Team Cornell

Dan Huttenlocher

Joint work with Mark Campbell and the Cornell DUC Team

Cornell University
College of Engineering

Cornell University
Faculty of Computing and Information Science

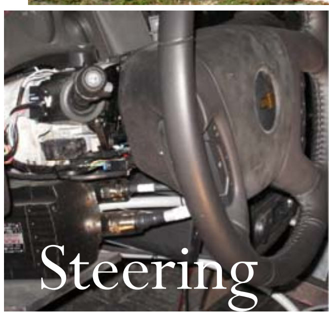
Cornell Urban Challenge Team

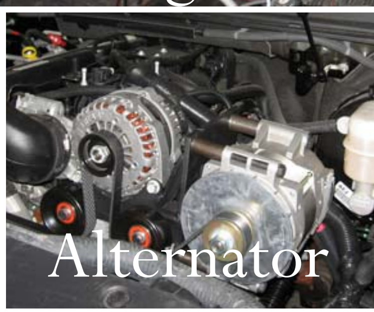
- Small team – 13 students (8 core), 2 faculty
- Track A DARPA funding ($1M)
- One of six vehicles to finish competition
  - But not one of top 3 prize winners
  - 11 selected for Nov final race
  - 35 selected for Oct semi-finals
  - ~75 received Jun/Jul site visits

Distinguishing Characteristics

- Designed and developed both for DUC and as subsequent research platform
  - Tightly integrated perception and planning
- Attention to engineering elegance
  - From clean appearance to “human like” driving
- In-house actuation and pose estimation
  - Actuation performed better than repurposed commercial human driver assistance
  - Pose estimation comparable using Applanix
- Object tracking and ID assignment

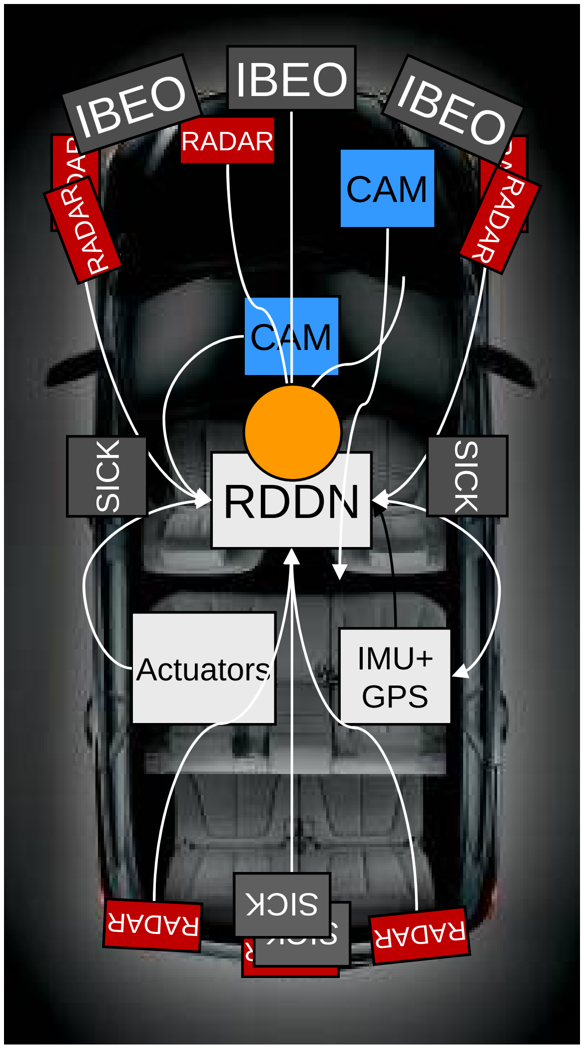
Vehicle Platform

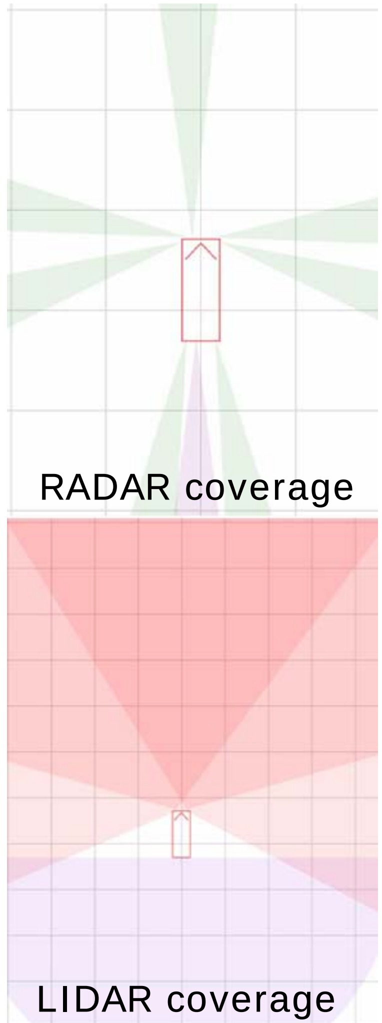




- In-house automation (based on NHTSA specs):
  - Steering: 700 deg/sec @ 24 Nm, 135 Nm max
  - Brake: 376 rpm @ 25 Nm, 50 Nm max
  - Throttle by wire
  - Human drivable
- 17 servers
  - Intel dual-core mobile processors
- Power (4 hr backup)
  - 24VDC 200-amp secondary alternator
  - Redundant 120VAC inverters
  - Deep cycle battery backup

Sensor Configuration

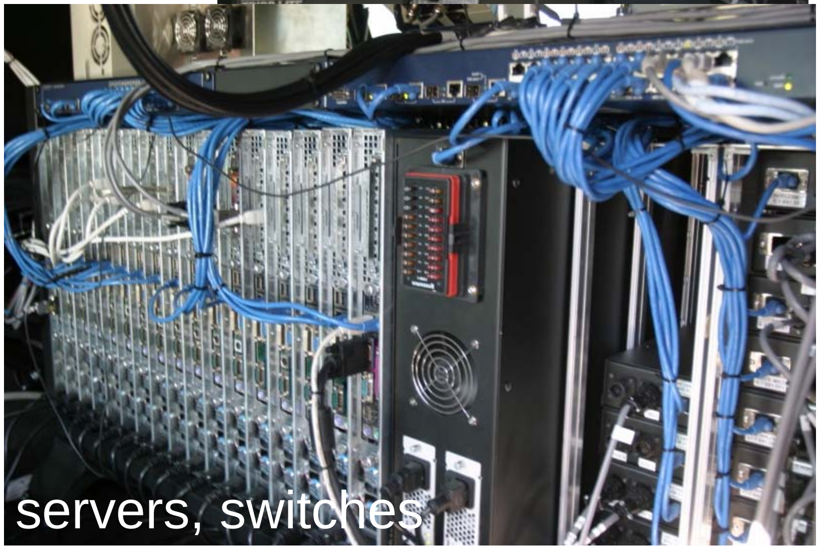




- SICK 1D LIDAR (60m)
- Ibeo 4x160 LIDAR (150m)
- Velodyne 64x360 LIDAR
- DELPHI mm-wave RADAR
- MobilEye SeeQ Vision
- Front and rear cameras
- Litton LN-200 IMU
- Septentrio 3-antenna GPS
- Trimble/Omnistar GPS
- Stock CAN wheel encoders

Real Time Data Distribution

- Grand challenge ’05 lessons
  - Complexity of nonstandard device interfaces
  - Data synchronization problems
- Devices all use same Ethernet-ready microcontrollers
  - Cameras, LIDAR, RADAR
  - IMU, GPS, CAN, actuators
- UDP multicast all data
  - Synchronized timestamps generated by micros



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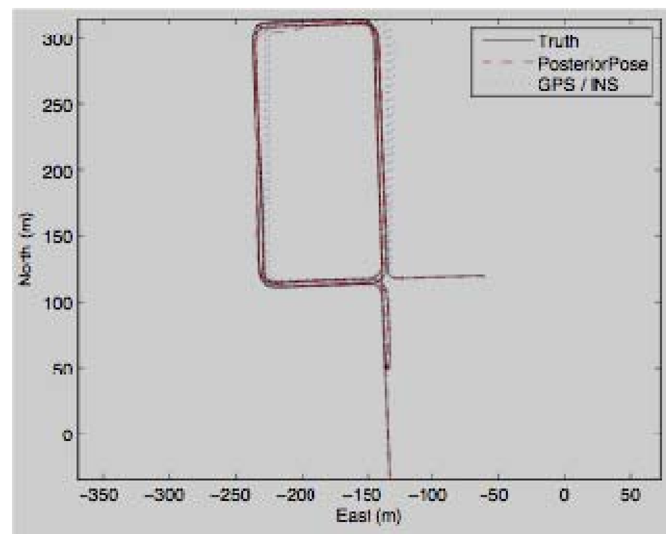
Pose Estimation

- Integrate information from multiple sources
  - Septentrio GPS, Trimble GPS, IMU, wheels, RNDF, visual detection of lanes and stop lines
  - Reject big jumps
- Particle filter to estimate lane probabilities
  - 2000 particles @ 100Hz
- Accurate in GPS blackout
  - E.g., m-level during 8 min. outage



Object Detection and Tracking

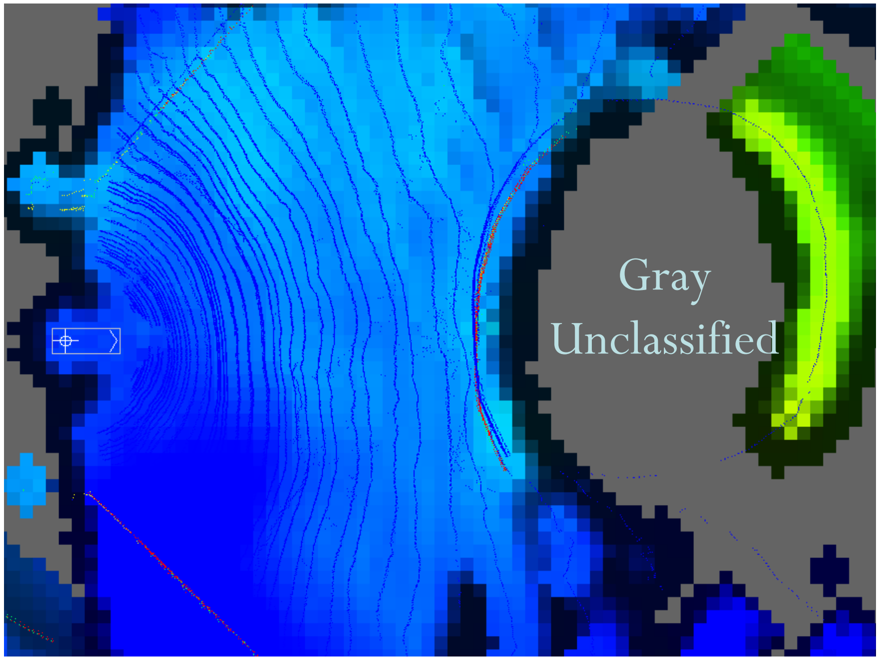
- Using LIDAR, RADAR (and vision)
  - Vision had too many false positives/negatives
- Processing overview
  - Segment LIDAR data
  - Determine number of objects
  - Update/initialize
  - Estimate tracked object metadata
  - Maintain stable track IDs

Segmenting LIDAR Data

- Cluster Ibeo data using Euclidean distance
  - Stable if same at two thresholds, 0.5m and 1m
- Measurements from stable clusters
  - Center of mass or fixed point not reliable
  - Use bearings of occluding contour(s) and range to closest point

Ground Estimation

- Long-range, high-res LIDAR such as Ibeo, SICK generates many false alarms unless good estimate of ground height
- Grid-based ground model constructed from dense LIDAR
  - Lower envelope of hits in nearby region from all LIDARs
  - Use to classify hits as ground, low, high

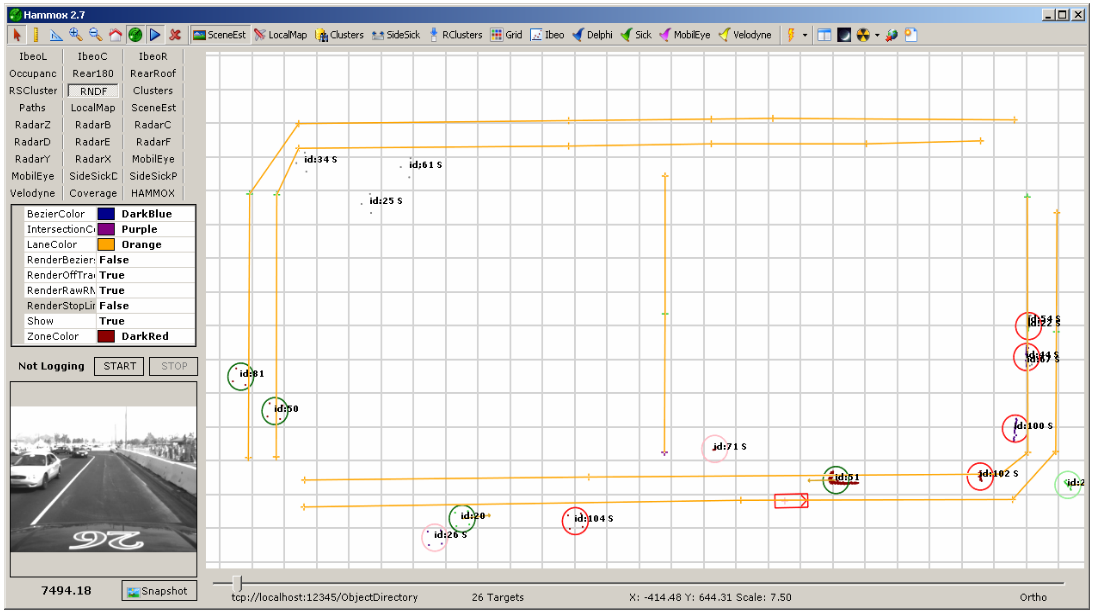


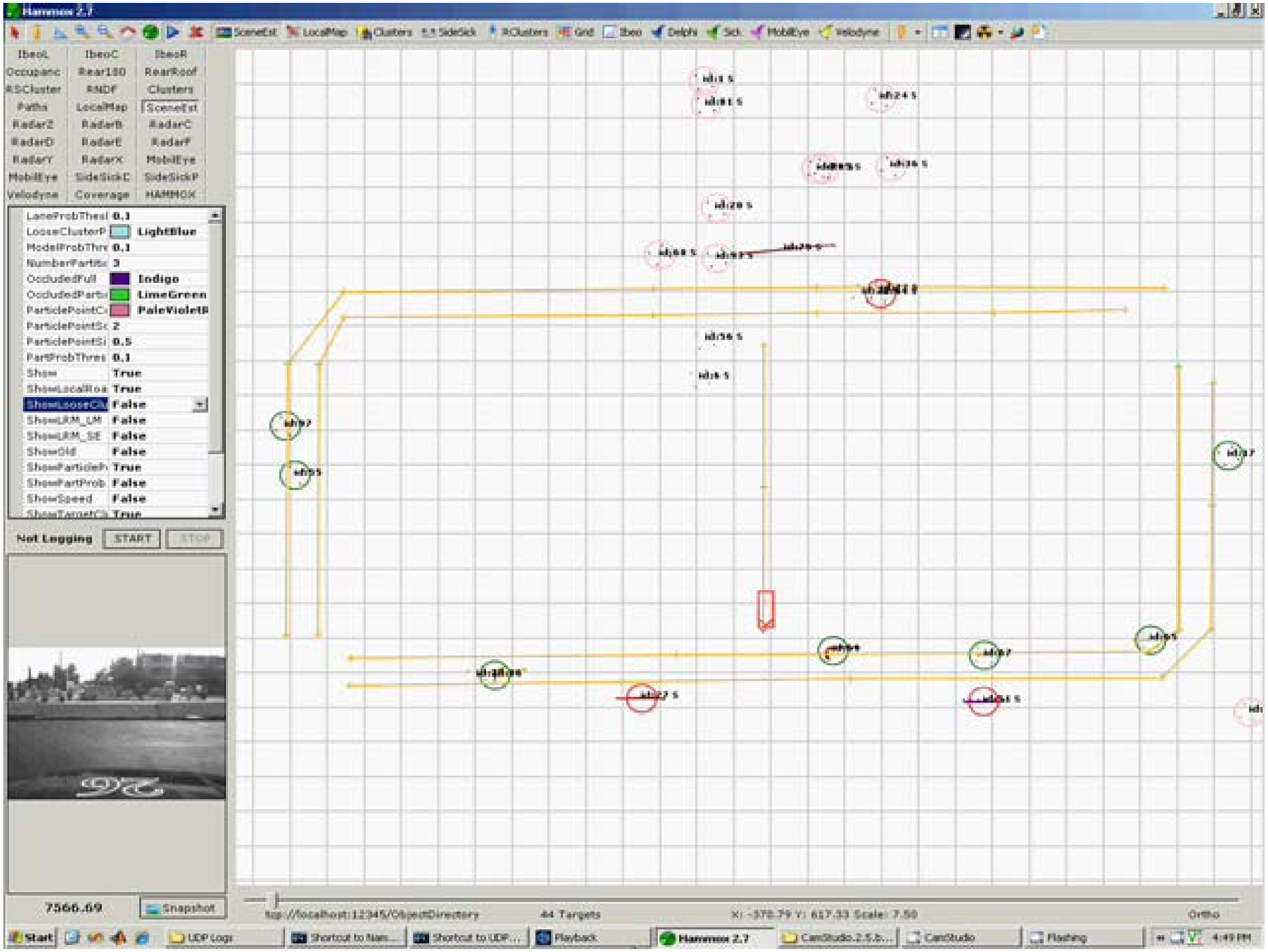
Object Tracking

- Object state: object-centered coordinate frame plus observed data points
  - 2D rigid body transform (relative)
  - Ground speed (absolute), heading (relative)
- EKF predicts point locations forward
- Update coordinate frame and velocity
- Replace points with new observed data
- Use particle filter to represent alternative hypotheses about objects (data association)
  - Small number of particles – 4 in DUC

Sensor Integration/Fusion

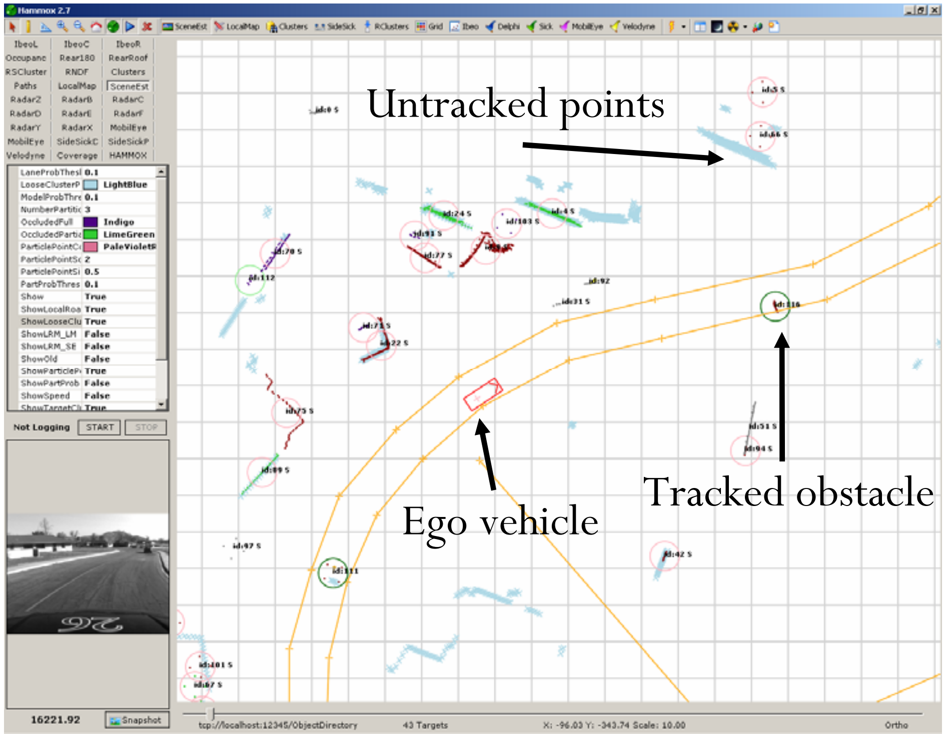
- LIDAR, RADAR (and vision) data combined at object tracking level
  - Data consistent with existing track or start new
- New tracks must meet certain requirements
  - E.g., for LIDAR need to see both occluding contours
- Often 50+ simultaneous tracks in DUC

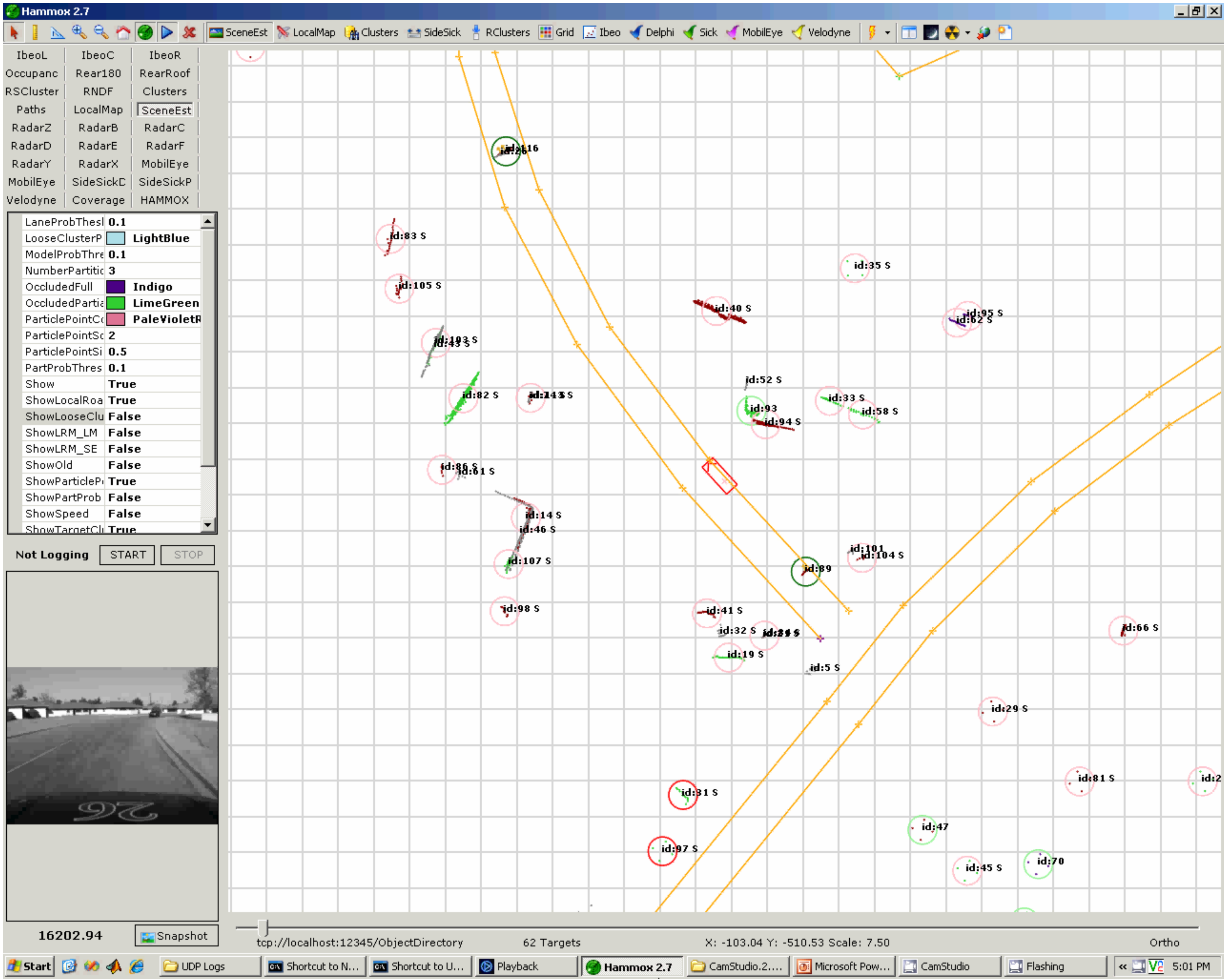



Not Logging
START
STOP
Snapshot
44 Targets
Ortho

Track ID's

- Maintain consistent identifiers for objects across frames
  - Global maximum likelihood matching to previous frame
  - Stable measures used to match tracks and new objects
    - Closest point and occlusion bearings
  - DP over likelihood table to solve for correspondences

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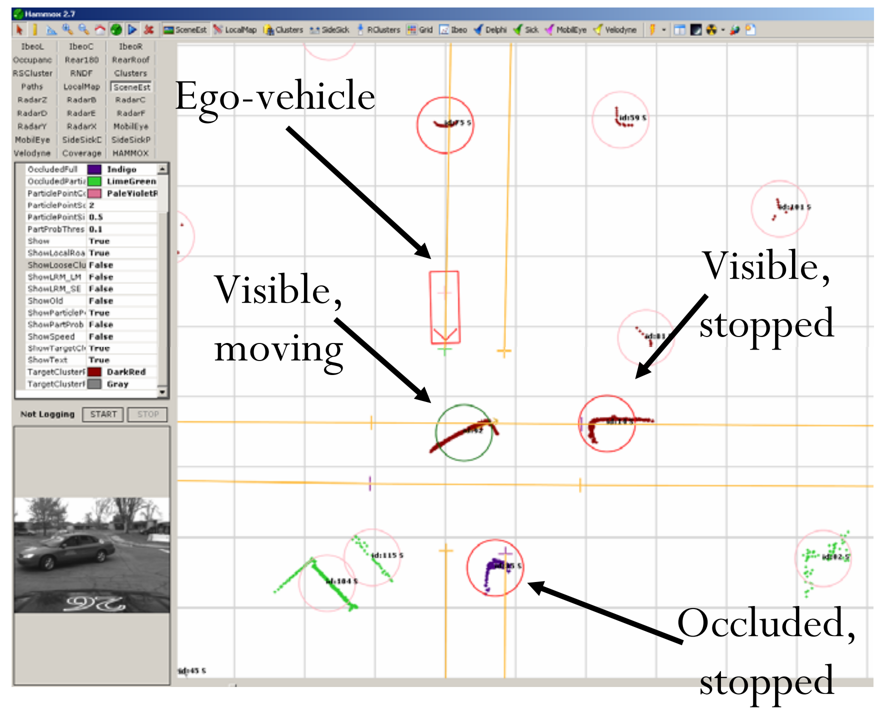
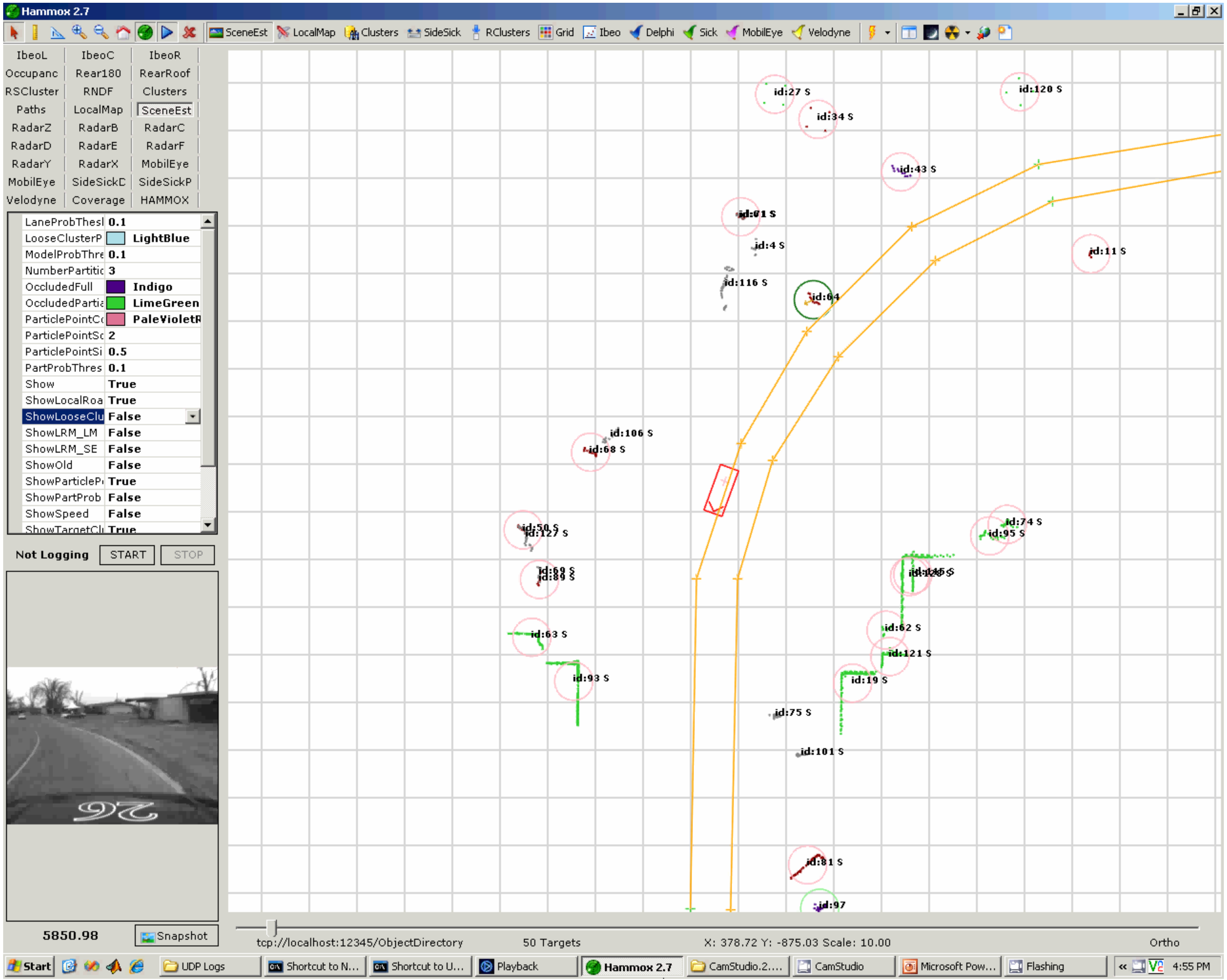
SceneEst LocalMap Clusters SideSick RClusters Grid Ibeo Delphi Sick MobilEye Velodyne
IbeoL IbeoC IbeoR
Occupanc Rear180 RearRoof
RSCluster RNDF Clusters
Paths LocalMap SceneEst
RadarZ RadarB RadarC
RadarD RadarE RadarF
RadarY RadarX MobilEye
MobilEye SideSickD SideSickP
Velodyne Coverage HAMMOX
LaneProbThesl 0.1
LooseClusterP LightBlue
ModelProbThre 0.1
NumberPartitic 3
OccludedFull Indigo
OccludedPartia LimeGreen
ParticlePointC PaleVioletR
ParticlePointSc 2
ParticlePointSi 0.5
PartProbThres 0.1
Show True
ShowLocalRoa True
ShowLooseClu False
ShowLRM_LM False
ShowLRM_SE False
ShowOld False
ShowParticleP True
ShowPartProb False
ShowSpeed False
ShowTargetCl True
Not Logging START STOP
16202.94 Snapshot
tcp://localhost:12345/ObjectDirectory
62 Targets
X: -103.04 Y: -510.53 Scale: 7.50
Ortho
Start UDP Logs Shortcut to N... Shortcut to U... Playback Hammox 2.7 CamStudio2.... Microsoft Pow... CamStudio Flashing 5:01 PM

Object Meta Data

- Attributes for higher-level planning
  - Car-like or not, HMM on width
  - Stopped or not, HMM on speed
  - Occluded or not, geometric reasoning
  - Lane probabilities, Monte Carlo sampling of object locations
    - From vehicle relative to map relative
    - Less certain with distance

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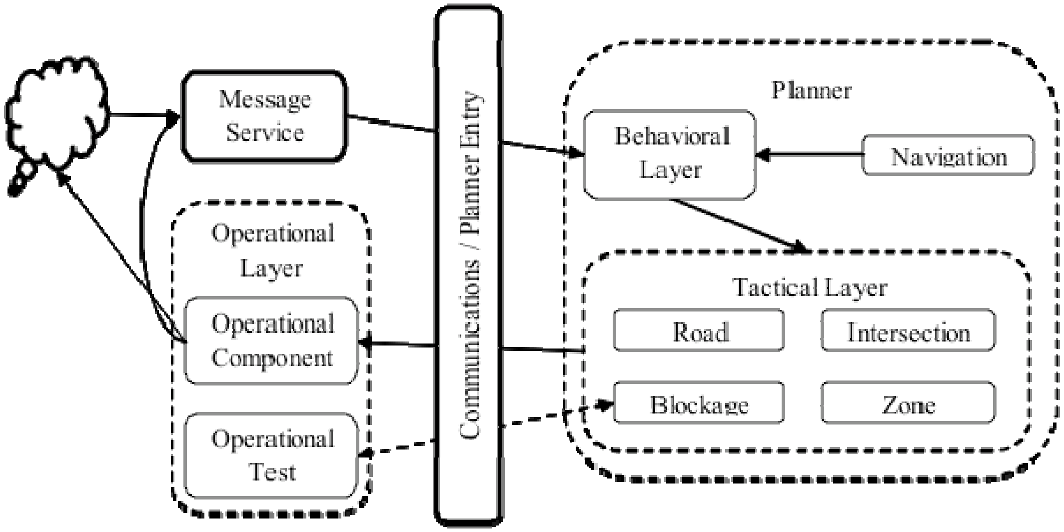
ShowOld False
ShowParticleP True
ShowPartProb False
ShowSpeed False
ShowTargetCli True
Not Logging START STOP
5850.98 Snapshot
tcp://localhost:12345/ObjectDirectory
50 Targets
X: 378.72 Y: -875.03 Scale: 10.00
Ortho
Start UDP Logs Shortcut to N... Shortcut to U... Playback Hammox 2.7 CamStudio.2.... CamStudio Microsoft Pow... Flashing 4:55 PM

Tracking vs. Occupancy

- Object identity over time enables perceiving behaviors of others
  - Rather than just responding to something there
- Currently at level required for intersection precedence and following but not more complex behaviors
  - Problems with long time periods and with changes in shape of object wrt vehicle as move
- Opportunity/need for better perception of behaviors
  - E.g., fender bender with MIT in final race

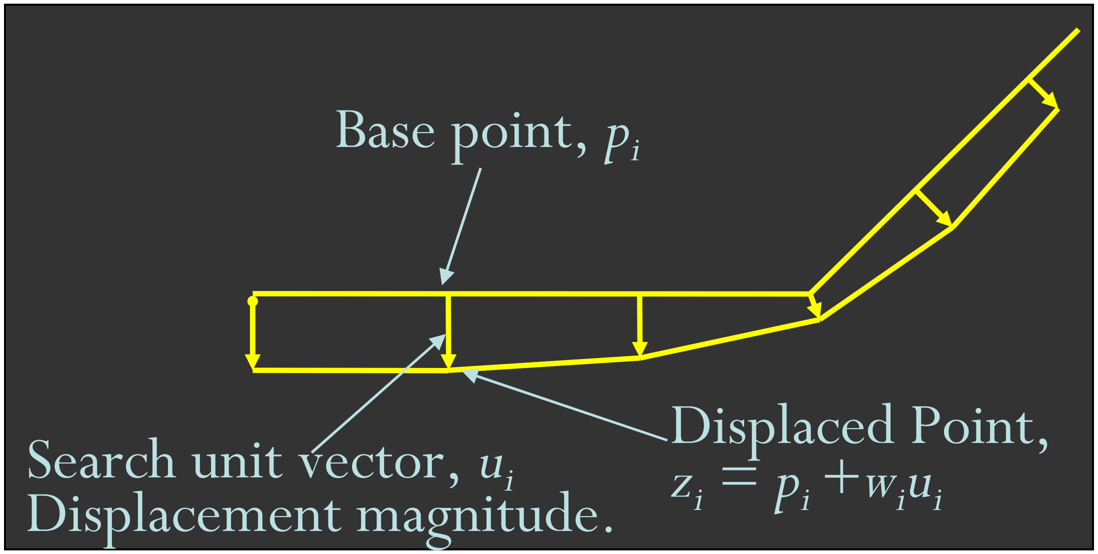
Decision Making and Execution



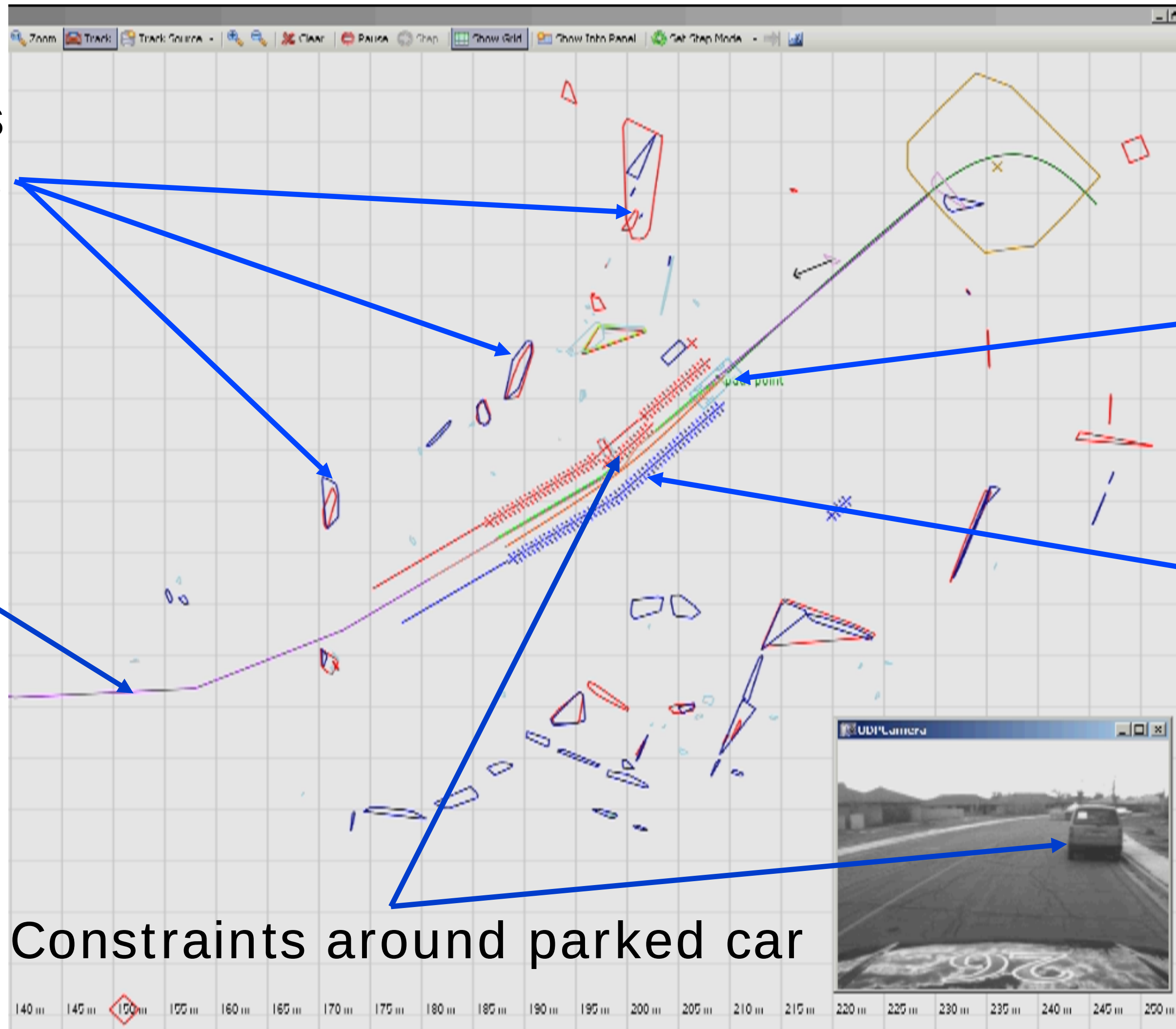
- Behavioral (macro planning)
  - E.g., route (re)planning – like consumer nav tools
- Tactical (local planning)
  - E.g., when to change lanes, pass
- Operational (plan execution)
  - E.g., path generation, obstacle avoidance

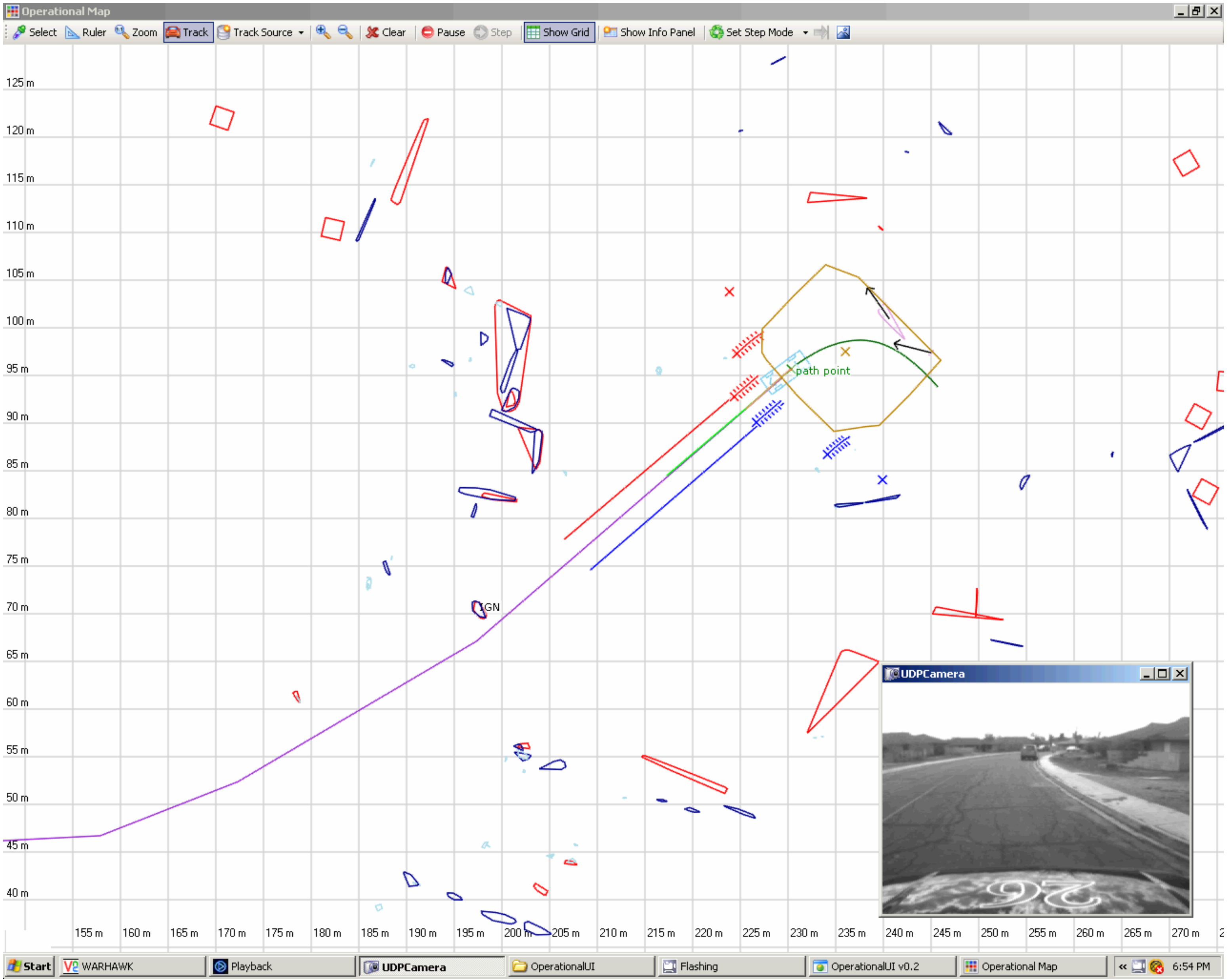
Operational: Path Planner

- Constrained nonlinear optimization
  - Base path, lane boundary constraints, target paths, starting/ending heading/position
- Label obstacles as being to left or right
- Complex but natural behavior by modifying constraints
- Off the shelf nonlinear solver – LOQO
- 10Hz rate



Path Planning Constraints





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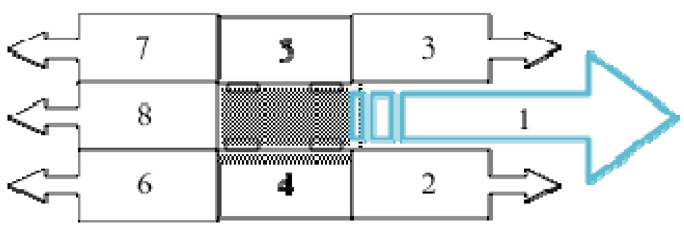
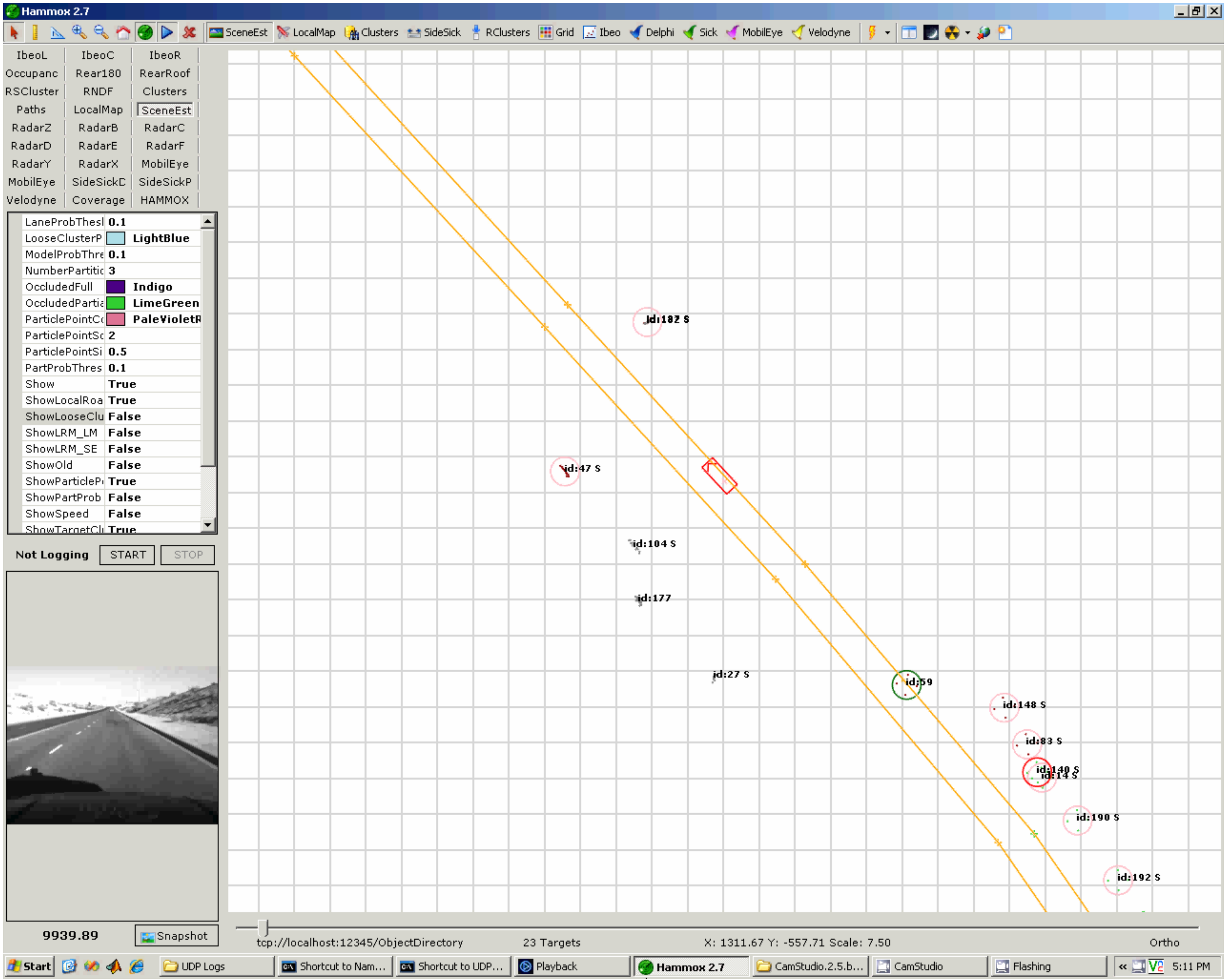
Tactical Planner

- Separate tactical components for road, intersection, zone, blockage
  - Designed to recover from not properly achieving desired state or starting in unknown state
- Road tactical
  - Monitors for forward, rear, lateral regions
    - E.g., closest vehicle in forward direction
  - States such as StayInLane, ChangeLanes

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Not Logging START STOP
9939.89 Snapshot
id:182 S
id:47 S
id:104 S
id:177
id:27 S
id:59
id:148 S
id:83 S
id:149 S
id:14 S
id:190 S
id:192 S
tcp://localhost:12345/ObjectDirectory
23 Targets
X: 1311.67 Y: -557.71 Scale: 7.50
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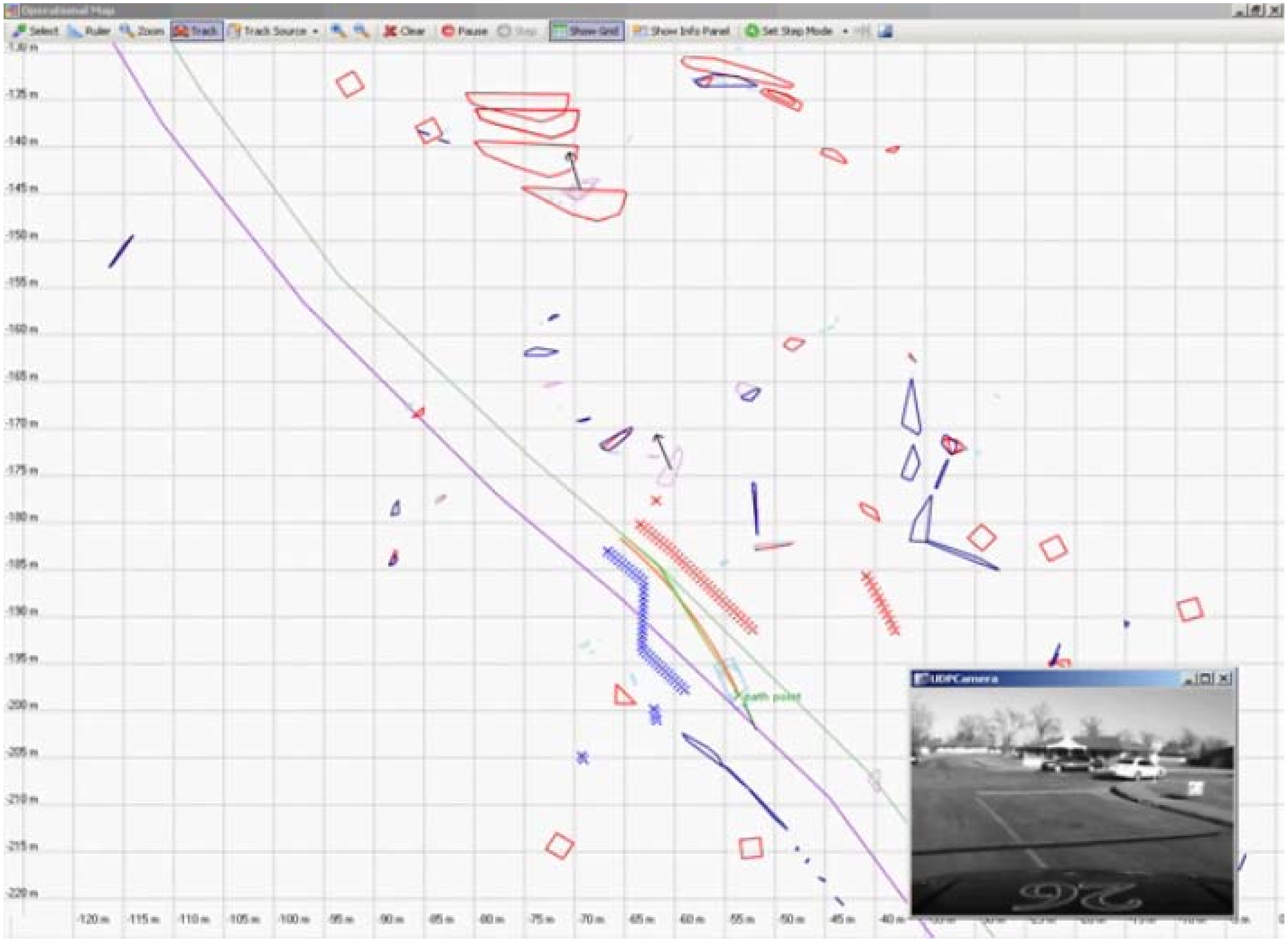
The Final Event

- Three missions, total of approx 56 mi
- Cornell vehicle completed in 5hr 53min
  - Half of time in third mission where throttle problem often limited vehicle speed to 5mph
- Hundreds of interactions with other vehicles, some interesting
  - Traffic jam in first mission caused by UCF vehicle stopped at intersection
  - Stunt driver going wrong way on one way road
  - Collision with MIT

Traffic Jam… Planning Ahead




UDPCamera

Traffic Jam: Local vs. Global

- Vehicle stopped for excessive time, far enough from intersection, visible gap
  - Fine to pass given available information but better sensing would have provided key data
- Value of perceiving behaviors over time
  - Had previously seen car just in front of us stop as it approached the line of stopped cars
- Reasoning using perception and map
  - Last car turned out not to be the problem and only gap just in front of it
  - Cross traffic at intersection, bad to pass there

Wrong Way Car

- One way dirt track heading downhill, with small berms on both sides
- Wide enough to pass parked car but tight for oncoming vehicle
- Traffic driver got lost and was going wrong way up the hill
  - While we were following another vehicle downhill in the proper direction
- Traffic driver stopped as got close
  - Saw as moving then as static and avoided


UDPCamera
Start
Shortcut to NameServic...
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Playback
UDPCamera
CamStudio
Flashing
9:52 AM

Fender Bender with MIT

- Our vehicle behaving erratically
  - Stop-and-go at and after stop sign
  - For observer to understand our behavior required tracking our vehicle for minutes
- MIT vehicle tried to pass
  - First in two-lane segment then after narrowed to single lane at intersection
  - For us, needed good rear sensing and tracking
- By time MIT alongside our vehicle
  - No good estimate of their speed, obstacles on both sides but clear in front

Fender Bender

Cornell ViewMIT View

Some Lessons Learned

- Competition largely about software and system testing
- Accurate timestamps critical for sensor integration
  - Also allows data playback and re-processing
- Multiple sensing modalities important for both vehicle localization and object detection/tracking
  - Good ground model important
  - Challenge to get stable measures from LIDAR points
- Constrained nonlinear optimization mature enough for real-world path planning problems
- Track metadata useful for high level reasoning
  - Going beyond occupancy models towards behaviors
- Deterministic high-level reasoning delicate for urban driving

Platform for Further Research

- Autonomous vehicles that can get you home more safely than you can yourself
  - Much more cluttered environments than DUC
    - Not only more cars but motorcycles, bikes, pedestrians, animals
- Big gap in technology for perception to enable planning ahead
  - Perceiving types of objects and their actions over time, not what space is free or occupied
    - High accuracy with respect to vehicle
    - Also with respect to map – location dependent

Some Research Directions

- Road detection and modeling
  - Difficult to reliably find road in urban setting
    - Short sight lines, objects on road, intersections
  - Rectifying conflicts with map
- Integrating vision into object detection and tracking
  - Draw on and extend recent recognition and learning work
- Better prediction of behavior
  - Pedestrians etc. more challenging

Team Cornell

Team Leaders: Mark Campbell, Dan Huttenlocher

Other Faculty: Ephrahim Garcia, Bart Selman, Hod Lipson

Project Manager: Pete Moran

Vehicle Automation: Noah Zych

Vehicle Packaging: Noah Zych, Pete Moran

Mechanical and Systems Support: Jason Wong

Pose: Isaac Miller, Brian Schimpf

Sensors and Data Network: Aaron Nathan, Sergei Lupashin, Jason Catlin, Adam Shapiro, Max Reitmann

Localization: Isaac Miller

Scene Estimation: Isaac Miller

Operational Planning: Brian Schimpf

Tactical and Strategic Planning: Frank-Robert Kline, Hikaru Fujishima

Testing and RNDF support: Mike Kurdziel