Automated Road Safety Analysis Using Video Sensors

Nicolas Saunier

Department of Civil Engineering,UBC

saunier@civil.ubc.ca
saunier@aist.enst.fr
http://www.confins.net/saunier/

supervised by Tarek Sayed

Outline

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

Motivation

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

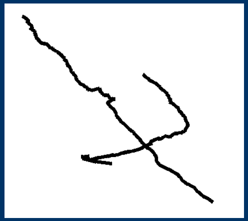
Video Sensors

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

Modular System

Vehicle Detection and Tracking

Conflicting Trajectories Detection



Vehicle Tracking

- Feature-based tracking is the most readily available method
  - Stan Birchfield's KLT implementation 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.

The data

- Vehicle trajectories: temporal sequence of positions.
- Problem characteristics
  - traffic conflicts are rare: data is limited for training and test,
  - false alarms are detrimental.

Traffic Conflict Detection

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

Trajectories Learning

- Limited labeled data.
- Unsupervised learning of the trajectories (vehicle dynamics) for prediction
  - extension of the direct approach.
- Traffic conflict detection
  - prediction of the movements and the future positions: collision probability estimation.

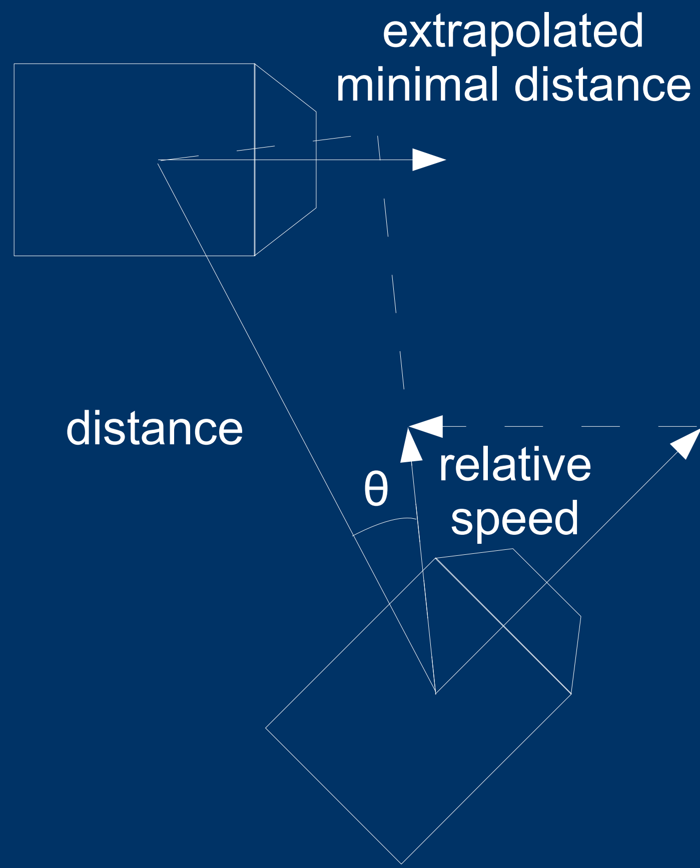
Semi-Supervised Learning

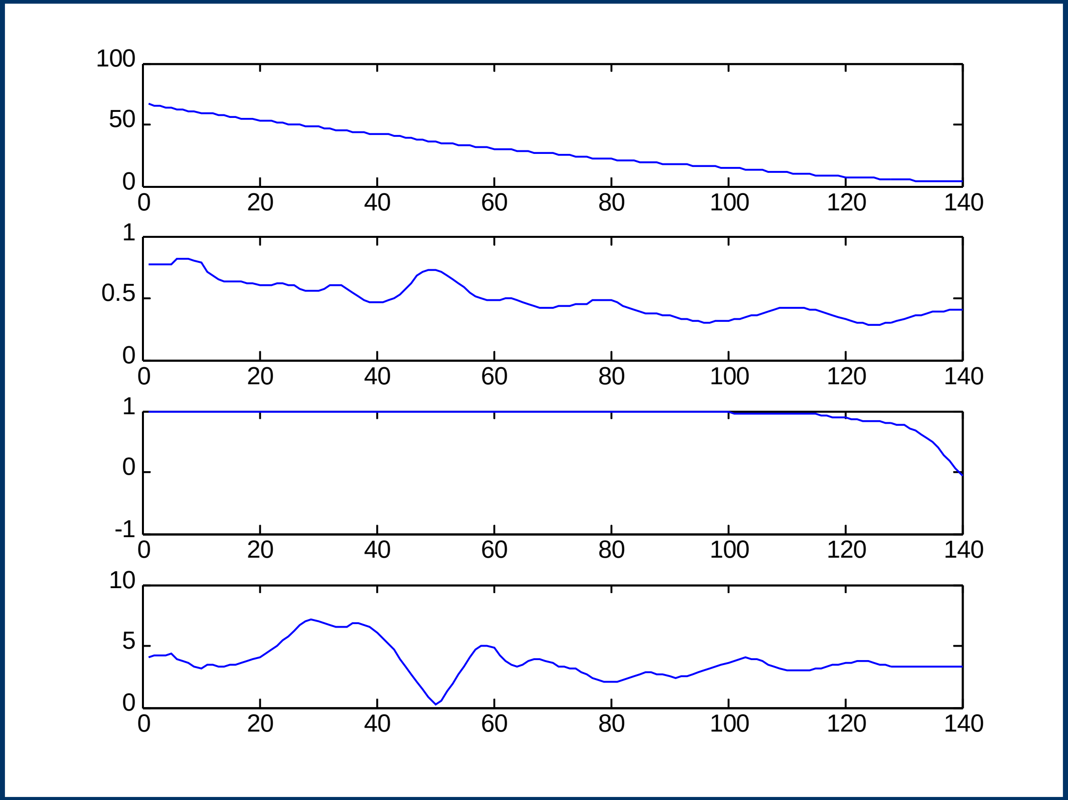
- HMM-based clustering of vehicle trajectories
  - k-means approach,
  - discard small clusters.
- Adaptation of HMMs to trajectories involved in few actual traffic conflicts.
- Detection: pairs of conflicting clusters.
- Limited results
  - HMM-based clustering is very sensitive to initialization.

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.

Experimental Results

- Test data
  - 10 video sequences used for the training of traffic conflict observers (1980s),
  - only 6 traffic conflicts.

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**

Future Work

- Most promising approach ?
- Collecting more data
  - other sources,
  - artificial data,
  - interactive labeling, active learning.
- Improve vehicle tracking performance: Intel OpenCV library.