Introduction Scenario and Method Experiments and Results Summary

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August 13, 2014

Outline

- Introduction
- Scenario and Method
- Experiments and Results
 - Hidden Markov Models
 - Comparisons
- Summary

Problem Description

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

Setting

- 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

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



Data collection

Required data:

- Map information
- High precision GPS information

Available options:

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

Data collection



Data collection



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

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

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



Outline

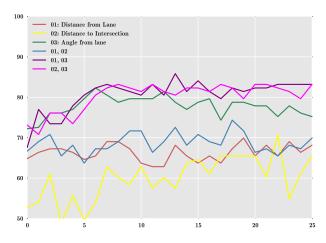
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HMM training

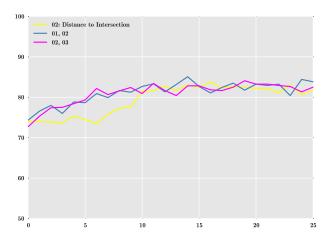
- Feature computation
 - Begins 15 meters from intersection
 - Ends 15 meters into intersection
- Separate HMM model trained for each event class
- Each model trained using a single gaussian per feature per state
- All gaussians initialized to large variances with zero means
- Training performed using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

HMM classification performance

Feature comparison



Hidden states



Event confusion

Demo video

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Performance comparison

- Rule based decision (baseline)
- SVM

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