Automated Road Safety Analysis Based on Video Sensors

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Outline

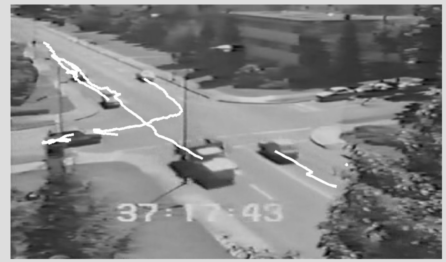
1. Introduction
2. Feature-based vehicle detection and tracking
3. Traffic Conflicts and Collision Probability
4. Experimental Results

1. The Need for Video Sensors

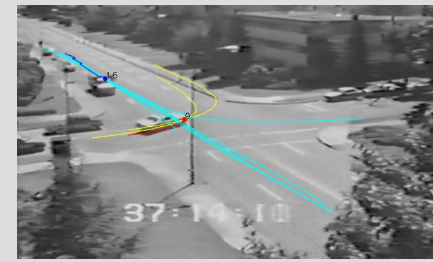
- Main bottlenecks of traffic conflict techniques
  - collection cost,
  - reliability and subjectivity of human observers.
- Advantages of video sensors
  - they are easy to install,
  - they can provide rich traffic description (e.g. vehicle tracking),
  - they can cover large areas,
  - they are cheap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

1. A Modular System

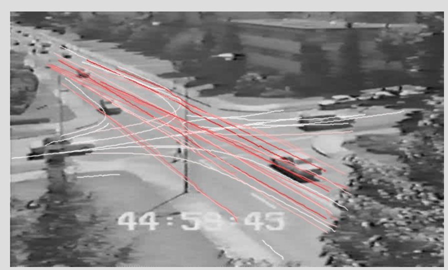
Image Sequence



Trajectory Database



Interaction Database



- Motion Patterns
- Volume, Origin-Destination Counts
- Driver Behavior...

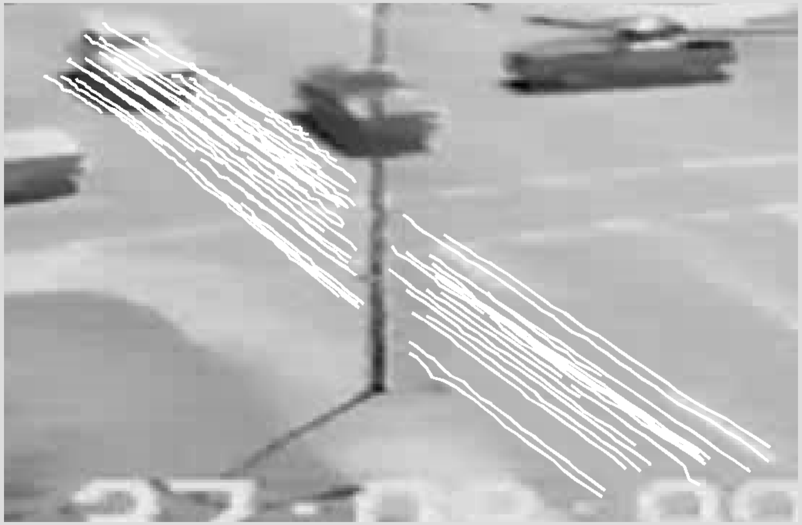
- Traffic Conflict Detection
- Exposure Measures
- Interacting Behavior...

Interpretation Modules

2. Feature-based Vehicle Detection and 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. Road Safety Analysis

3.1 Traffic Conflicts

- Traffic conflicts are characterized by
  - road users on a collision course,
  - and at least one emergency evasive action.
- Focus on the collision course: "unless the speed and/or the direction of the road users changes, they will collide".
  - movement extrapolation hypotheses are required.

3.1 The Possibility and Probability of Collision

- Given 2 interacting road users, various chain of events can lead them to collide.
- If a collision is possible, the collision probability can be computed, as the sum of the probability of all chain of events that can lead to a collision.
- The collision probability is a (the ?) severity indicator.
- "Better" definition of a collision course.

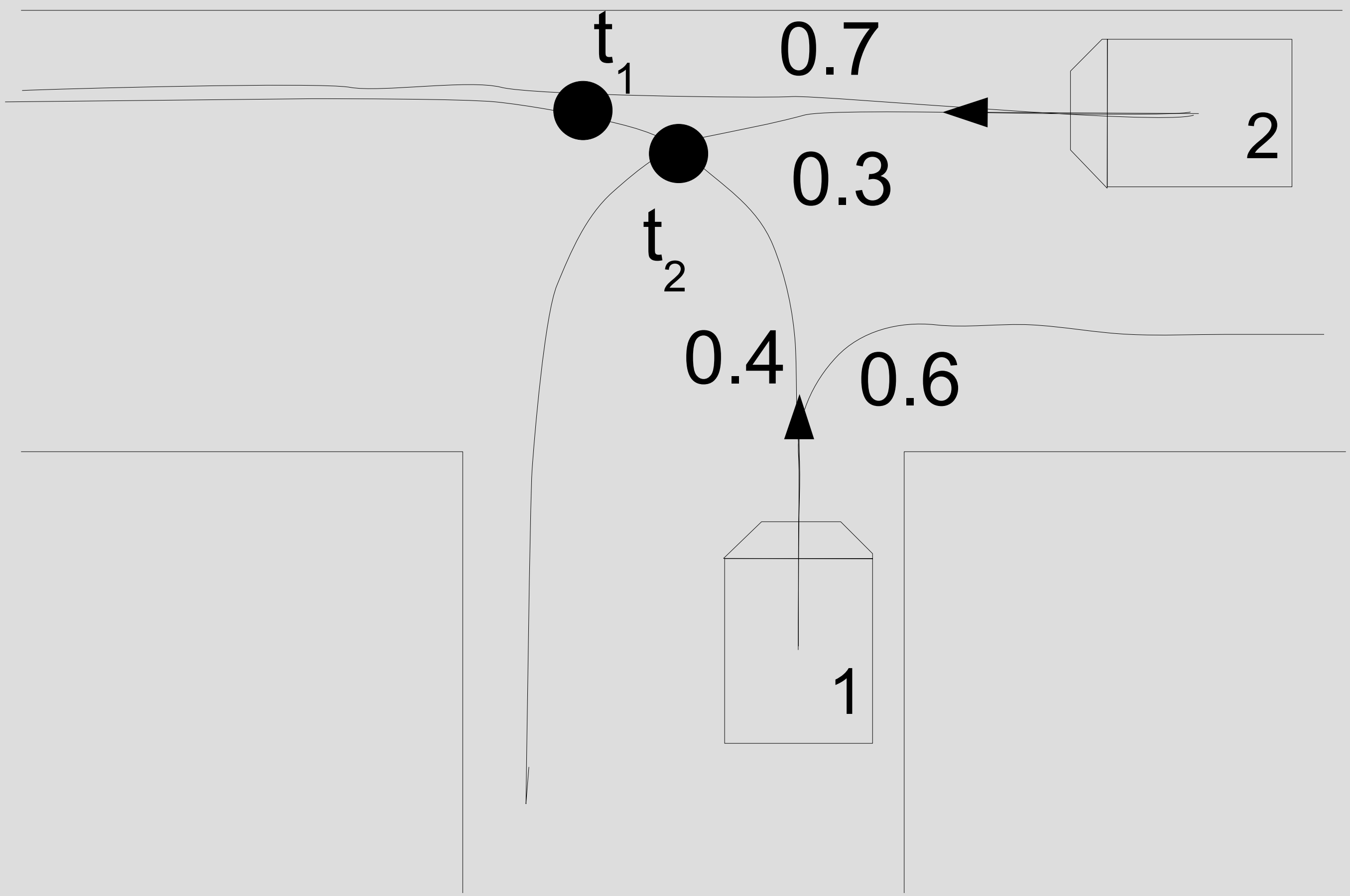
3.1 Computation of the Collision Probability

$$P(Collision|A_{1,t\leq t_0}, A_{2,t\leq t_0}) = \sum_{i,j} P(H_i|A_{1,t\leq t_0})P(H_j|A_{2,t\leq t_0})\, e^{-\frac{(t_{i,j}-t_0)^2}{2\sigma^2}}$$

where $P(H_i|A_{1,t\leq t_0})$ is the probability of road user A_1 to move according to extrapolation hypothesis H_i (same for A_2 and H_j).

3.1 Simple Example

$$P(Collision) = 0.4 \times 0.7 \times e^{-\frac{(t_1-t_0)^2}{2\sigma^2}} + 0.4 \times 0.3 \times e^{-\frac{(t_2-t_0)^2}{2\sigma^2}}$$

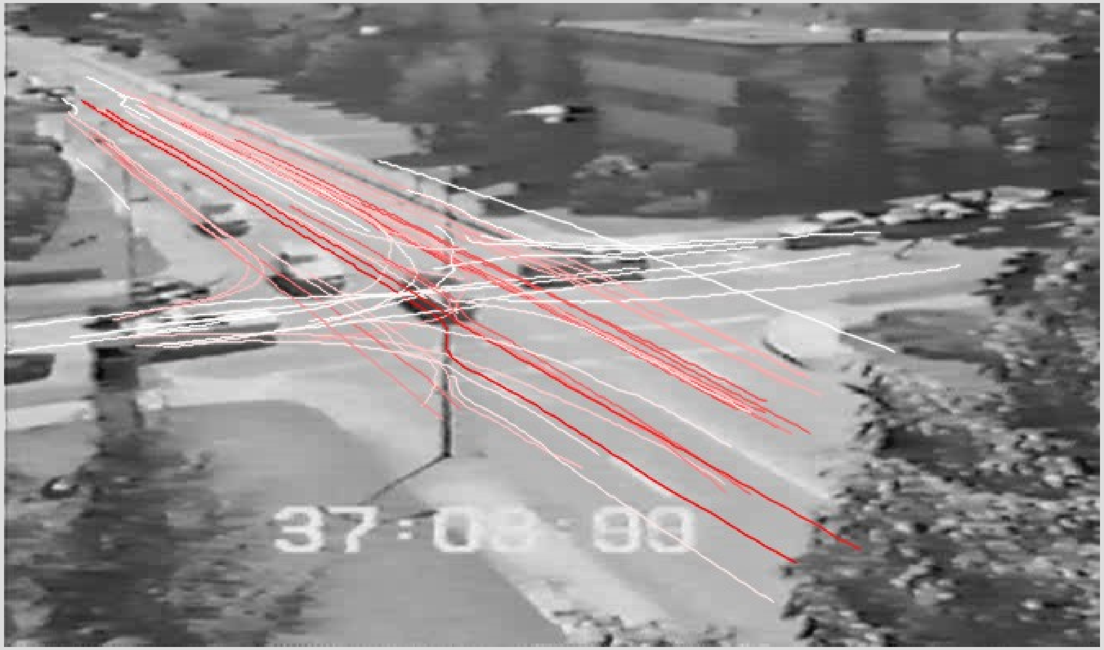


3.2 Motion Patterns

- How to predict road users' movements to compute the collision probability ?
- Road users do not move randomly. Typical road users movements, traffic motion patterns, can be learnt from the observation of traffic data.
- Incremental learning of trajectory prototypes.

4. Experimental Results

4. Motion Patterns



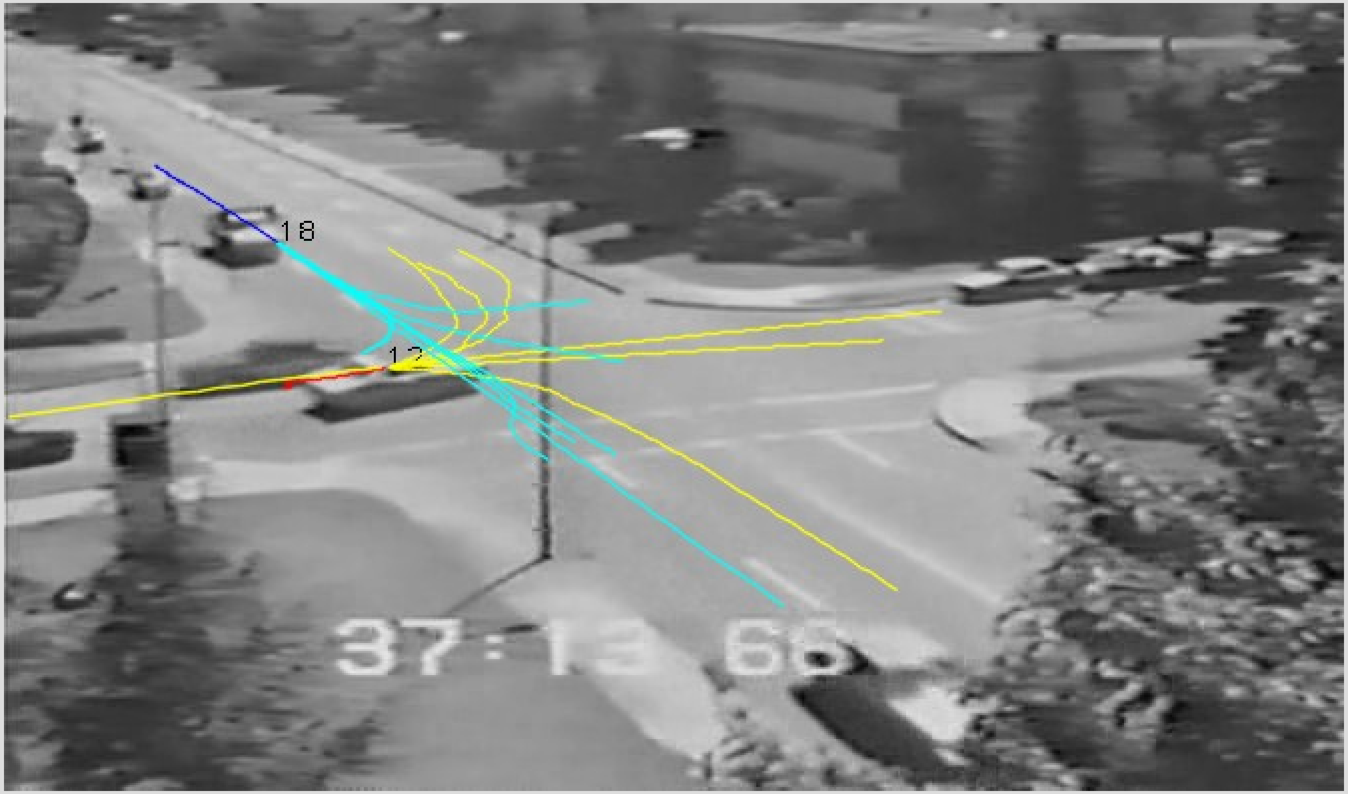
128 prototype trajectories
(47084 trajectories)

58 prototype trajectories
(2941 trajectories)

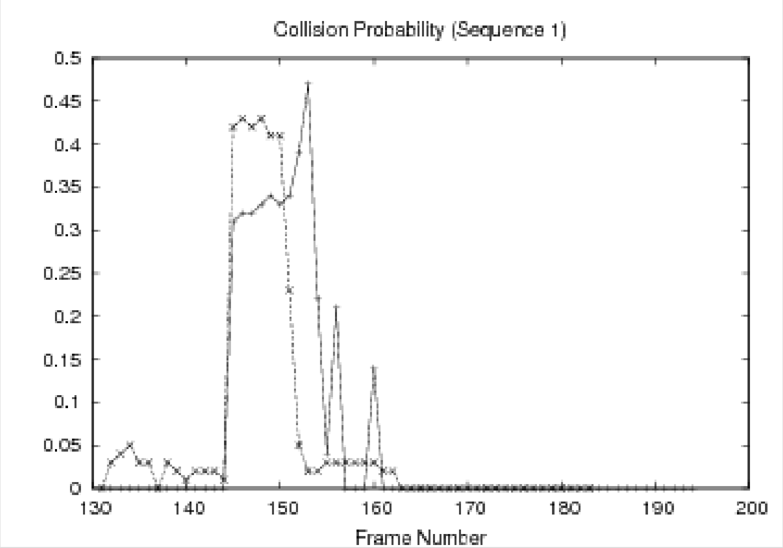
Video

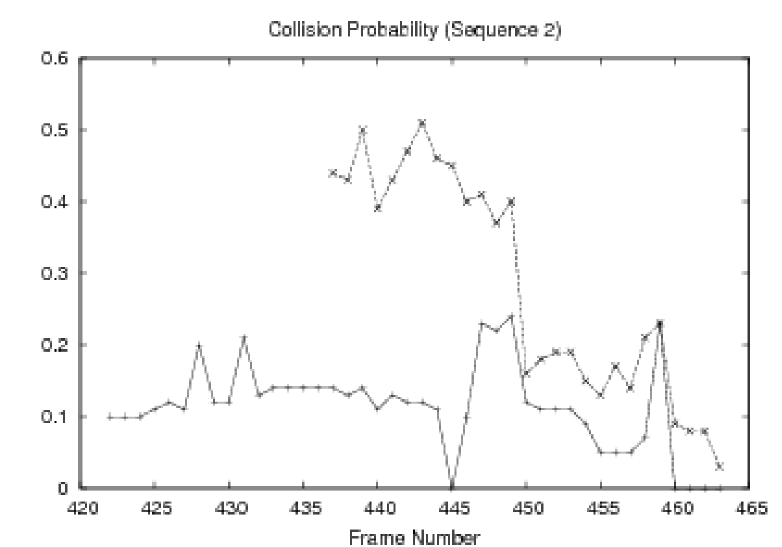
4. Traffic Conflicts

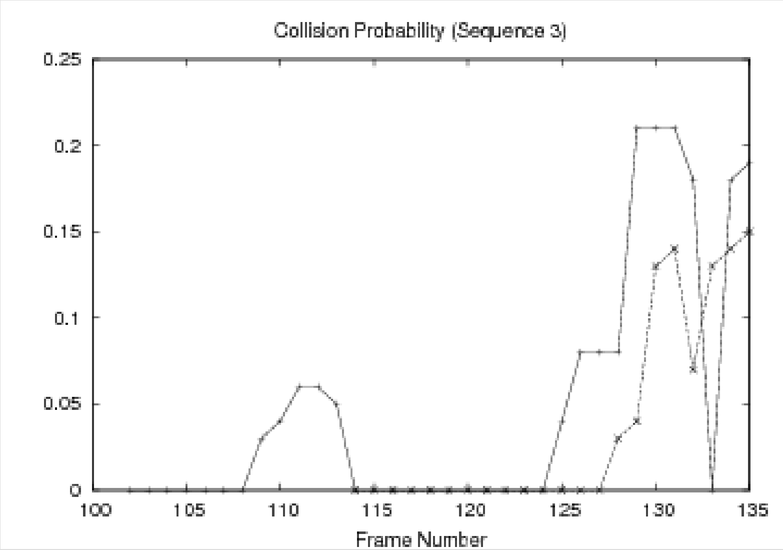
Demo



4. Collision Probability







Conclusion

- Framework for automated traffic data collection, and specifically traffic safety data.
- Work in progress:
  - improve vehicle detection and tracking: detect shadows, estimate vehicle size.
- Need for more data:
  - other sources,
  - artificial data,
  - interactive labeling, active learning.

Annex

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.

3.2 Motion Pattern Learning

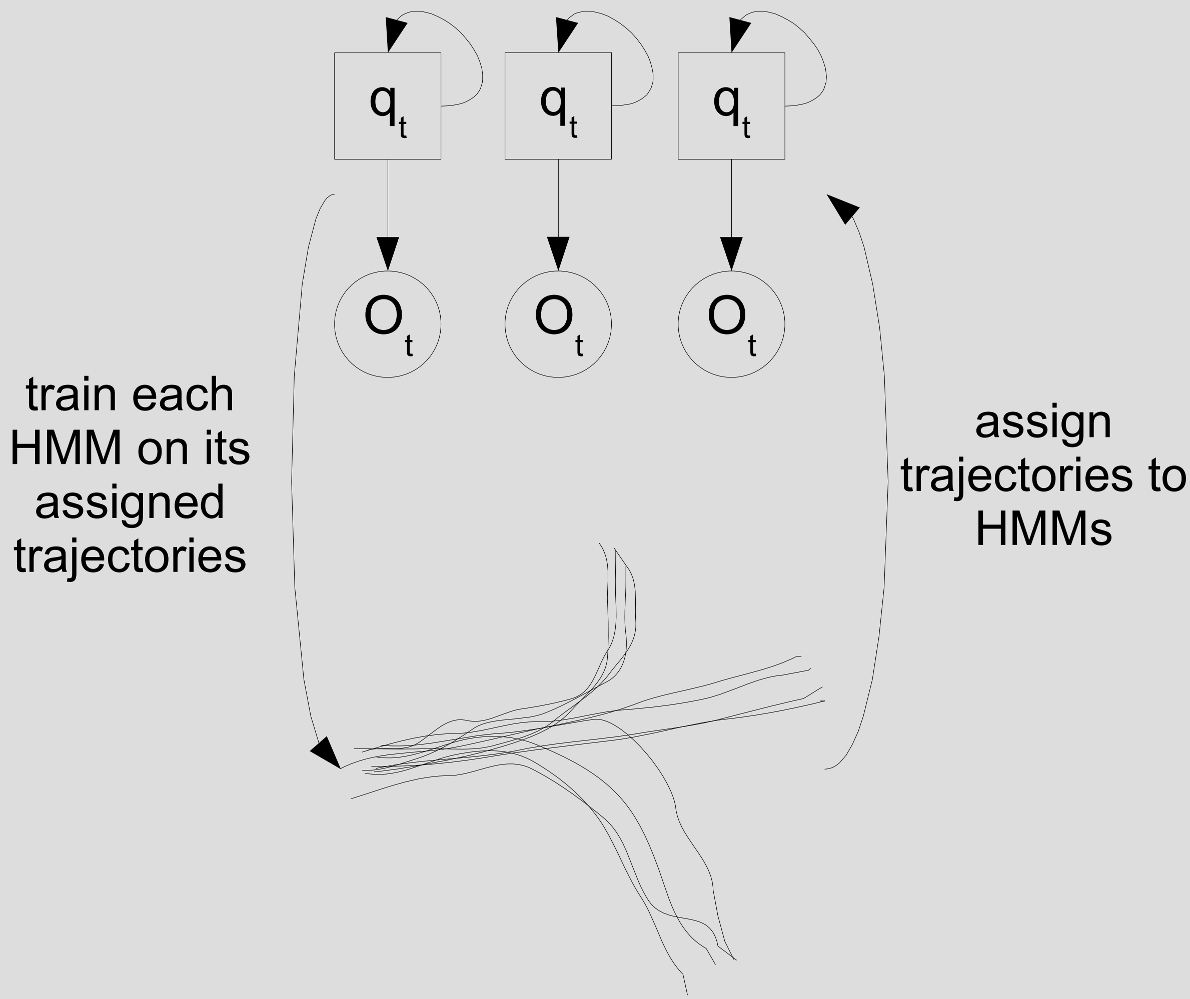
- Similarly to trajectory clustering algorithms, a method to learn motion patterns must address three problems:
  - choose a suitable data representation of motion patterns,
  - define a distance or similarity measure between trajectories or between trajectories and motion patterns,
  - define a method to update the motion patterns.

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 HMM-based Motion Pattern Learning

- 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.

Demo

3.1 Limits

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.
- In reality, there is a continuum of traffic events.

3.2 Longest Common Subsequence Similarity

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 $|y_{i,k_1} - y_{j,k_2}| < \epsilon$.