Automated Road Safety Analysis Using Video Sensors

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Outline

- Introduction
  - traffic safety analysis,
  - traffic conflicts,
  - video sensors,
  - vehicle tracking.
- Traffic conflict detection
  - semi-supervised learning.
- Future work.

1. Motivation

- Traditional road safety is a reactive approach, based on historical collision data.
- Pro-active approach: "Don't wait for accidents to happen".
- Need for surrogate safety measures that
  - bring complementary information,
  - that can be easily collected,
  - are based on more frequent events,
  - are still related to safety (accidents).
- Traffic conflicts (near-misses).

1. Video Sensors

- Main bottleneck of traffic conflict techniques
  - collection cost,
  - reliability and subjectivity of human observers.
- Advantages of video sensors
  - they are easy to install,
  - they can provide rich traffic description (vehicle tracking),
  - they can cover large areas,
  - they are cheap sensors.
- Computer vision is required to interpret video data.

1. Modular System

Vehicle Detection and Tracking

Conflicting Trajectories Detection

Implement a complete system

1. Vehicle Tracking

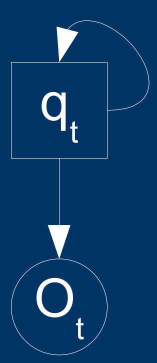
- Feature-based tracking is the most readily available method
  - KLT implementation (Stan Birchfield's or Intel OpenCV Library).
- Extension of the feature-based tracking algorithm by Beymer et al. (1997) to intersections.
- Poster at the Third Canadian Conference on Computer and Robot Vision 2006.

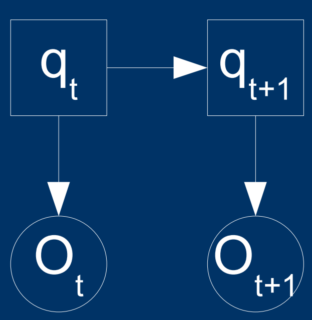
2. Detecting Traffic Conflicts

- Input: vehicle trajectories $(x_1, y_1, ..., x_n, y_n)$.
- Output: traffic conflicts, or selected short sequences containing the traffic conflicts.
- Traffic conflicts are rare events. Data is limited for training and test.

2. Traffic Conflict Detection

- Direct extrapolation method is difficult because of imperfect tracking data.
- Learning is more generic
  - learning and prediction of vehicle movements,
  - interaction classification.
- Probabilistic models for sequential data: HMMs, DBNs.

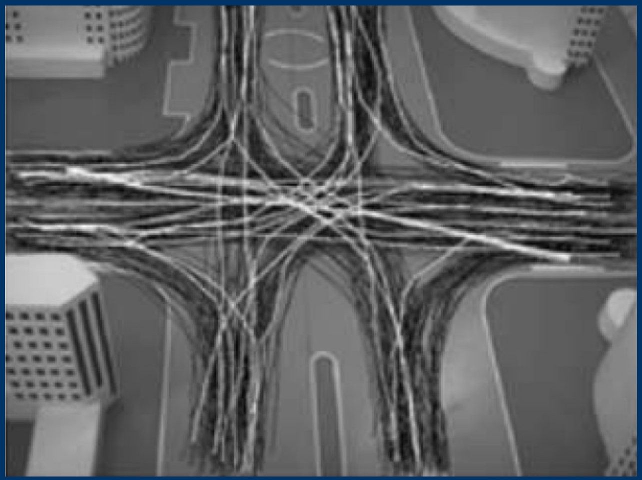


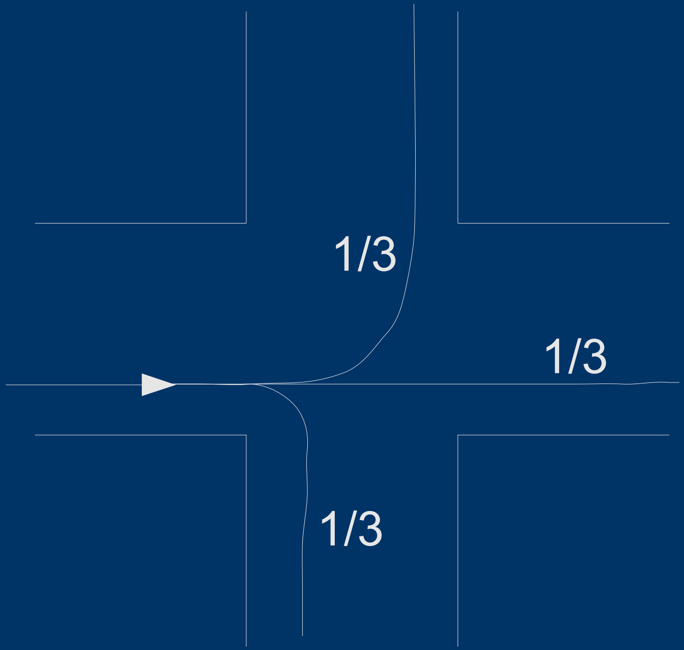


prior probabilities,
transition probabilities,
output distributions.

2. Trajectories Learning

- Learning motion patterns for movement prediction (unsupervised).
- Movement prediction and traffic conflict detection.





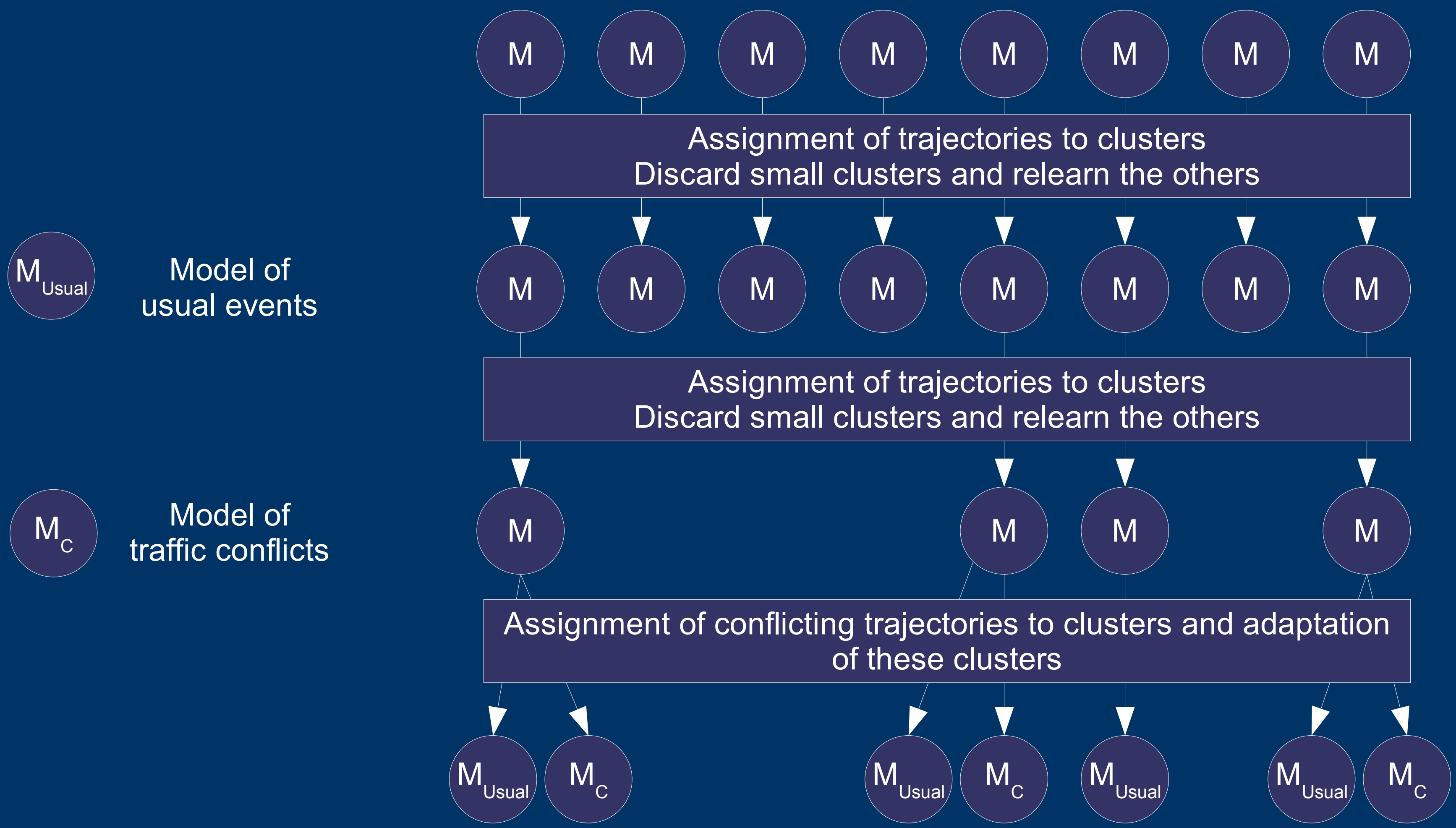
2. Sequential Data Clustering

- Sequence similarity: distance over sequences.
  - ex: edit distance.
- Extract a set of features for each sequences, for use with traditional fixed length vector-based clustering methods.
  - ex: leading Fourier coefficients.
- Statistical sequence clustering: sequences are similar if they have a common similarity to a model, computed by the likelihood *P(Observation|Model)*.

2. Semi-Supervised Learning

- HMM-based clustering of vehicle trajectories
  - k-means approach,
  - discard small clusters.
- Adaptation of HMMs to trajectories involved in few actual traffic conflicts.
- Detection: pairs of conflicting clusters.

2. Algorithm Figure



3. Experimental Results

- 10 video sequences used for the training of traffic conflict observers (1980s),
- 560 trajectories in 8 sequences used for learning,
- only 5 traffic conflicts.

3. Detection Results

- HMM-based clustering is very sensitive to initialization.

α	CD	Uncertain TC	FA
"0"	10	17	38
0.05	10	13	6
0.10	10	13	10
0.15	10	12	6
0.20	10	3	3
0.25	10	5	2
0.30	10	5	2
0.35	10	4	1
0.40	10	4	0
0.45	10	4	0
0.50	10	3	0

Conclusion and Future Work

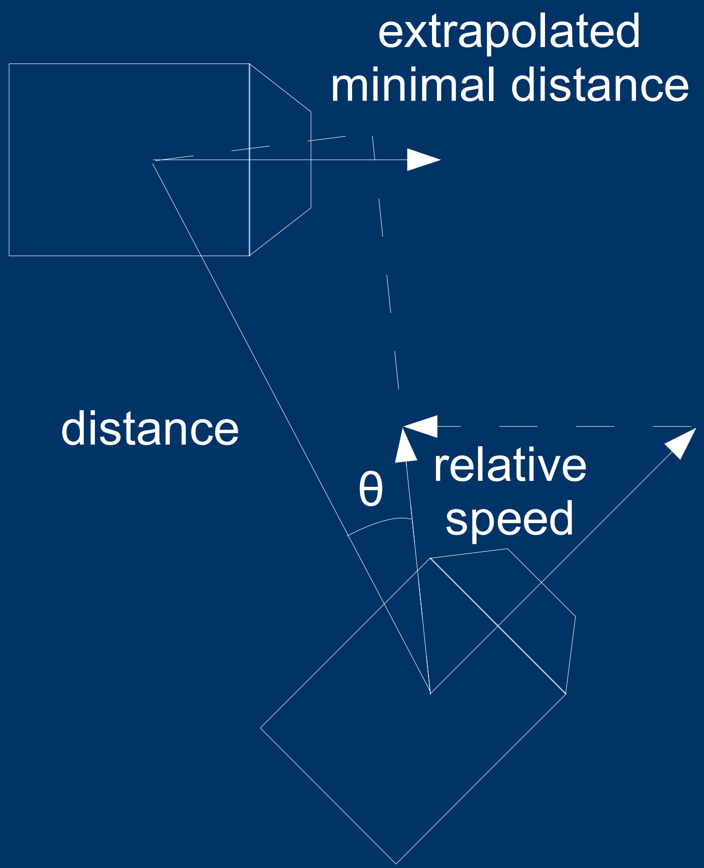
- Traffic conflict detection is feasible.
- Computational improvements (Intel OpenCV library).
- Collecting more data
  - other sources,
  - artificial data,
  - interactive labeling, active learning.
- Collision probability computation.

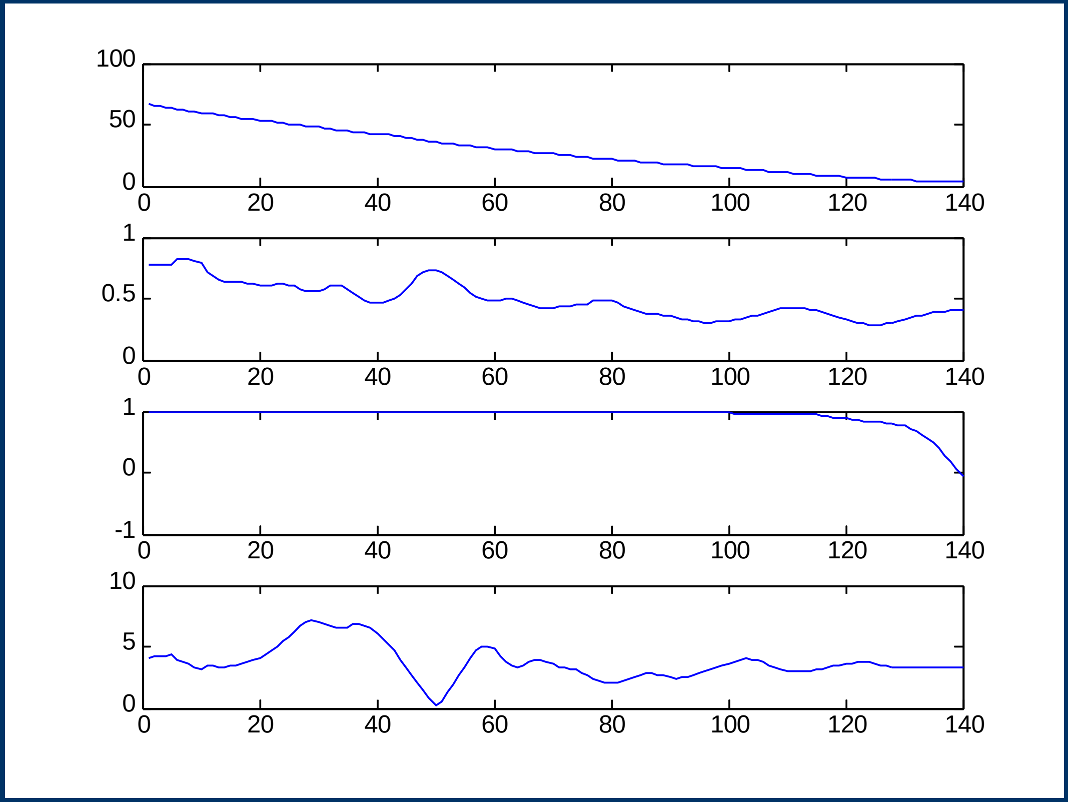
Thank you !

Annex: Interaction Classification

- Binary classification: conflicts / non-conflict interactions.
- For a more generic system, relevant features for an interaction should
  - be symmetric with respect to the vehicles,
  - describe the relative vehicle movements.

Interaction Features





HMM Ensemble

- Traditional HMM-based classification: 1 HMM per class.
- Very imbalanced dataset: improve performance by monitoring results per class.
- Train an ensemble of HMMs on misclassified instances:
  - until a given accuracy is reached, add new HMMs trained on the sets of misclassified instances of each class.

Interaction Classification

- 10 runs of leave-one-out:
  - HMM ensemble / 2-HMMs base classifier.

Predicted \ Correct	Conflicts	Non-conflict Interactions
Conflicts	0.1	**7.4**
Non-conflict Interactions	5.9	**348.6**
Conflicts	1.3	**62.9**
Non-conflict Interactions	4.7	**293.1**