Team Cornell

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Joint work with Mark Campbell and the Cornell DUC Team
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
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
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
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
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

Displaced Point, $z_i = p_i + w_i u_i$
Path Planning Constraints

- Convex hulls of obstacles
- RNDF base path
- Constraints around parked car
- Ego-vehicle
- Lane Boundaries
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
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
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
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 View MIT 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