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A Probabilistic Framework for the Automated Analysis of the Exposure to Road Collision

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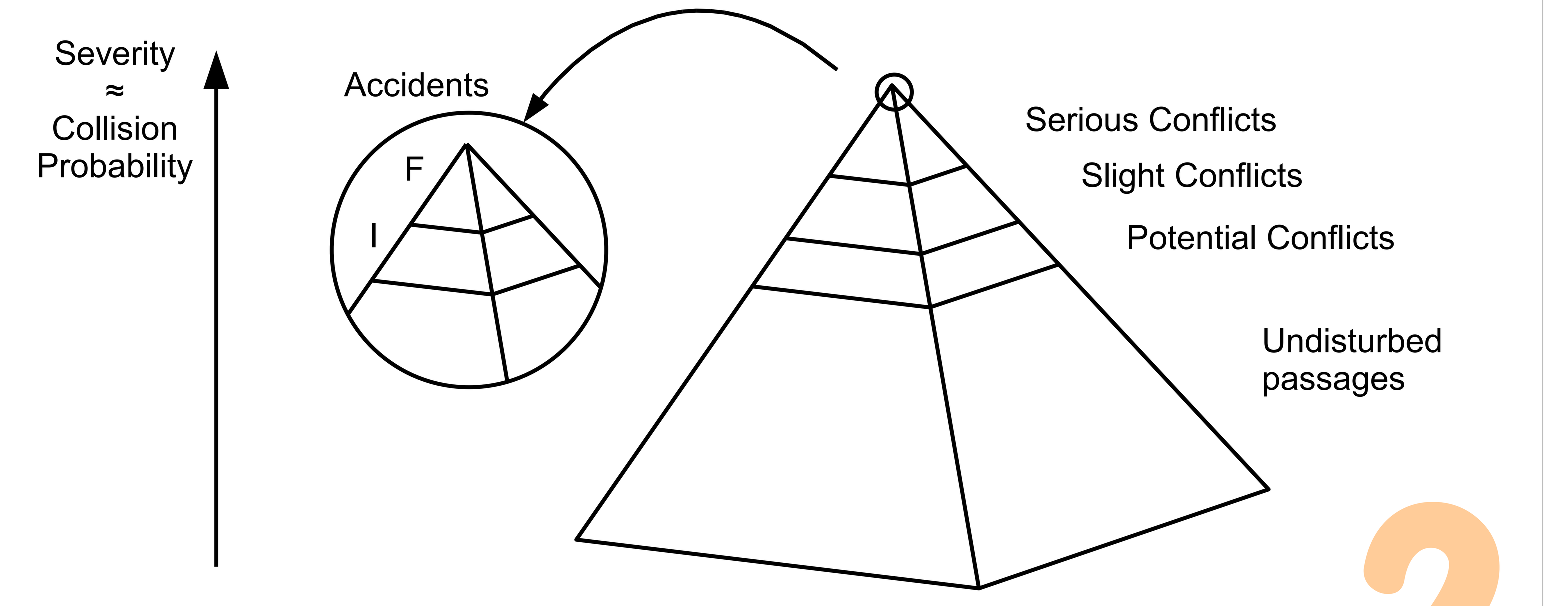
MOTIVATION

Traditional road safety diagnosis is a reactive approach, based on historical collision data. This work aims at developing a proactive approach which avoids waiting for accidents to happen. There is a need for surrogate safety measures that can also provide complementary information and are easy to collect, e.g. requiring shorter observation periods. The observation of traffic conflicts, near-misses, has been advocated as an alternative approach. The advent of powerful sensing technologies, especially video sensors and computer vision techniques, has allowed for the collection of large quantities of detailed traffic data. This work presents a comprehensive probabilistic framework for completely automated systems for road safety analysis. It provides definitions and computational details of the probability of collision for road users involved in an interaction.

THE SAFETY HIERARCHY



Severity Indicators:
Time To Collision, Post-Encroachment Time...

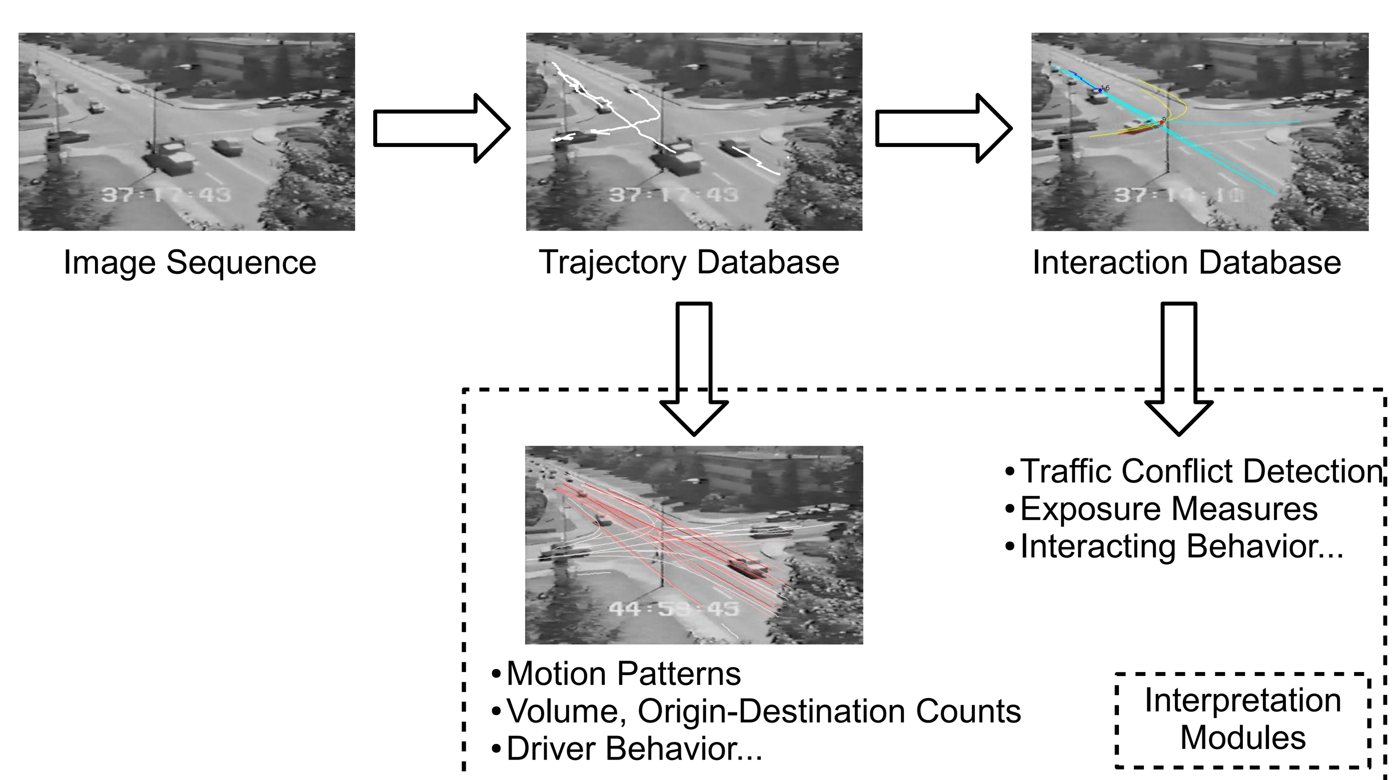
(Svensson 06)

BACKGROUND

Considerable work has been done to validate the Traffic Conflict Techniques (TCT) and the use of traffic conflicts as surrogate safety measures. While most TCTs focus strictly on traffic conflicts, the whole continuum of interactions and their severity distribution can be studied for road safety analysis (1), as well as provide detailed exposure measures and help to better understand the processes that lead to collisions.

To our knowledge, there is limited research on automated systems that can detect traffic conflicts and provide severity indicators (2, 3).

THE VISION-BASED AUTOMATED SYSTEM



The road user detection and tracking module used in this system relies on a feature-based tracking method (4). The tracking accuracy for motor vehicles has been measured between 84.7% and 94.4% on three different sets of sequences.

Motion patterns, represented by actual prototype trajectories without any special pre-processing, and their probabilities, are learnt incrementally using the Longest Common Sub-sequence Similarity (LCSS) (5), suitable for continuous online update for real-time applications, as traffic patterns change in time. For collision probability computation, the partial trajectories of the road users are matched against the set of learnt prototypes using the LCSS.

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PROBABILISTIC FRAMEWORK

For two interacting road users, there are various chains of events that can lead to a collision, over which the collision probability must be summed. This implies the existence of a probability distribution over all traffic events, and requires the practical ability to predict road users' future positions from their past observed positions.

For 2 isolated road users A_1 and A_2 at time t_0 (with observed trajectories Q_1 and Q_2) (2),

- following two extrapolation hypotheses H_i and H_j,

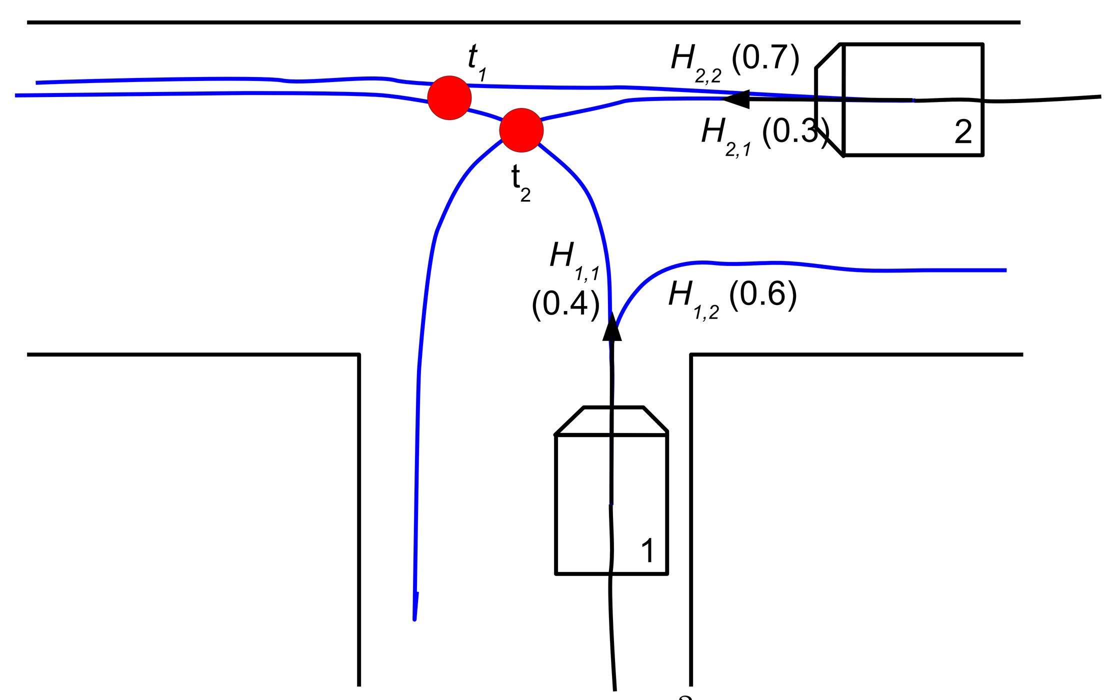
$$P(Collision(A_1, A_2)|H_i, H_j) = e^{-\frac{\Delta_{i,j}^2}{2\sigma^2}}$$

σ is a normalizing constant (typically an average user reaction time); Δ is the time needed to reach the potential collision point.

- summing over all hypotheses,

$$P(Collision(A_1, A_2)|Q_{1,t\leq t_0}, Q_{2,t\leq t_0}) = \sum_{i,j} P(H_i|Q_{1,t\leq t_0})P(H_j|Q_{2,t\leq t_0})\ e^{-\frac{\Delta_{i,j}^2}{2\sigma^2}}$$

A simple example



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

To aggregate measures over time, a single value to describe the severity of the whole interaction is needed: $SeverityIndex(A_1,A_2)$ is the average of the n largest values taken by $P(Collision(A_1, A_2)|Q_{1,t\leq t_0}, Q_{2,t\leq t_0})$ over time. A severity index can therefore be defined by

$$InteractionSeverityIndex([t_1\ t_2]) = \sum_{(i,j)} SeverityIndex(A_i, A_j)$$

FUTURE WORK

This framework needs to be extended, in particular to take into account multiple collisions. New data is currently being collected to expand the results and validate the computed measures. Further research is needed to investigate and validate the relationship of collision probability to safety.

REFERENCES

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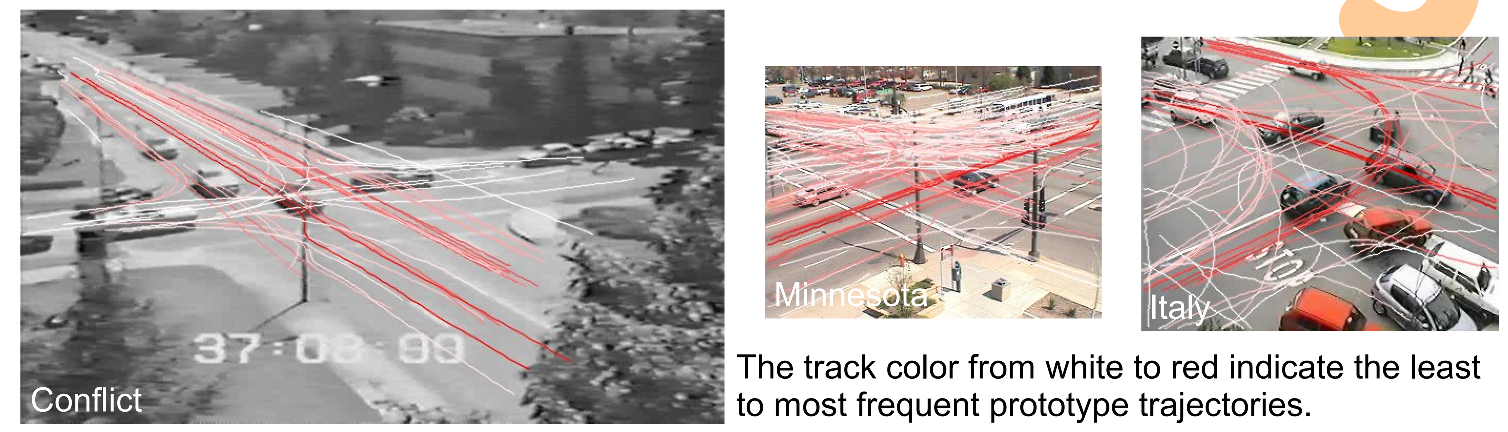
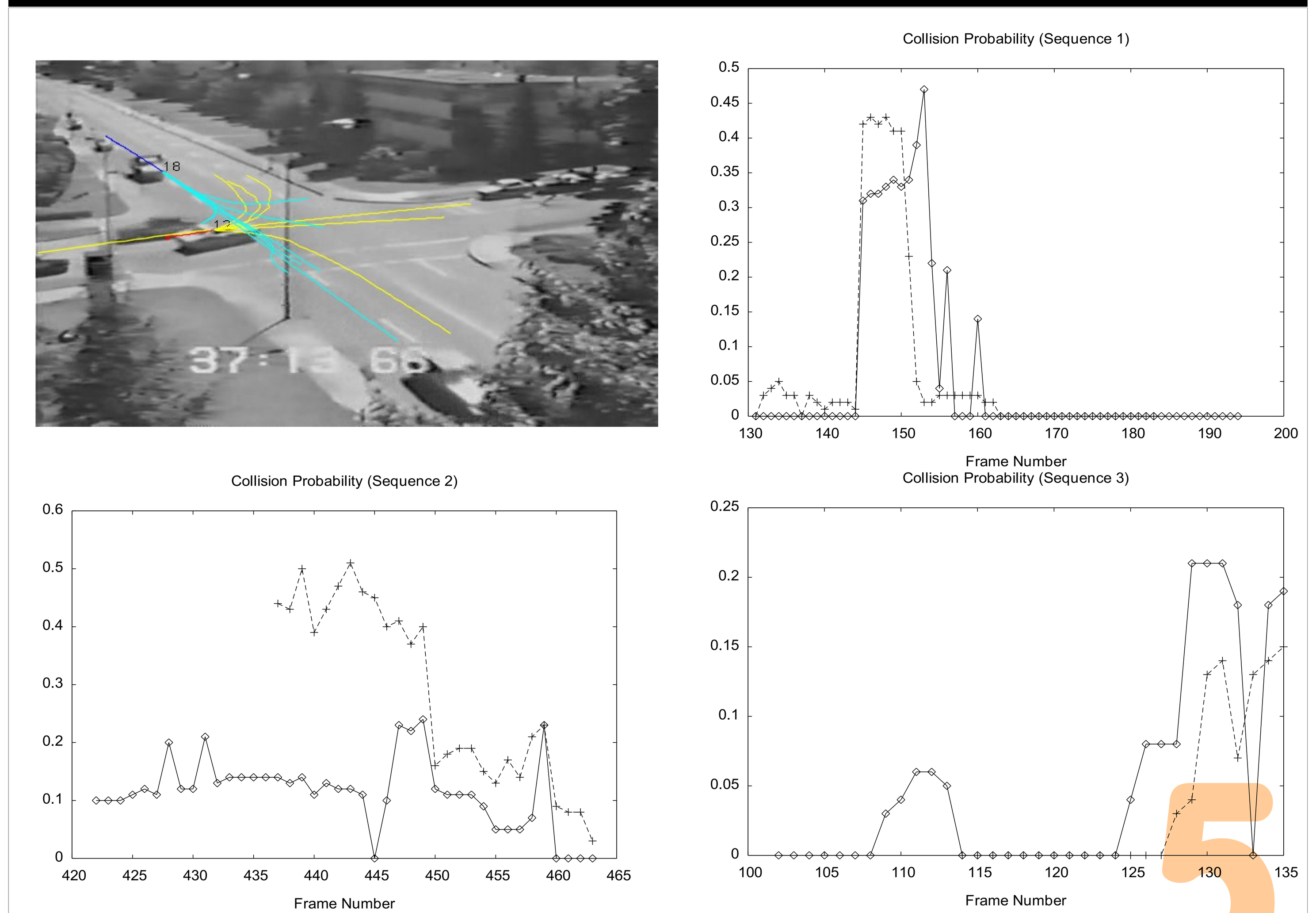
MOTION PATTERNS LEARNING

	Length (min)	Feature Trajectories	Prototypes
Conflict	00:02:58	2941	58
Minnesota	02:14:27	88255	128
Italy	01:38:53	138009	58



The track color from white to red indicate the least to most frequent prototype trajectories.

TRAFFIC CONFLICT STUDY



For 2 of the 3 traffic conflict instances for which the collision probability over time is plotted above, querying interactions for which the severity index is superior to 0.1 returns no false positive.

SEVERITY INDICES