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Outline

Problem Description

- Risk assessment at intersections
- Prediction of future paths of observed vehicles

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- At an intersection:
  - Observe other vehicles at other ends of the intersection
  - Estimate their GPS position
  - Compyte features using map data
  - Make a prediction about their future behavior

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Setting

An ideal scenario:

- V2V communication between our vehicle and observed vehicles
- Transfer of GPS position information

Our setting:

- unavailable: V2V communication
- available: High precision GPS unit
- Experimental setting assumptions:
  - The vehicle with a GPS unit is the 'observed' vehicle
  - Data from the observed vehicle is transferred to us
  - We have to predict future behavior of the driven vehicle
  - Our own vehicle is at the same intersection, but
  - Our exact position is irrelevant for the prediction

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Data collection

Required data:

- Map information
- High precision GPS information

Available options:

- KITTI dataset and open street maps
- Zenrin and our own collected data

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Features

Available information:

- Vehicle pose from the CAN bus
  - only latitude and longitude are used
- Zenrin map data

Features computed:

- Distance from lane center
- Distance from intersection
- Angle between lane orientation and vehicle heading

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Track pre-processing

We get continuous GPS track from one drive

- Tracks are clipped at a specified distance from intersection centers
- Stops are detected and removed before model learning or testing

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Learning model

- A time series of vector data
  - time series may be of unequal lengths due to:
    - stops
    - unequal velocity
    - intersection structure
- Event classes
  - Left turn
  - Right turn
  - Straight
- Train a hidden markov model for each event
- Compute probabilities at test time from trained models

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Outline

HMM training

- Feature computation
  - Begins 15 meters from intersection
  - Ends 15 meters into intersection
- Separate HMM model trained for each event class
- Each model trained using a single gaussian per feature per state
- All gaussians initialized to large variances with zero means
- Training performed using a 80-20 split
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HMM classification performance

Feature comparison

Hidden states

HMM feature input

Event confusion

Demo video

Outline

Performance comparison

- Rule based decision (baseline)
- SVM

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Conclusions:

- HMM prediction with given features caps at 85-88 %
- Multi-modal HMM prediction may improve learning
- We are trying a Dynamic Bayesian Network to improve performance

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