Automated Road Safety Analysis Using Video Data

Nicolas Saunier

Department of Civil Engineering,
University of British Columbia

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

Outline

1. Introduction
2. Vehicle Detection and Tracking
3. Traffic Conflict Detection
4. Future Work

1. Motivation

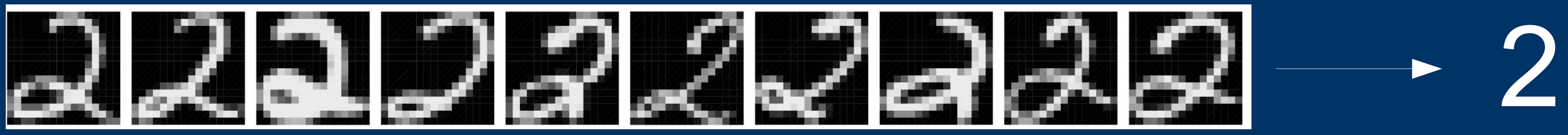
- Traditional road safety is a reactive approach, based on historical collision data.
- Pro-active approach: "Don't wait for accidents to happen".
- Need for surrogate safety measures that
  - bring complementary information,
  - that can be easily collected,
  - are based on more frequent events,
 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

1. Video Sensors

- Main bottlenecks 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 (e.g. vehicle tracking),
  - they can cover large areas,
  - they are cheap sensors.
- Computer vision is required to interpret video data.

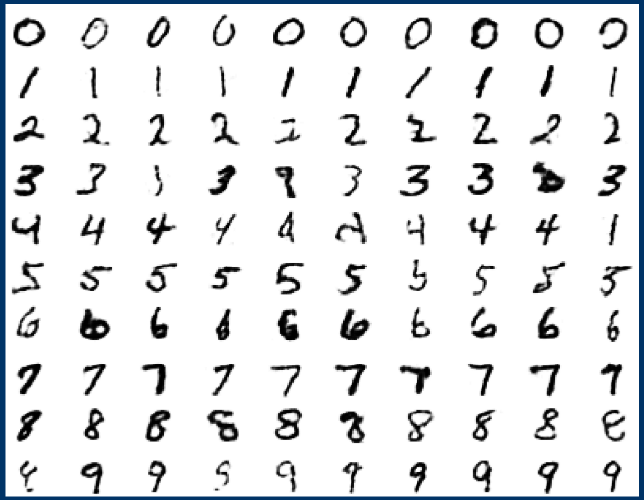
1. Computer Vision

- Subfield of Artificial Intelligence.
- The purpose is to program a computer to "understand" a scene or features in an image or a sequence of images.
- Some computer vision systems:
  - optical character recognition, event detection (video surveillance), image database indexing and querying, tracking, object modeling (medical image analysis), human-computer interfaces...



1. Pattern Recognition and Machine Learning

- Required for higher level interpretation.
- Supervised learning: the algorithm learns a function (classifier) that maps input to outputs, given labeled training examples.
- Unsupervised learning: the algorithm models a set of inputs.



1. Modular System

Vehicle Detection and Tracking

Traffic Conflict Detection

Implement a complete system

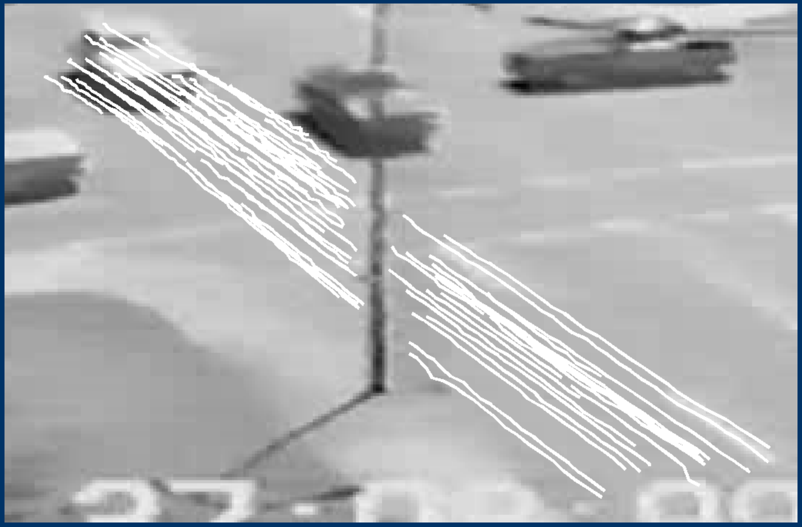
2. Vehicle Detection and Tracking

- 4 categories of methods:
  - Model-based tracking (often using 3D models),
  - Blob-based tracking (often using background/foreground segmentation),
  - Contour-based tracking,
  - Feature-based tracking.
- Feature-based tracking was chosen since
  - it is the most readily available method (Kanade Lucas Tomasi implementation in Stan Birchfield's or Intel OpenCV Library),
  - it is robust to partial occlusion, variable lighting conditions, and requires no special initialization.

2. Feature-based Tracking

- Extension of the feature-based tracking algorithm by Beymer et al. (1997) to intersections (CRV 06):
  - Accuracy between 84.7 % and 94.4 % on 3 sets of sequences.

Demo



3. Detecting Traffic Conflicts

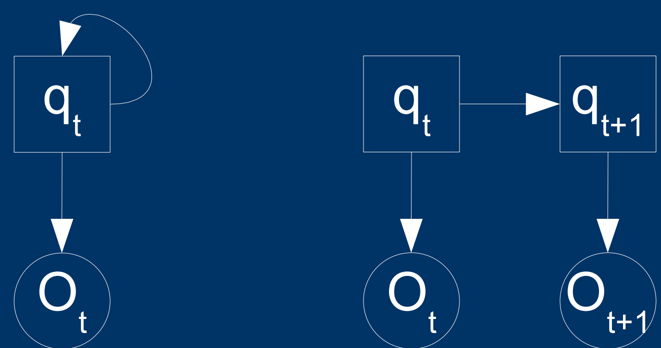
- Input
  - vehicle trajectories (x_1, y_1, ..., x_n, y_n), and velocities (vx_1, vy_1, ..., vx_n, vy_n).
- Output
  - actual traffic conflicts,
  - selected short sequences containing the traffic conflicts for further human review.

3. Traffic Conflicts Description

- Traffic conflicts are rare events. Data is limited for training and test.
- Characteristics:
  - collision course (extrapolation hypotheses),
  - evasive action,
  - actual spatiotemporal proximity.
- Detection should be based on these characteristics:
  - simple manual rules,
  - classifiers learnt on traffic conflict examples.

3. Collision Course Estimation

- Extrapolation hypotheses for motion prediction:
  - default: constant speed and direction,
  - learn (automatically) additional knowledge from the observation of traffic data: typical motion patterns.
- Motion patterns can be stored as trajectories or more complicated models, such as probabilistic models for sequential data (DBNs, HMMs).



Defined by
- prior probabilities,
- transition probabilities,
- output distributions.

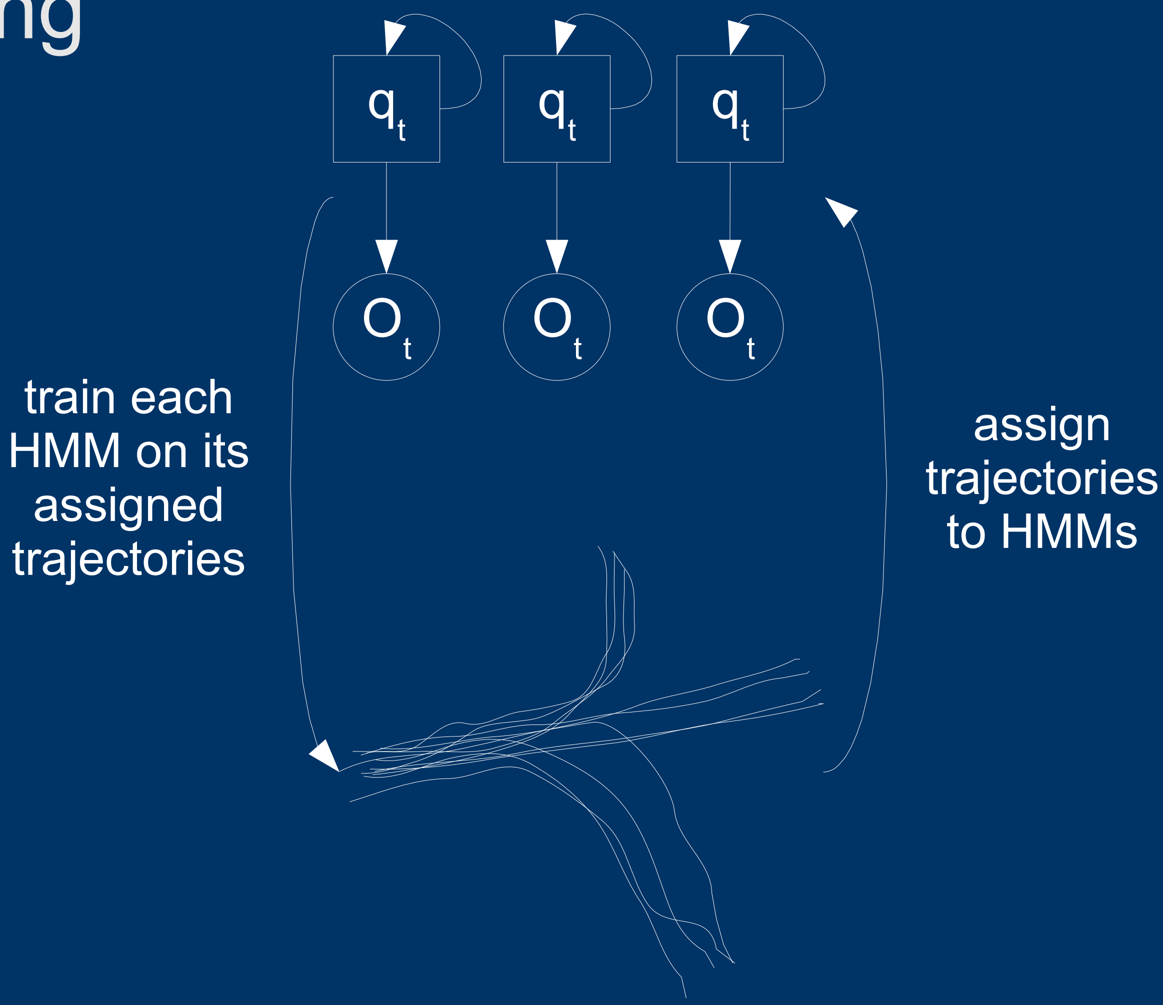
3. Learning Motion Patterns and Sequential Data Clustering

- Sequence similarity / distance.
  - ex: Euclidean distance, edit distance, DTW, LCSS.
- 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 $P(Observation|Model)$.

3.1. First Approach

HMM-based clustering of trajectories

- iterative K-means approach,
- discard small clusters.



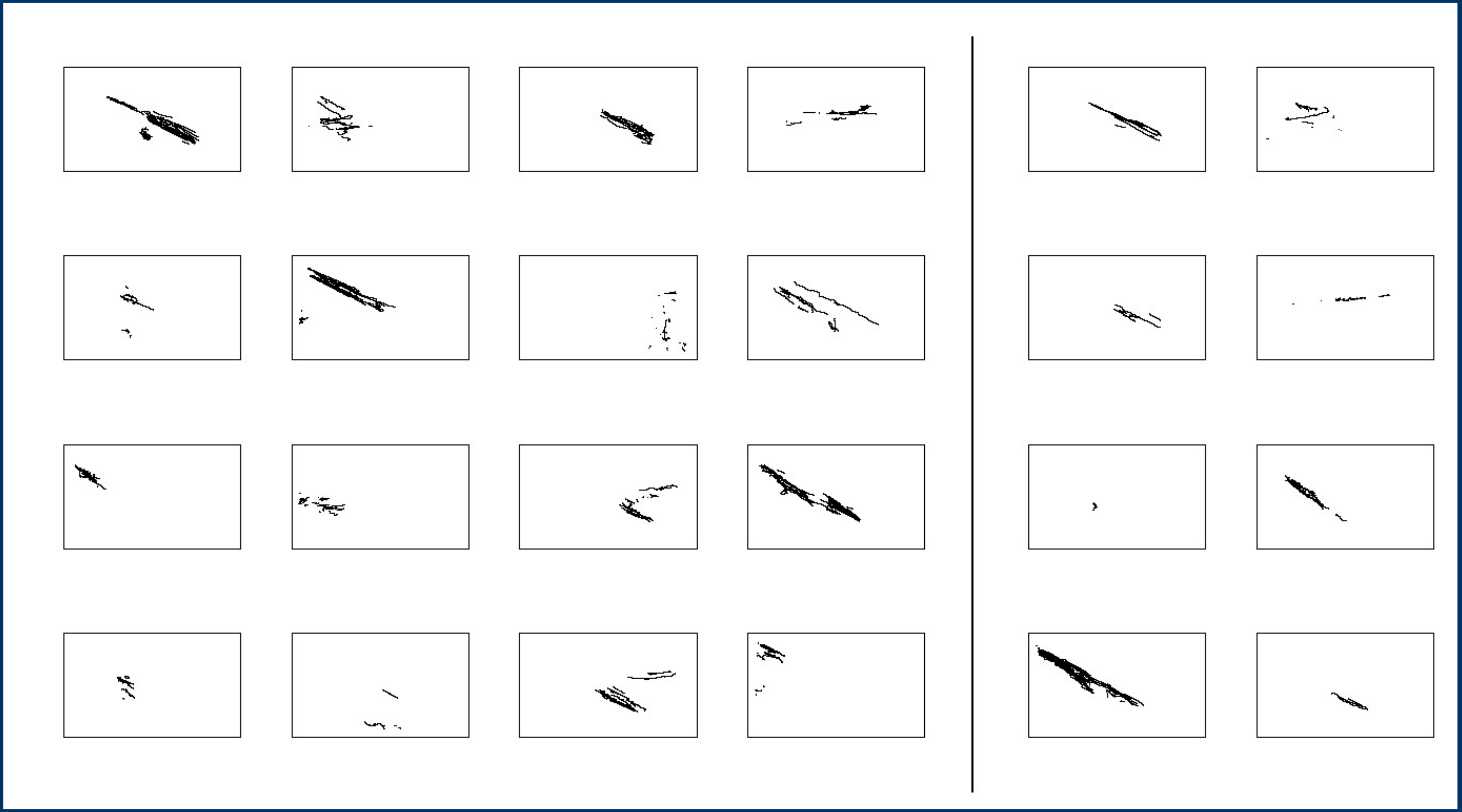
3.1. Semi-Supervised Learning

- An extra training step uses some available traffic conflict instances
  - to adapt HMMs (means and covariances of the Gaussian output distributions),
  - to memorize "conflicting" models.
- Detection process
  - interacting vehicles (close and nearing each other) are detected,
  - the 2 trajectories are assigned to models,
  - if the models were memorized as conflicting, a traffic conflict is detected.

3.1. 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.

3.1. Example of Trajectories Clustering



3.1. Detection Results

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

- HMM-based clustering is very sensitive to initialization.
- Continuum of traffic events.

Demo

3.2. Learning Prototype Trajectories

- Keep actual trajectories as prototypes for motion patterns.
- Use Longest Common Subsequence Similarity (LCSS):

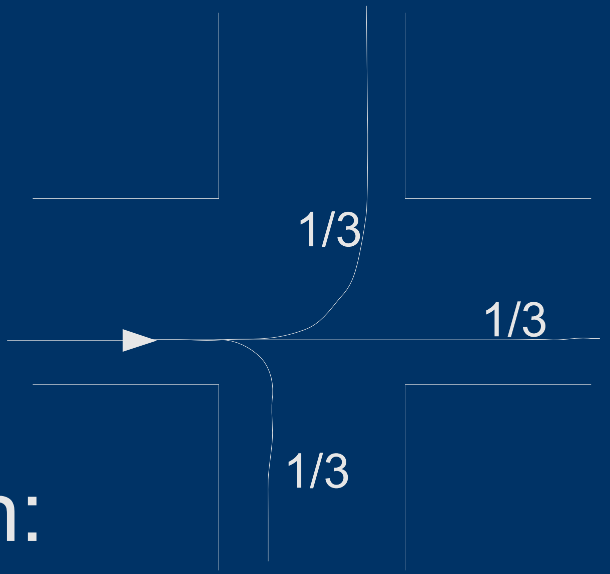
Let $Head(T_i)$ be the sequence $\{t_{i,1}, ...t_{i,n-1}\}$. Given a real number $0 < \epsilon < 1$, the LCSS similarity of two trajectories T_i and T_j of respective lengths m and n is defined as

$$LCSS_\epsilon(T_i, T_j) = \begin{cases} 0 & if\ m = 0 \\ 0 & if\ n = 0 \\ 1 + LCSS_\epsilon(Head(T_i), Head(T_j)) & if \text{ the points match} \\ max(LCSS_\epsilon(Head(T_i), T_j), LCSS_\epsilon(T_i, Head(T_j))) & otherwise \end{cases}$$

Two points t_{i,k_1} and t_{j,k_2} match if $|x_{i,k_1} - x_{j,k_2}| < \epsilon$ and $|y_{i,k_1} - y_{j,k_2}| < \epsilon$.

- Online learning of prototypes.

3.2. Collision Probability



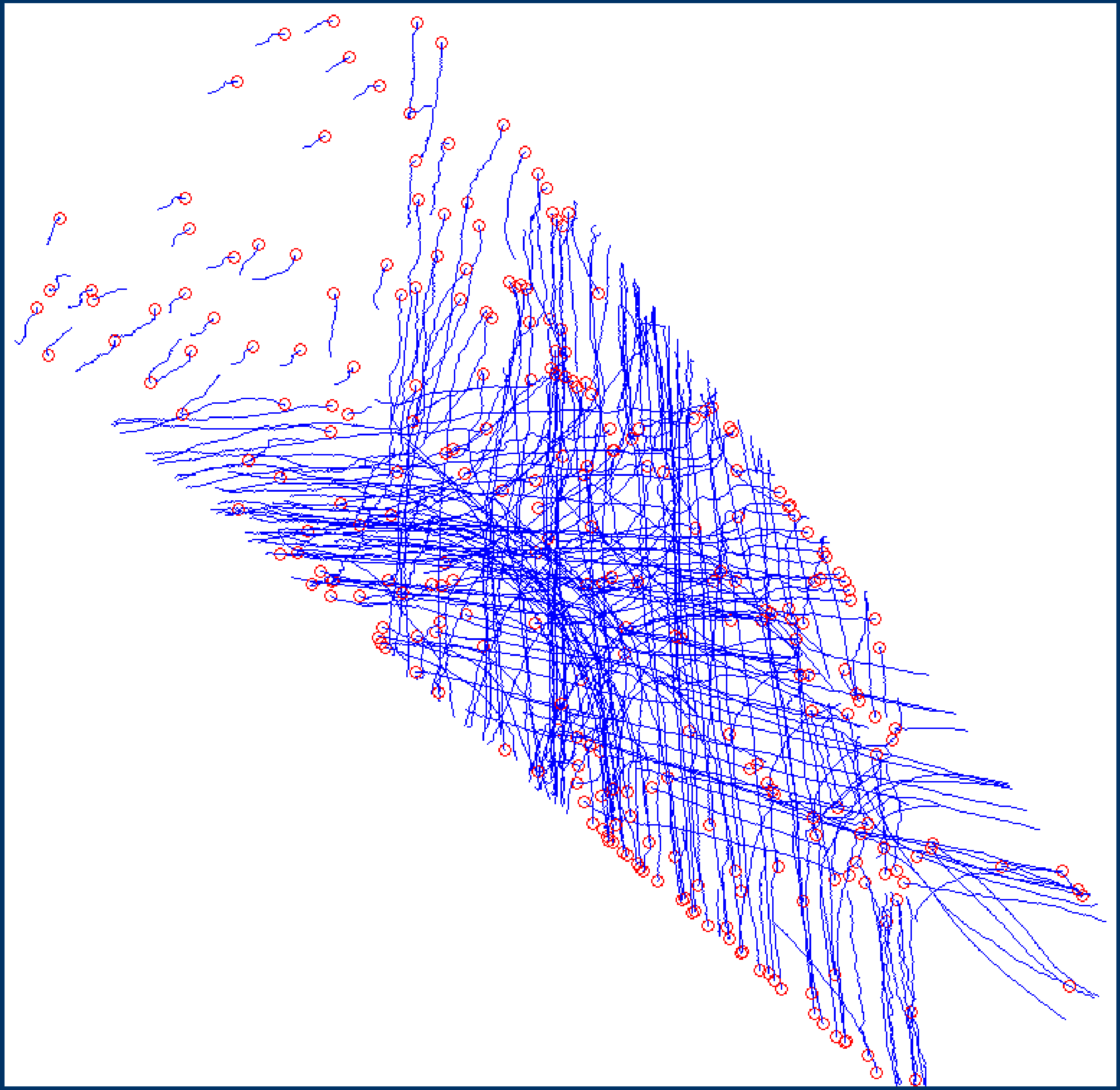
- Prototype trajectories are used for collision probability estimation:

$$\sum_{i,j} P(T_i|A)P(T_j|B)\, e^{-\frac{t^2}{2\sigma^2}}$$

where t is the predicted time of the potential collision if A follows trajectory T_i and B follows trajectory T_j.

- This is an additional indicator for traffic conflict detection.
- Other uses include detailed exposure measurements unavailable to this day.

3.2. Experimental Data



Demo

4. Conclusion and Future Work

- Traffic conflict detection is feasible.
- Collecting more data:
  - other sources,
  - artificial data,
  - interactive labeling, active learning.
- Traffic Intelligence: automatically collect traffic data for traffic diagnosis and management.

Thank you !

Sequence of Indicators

Vehicle Trajectories

$a_1(t)$

$a_2(t)$

$a_3(t)$

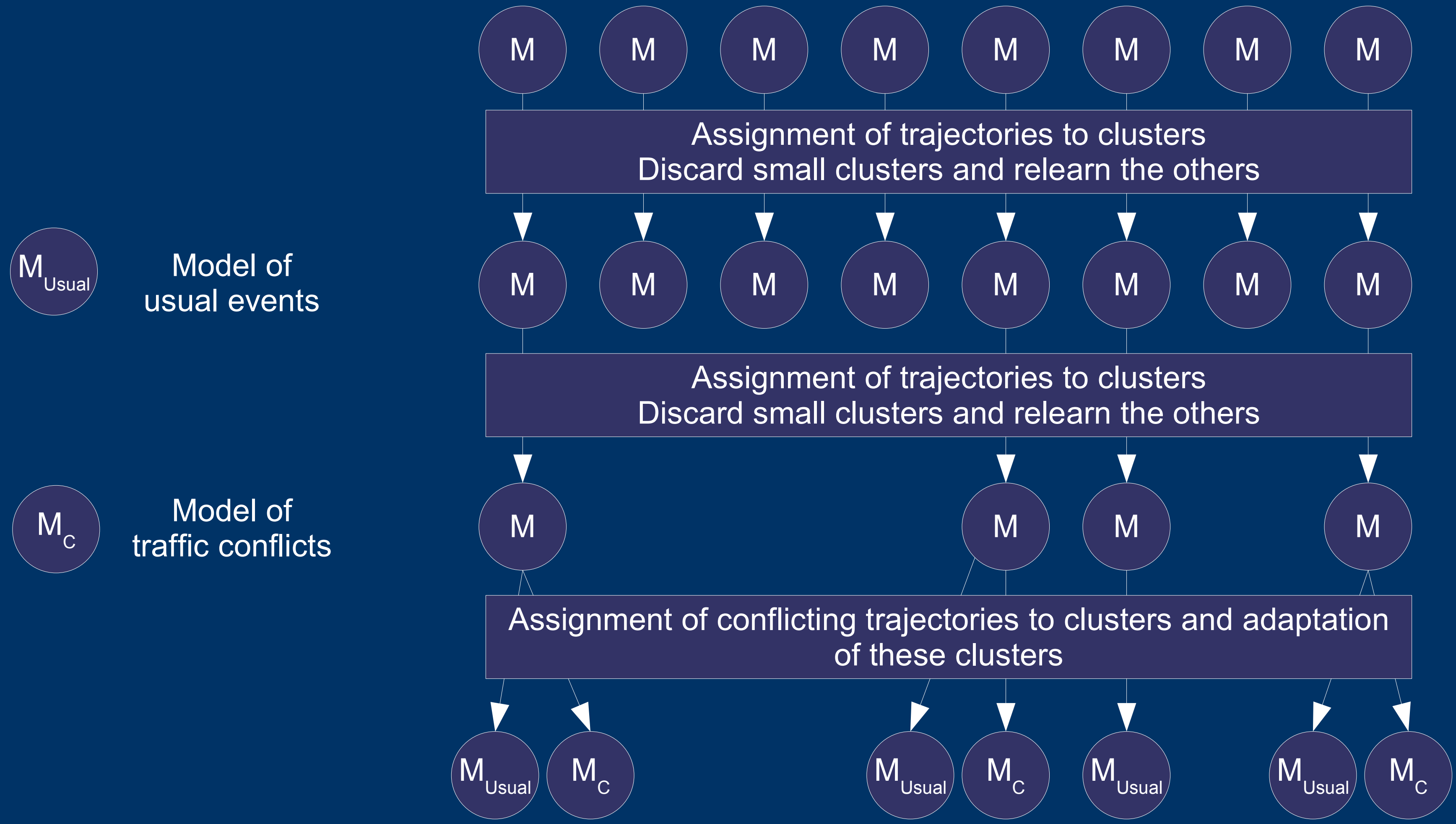
...

t

Interaction characteristics: distance, relative velocity, Time To Collision, collision probability...

Detection Method: manually-tuned rules, classifiers learnt on examples...

Annex. Algorithm Figure



3. Influence of the Number of Models