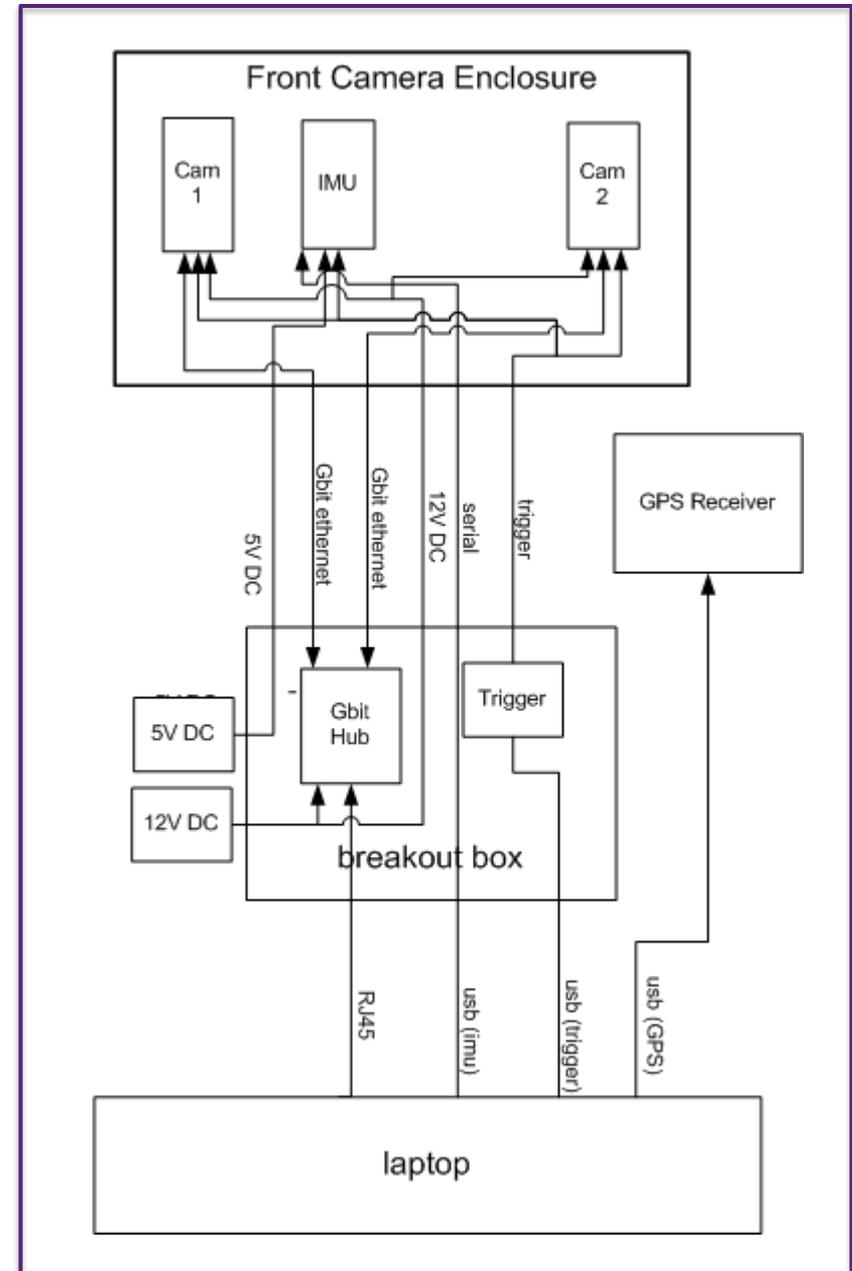
- **Landmark image**: a constellation of HOG features, each associated with a 3D point (from stereo)
- **Landmark database**: a collection of automatically selected landmark images, referenced by the 6DOF viewing pose.
- **Landmark matching**: retrieving and recognizing a landmark image (uses vocabulary tree and spatial caching for speed), then estimating new viewing pose.



Auburn Test Vehicle Sensor Mount

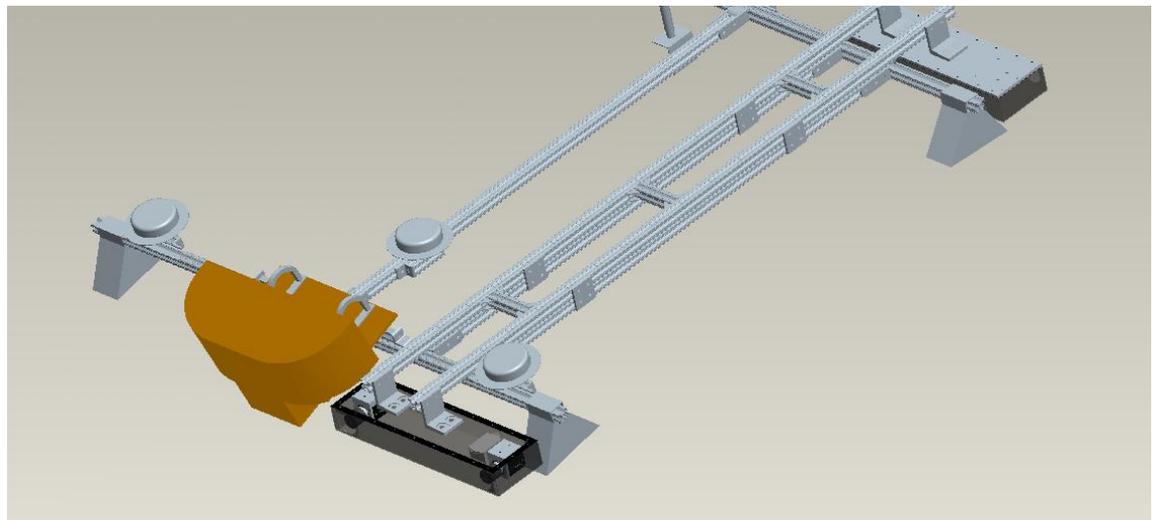
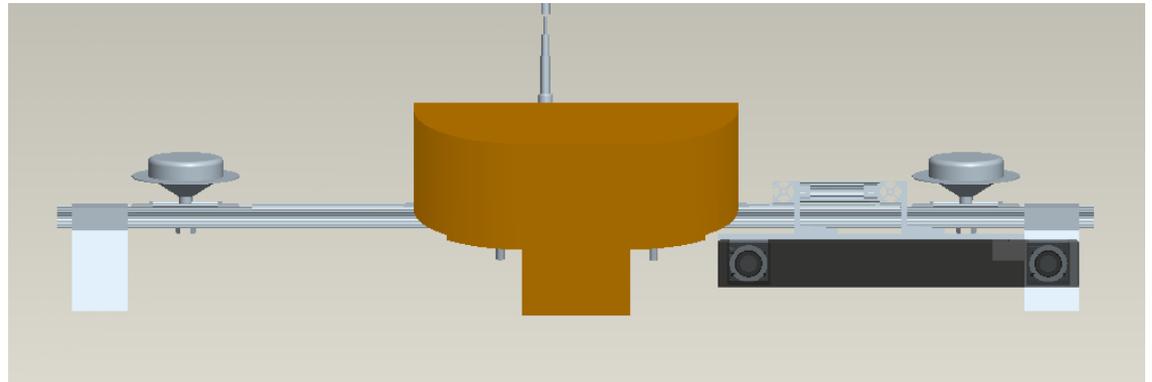
Components:

- **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

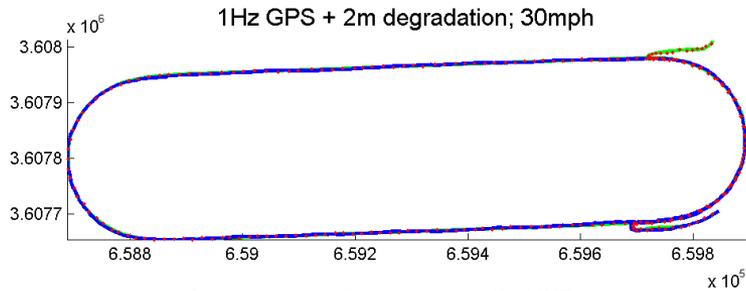


Auburn Test Vehicle Sensor Mount

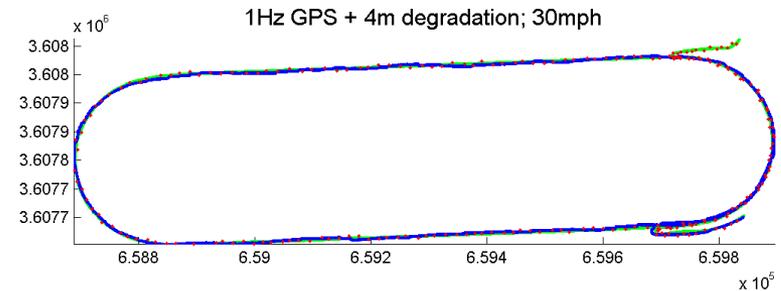
- Front stereo camera pair has 35cm baseline
- Flat azimuthal positioning
- Original design had front and back stereo cameras
- Downsized to front stereo only after water damage to rear camera set.
- Visual Navigation runs realtime (30 frames per second, < 1 frame latency) on quad core laptop
- Pose estimates are sent to vehicle computer over TCP/IP.



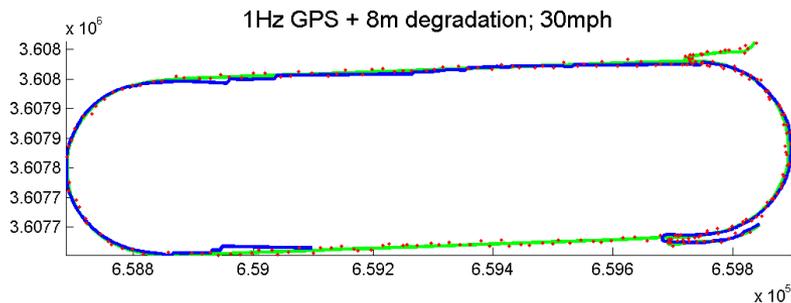
Results with GPS Degradation at 30 mph



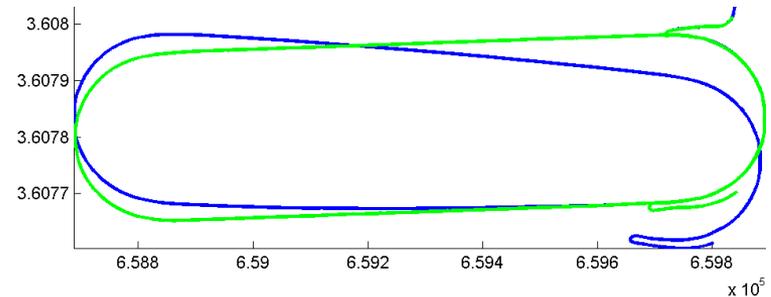
drift: total 1.16m, mean 2.007m
(over 4305 m traveled distance)



drift: total 2.296m, mean 3.21m
(over 4305 m traveled distance)

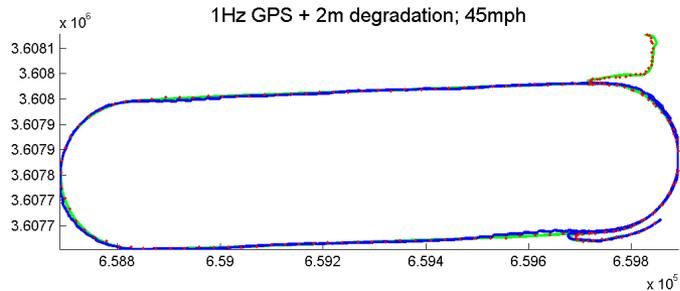


drift: total 1.995m, mean 4.572m
(over 4305 m traveled distance)

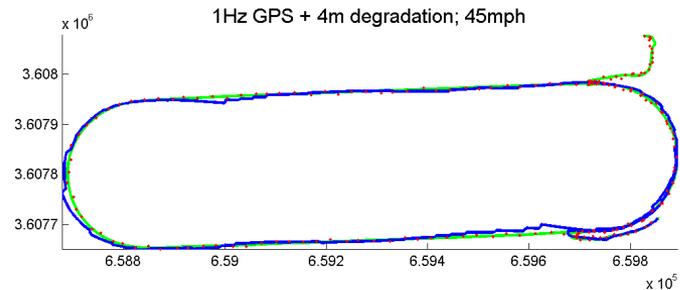


drift: total 99.95m, mean 31.201m
(over 4305 m traveled distance)

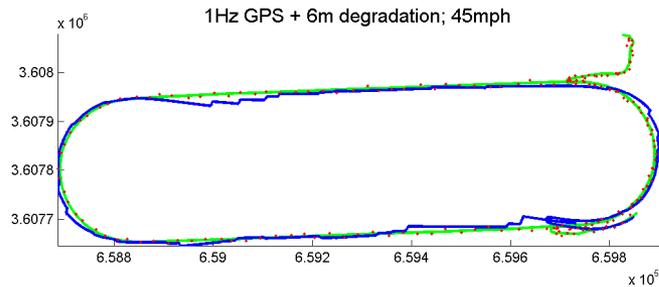
Results with GPS Degradation at 50 mph



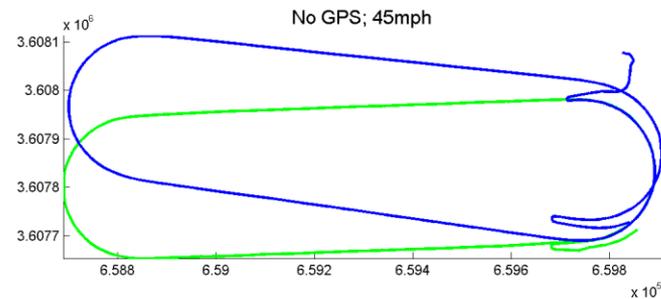
drift: total 1.415m, mean 2.857m
(over 4305 m traveled distance)



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

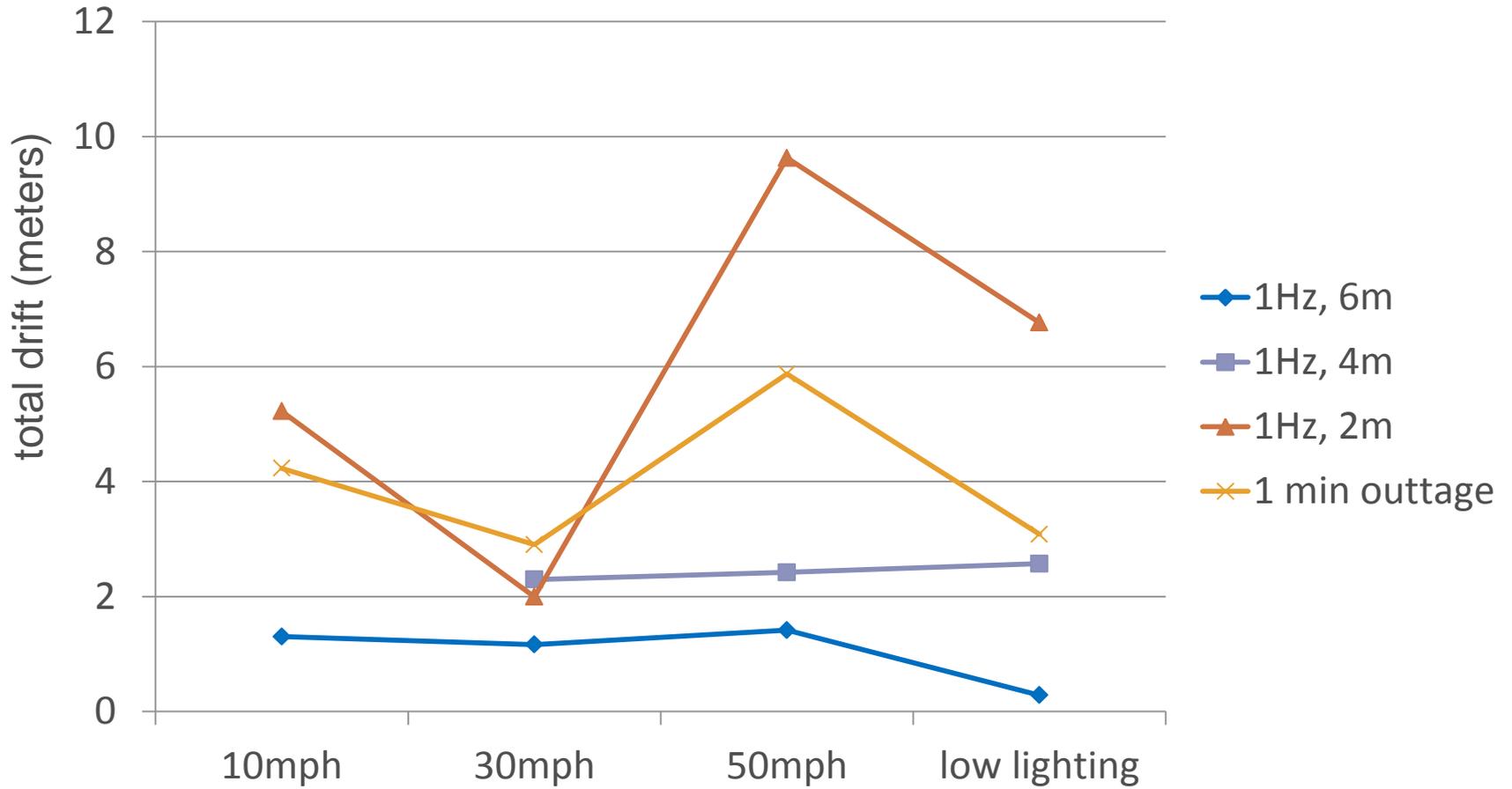


drift: total 9.629m, mean 9.258m
(over 4305 m traveled distance)



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

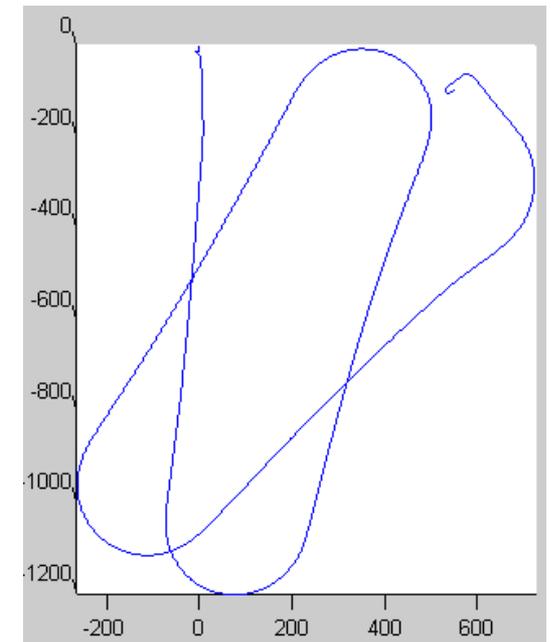
Results over all speeds



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.



Next Steps

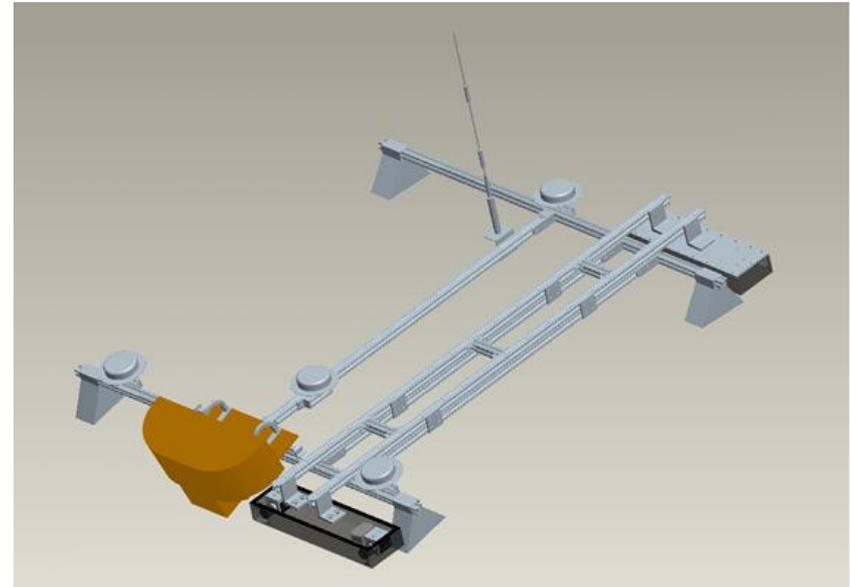
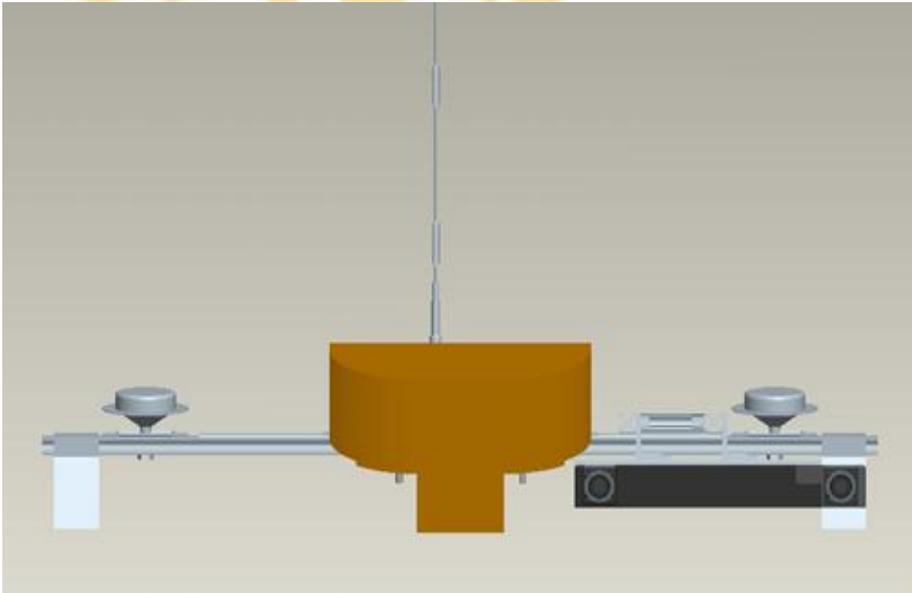
- Integration of Landmark matching with GPS fitting
- Assessment in poor lighting, fog.
- Assessment with moving obstacles (other vehicles)



Overview of Integrated Positioning System (IPS) Auburn

Interfacing Status

- Sensors have been mounted to the test vehicle
 - SRI: stereo cameras
 - Lidar
 - GPS antennas



IPS - Measurements

- Measurements
 - Penn State
 - ECEF position, covariance, timestamp
 - SRI
 - ECEF position(drifting), covariance, timestamp
 - Kapsch
 - angle of arrival, range, timestamp
 - GPS
 - Lane Detection
 - lidar
 - camera

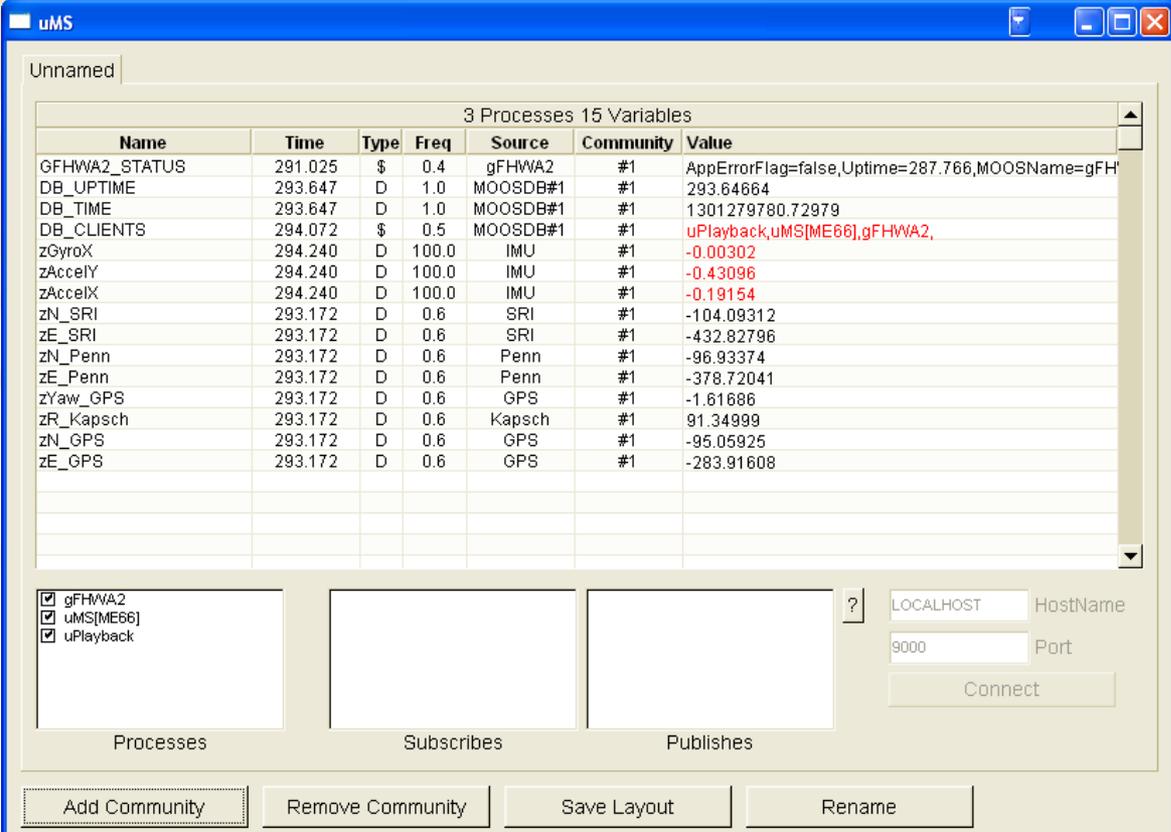
Interfacing Status

- SRI
 - Complete: data sent over ethernet
- Penn State
 - Able to communicate over ethernet
 - Data packet structure needs to be finalized
- Kapsch
 - Serial / ethernet available: ongoing work

- MOOS
 - Mission Oriented Operating Suite
 - Developed/developing at MIT
 - Centralized database architecture
 - Cross platform (advantage over ROS)
 - Realtime Simulation
 - Playback capabilities of logged data
 - Time synchronization
 - C++
 - Data from subsystems must be moved into the database

MOOS Database

- MOOS Database
 - Centralized structure
 - Database is the hub of communications
 - Sensor data is easily collected and stored within the database



uMS

Unnamed

3 Processes 15 Variables

Name	Time	Type	Freq	Source	Community	Value
GFHWA2_STATUS	291.025	\$	0.4	gFHWA2	#1	AppErrorFlag=false,Uptime=287.766,MOOSName=gFH
DB_UPTIME	293.647	D	1.0	MOOSDB#1	#1	293.64664
DB_TIME	293.647	D	1.0	MOOSDB#1	#1	1301279780.72979
DB_CLIENTS	294.072	\$	0.5	MOOSDB#1	#1	uPlayback,uMS[ME66],gFHWA2,
zGyroX	294.240	D	100.0	IMU	#1	-0.00302
zAccelY	294.240	D	100.0	IMU	#1	-0.43096
zAccelX	294.240	D	100.0	IMU	#1	-0.19154
zN_SRI	293.172	D	0.6	SRI	#1	-104.09312
zE_SRI	293.172	D	0.6	SRI	#1	-432.82796
zN_Penn	293.172	D	0.6	Penn	#1	-96.93374
zE_Penn	293.172	D	0.6	Penn	#1	-378.72041
zYaw_GPS	293.172	D	0.6	GPS	#1	-1.61686
zR_Kapsch	293.172	D	0.6	Kapsch	#1	91.34999
zN_GPS	293.172	D	0.6	GPS	#1	-95.05925
zE_GPS	293.172	D	0.6	GPS	#1	-283.91608

Processes: gFHWA2, uMS[ME66], uPlayback

Subscribes: [Empty]

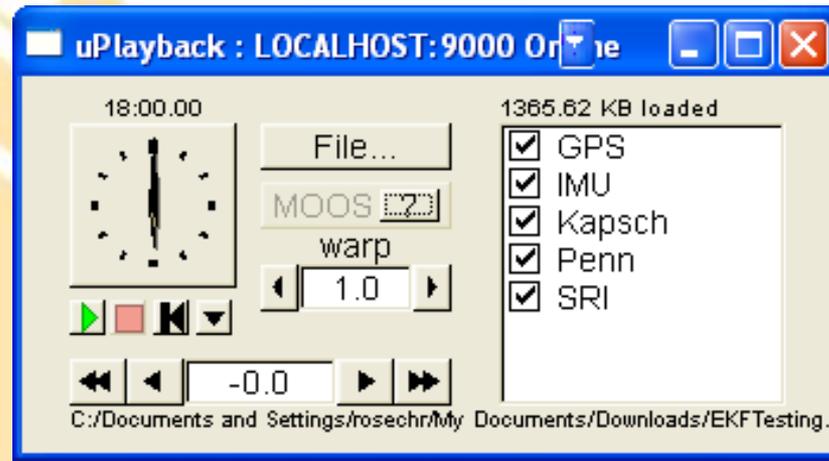
Publishes: [Empty]

HostName: LOCALHOST, Port: 9000, Connect

Add Community, Remove Community, Save Layout, Rename

MOOS Playback

- “Mail” system
 - When a value in the database changes, “new mail” is delivered which signifies that change
 - Used for determining when new data is available for Kalman filter
- MOOS Playback
 - Simulation of data entering the database in real time
 - Allows realtime simulation of logged data
 - Can speed up or slow down time
 - Tuning filters without being at test site
 - Easily move to live implementation
 - Quickly change sensor configurations



Two approaches

- Extended Kalman Filter (EKF)
 - Well studied
 - *ad hoc* state estimator
 - approximates the optimality of Bayes' rule by linearization
- Unscented Kalman Filter (UKF)
 - Improvement on nonlinearities on ranging
 - Cost: increased computation time (RK4)
 - More efficient(less accurate) integration method
 - Assume noise uncorrelated
 - complications with varying measurement times

MOOS IPS

- On change in database
 - updates based on what data changed:
 - if IMU input: time update
 - if measurement: measurement update
 - Easy to simulate sensor outages from each sensor

Measurement Validity

- How do you know if measurements are valid?
 - GPS: Fault detection and exclusion (FDE)
 - Covariance from measurements: filter knows if measurements have unusual characteristics

Future Work

- Evaluate EKF vs. UKF
 - Linearization in EKF adequate?
- Ensure valid time synchronization
 - Mail delivery from database
- Use truth for determining validity

Year Two Tasks and Progress

- Complete integration of systems
- Evaluate Integrated Positioning System (IPS) at NCAT test track
- Evaluate IPS on roadway scenarios
 - Scenarios to be specified by FHWA and Automotive Panel?
- Data Characterization and Analysis of Results
- Final Demonstration/Report
 - Winter