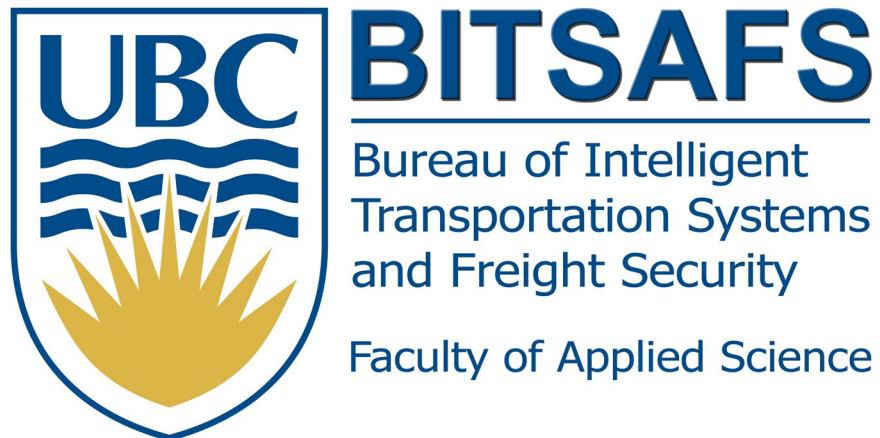


Probabilistic Collision Prediction for Vision-Based Automated Road Safety Analysis

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Outline

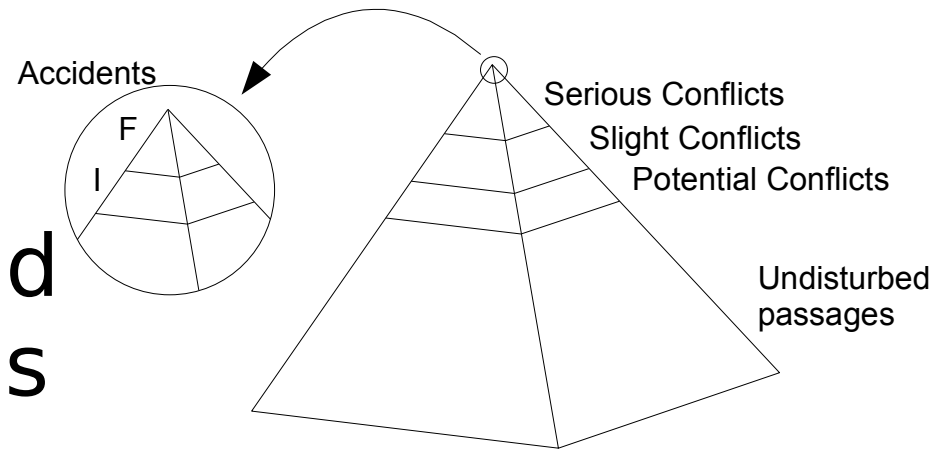
1. Road Safety in a Probabilistic Framework
2. Learning Motion Patterns for Motion Prediction
3. Experimental Results in Road Safety
4. Conclusion and Future Work

1. Road Safety

- Traditional road safety reactive approach, based on historical collision data.
- Pro-active approach: "Don't wait for accidents to happen".
- Need for surrogate safety measures that provide complementary information and are easy to collect (more frequent).
- Traffic conflicts (near-misses).

1. The Collision Probability

- The safety/severity hierarchy.
- For two interacting road users, there are various chain of events that can lead to a collision.



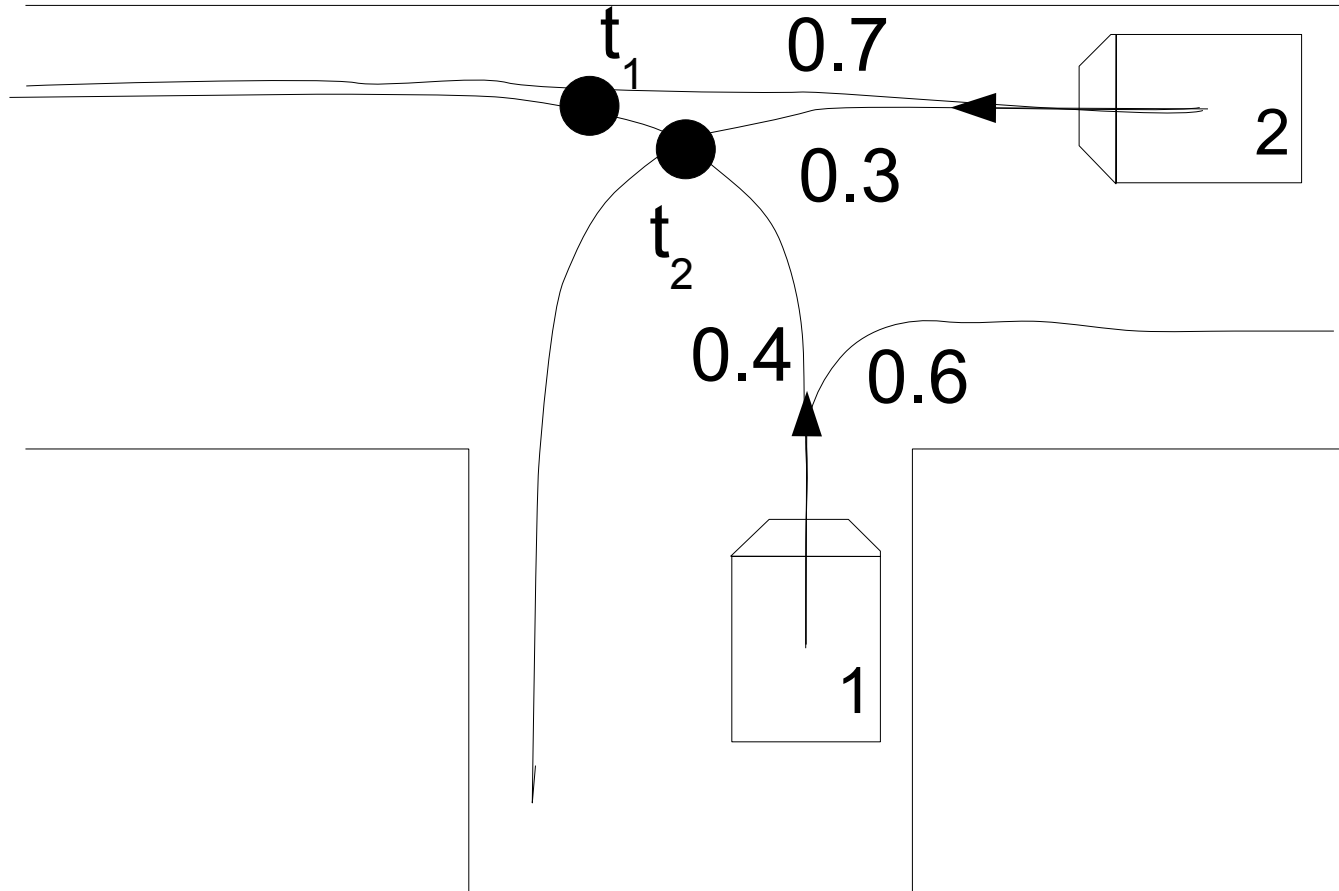
- Given extrapolation hypotheses for road users,

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

$$P(\text{Collision}(A_1, A_2) | Q_{1,t \leq t_0}, Q_{2,t \leq t_0}) =$$

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

1. Simple Example

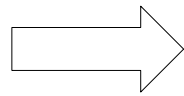


$$P(\text{Collision}) = 0.4 \times 0.7 \times e^{-\frac{(t_1 - t_0)^2}{2\sigma^2}} + 0.4 \times 0.3 \times e^{-\frac{(t_2 - t_0)^2}{2\sigma^2}}$$

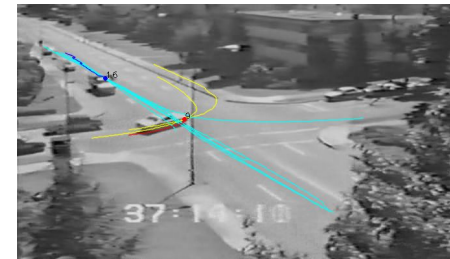
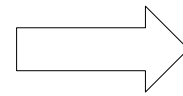
1. A Modular System



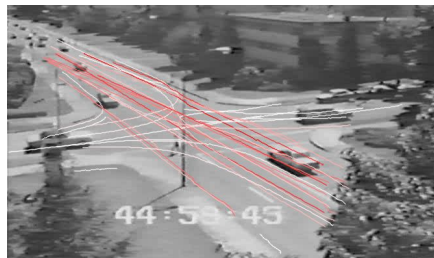
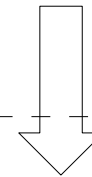
Image Sequence



Trajectory Database



Interaction Database



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

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

Interpretation Modules

2. Motion Patterns

- How to predict road users' future positions 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.

2. Algorithm Ingredients

- choose a suitable data representation of motion patterns, → *trajectory prototypes*
- define a distance or similarity measure between trajectories or between trajectories and motion patterns, → *LCSS*
- define a method to update the motion patterns. → *keep longer trajectories*

2. Longest Common Subsequence Similarity

Let $Head(T_i)$ be the sequence $\{t_{i,1}, \dots, t_{i,n-1}\}$. 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

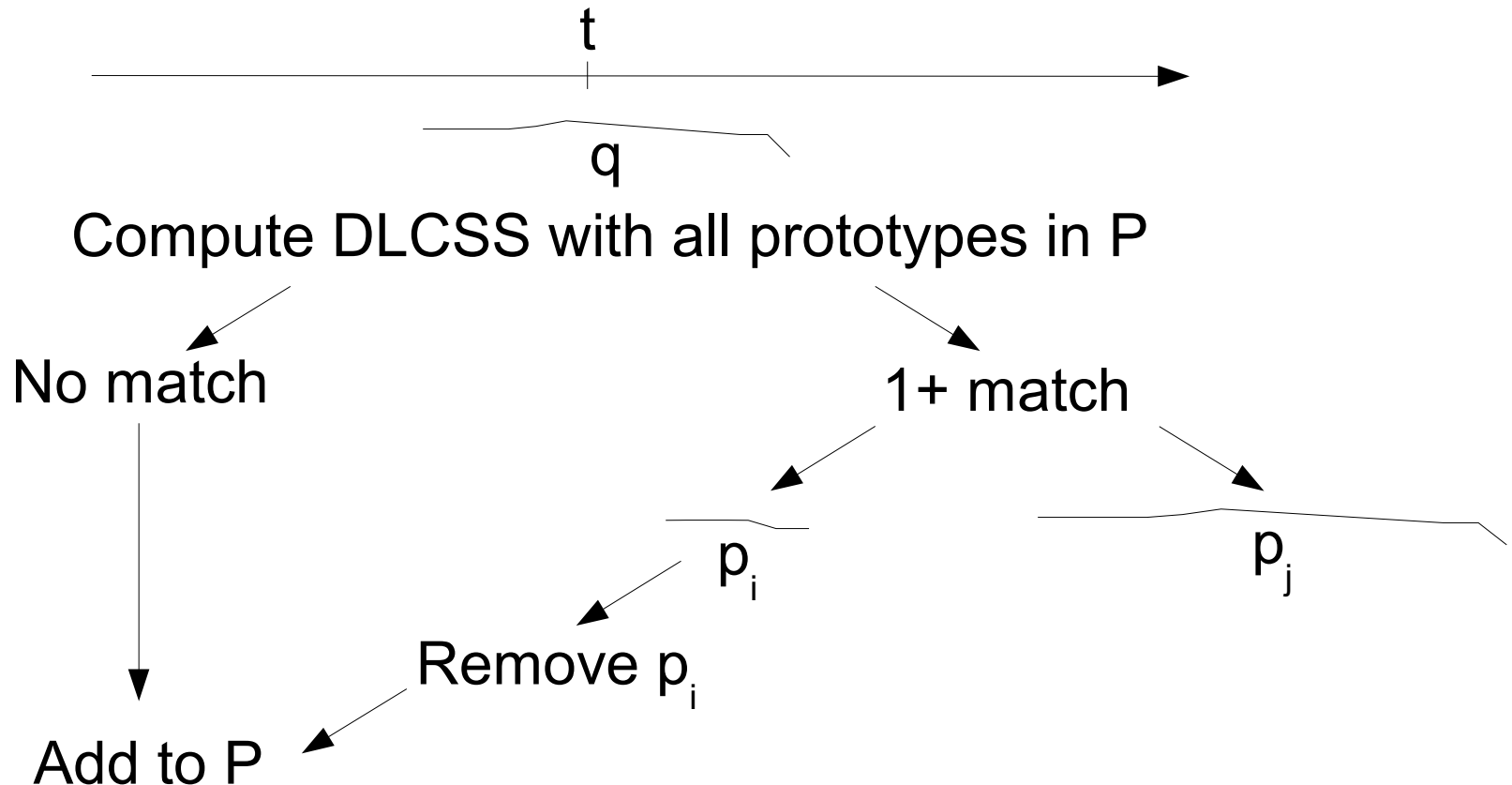
$$LCSS_{\epsilon}(T_i, T_j) = \begin{cases} 0 & \text{if } m = 0 \\ 0 & \text{if } n = 0 \\ 1 + LCSS_{\epsilon}(Head(T_i), Head(T_j)) & \text{if the points match} \\ \max(LCSS_{\epsilon}(Head(T_i), T_j), LCSS_{\epsilon}(T_i, Head(T_j))) & \text{otherwise} \end{cases}$$

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

- Distance DLCSS = $1 - LCSS/\min(n,m)$.
- The LCSS can be computed by a dynamic programming algorithm in $O(nm)$.
- This is costly but robust and flexible.

2. Learning Algorithm

- Parameters: matching distance, matching threshold, NOT the number of patterns.



2. Use of Prototype Trajectories

- Probabilities of hypotheses are derived from the number of matched trajectories.
- The input to the algorithm are feature trajectories (available in abundance), instead of noisy reconstituted object trajectories.
- At prediction time, the feature trajectories are matched against all prototype trajectories.

3. Motion Patterns



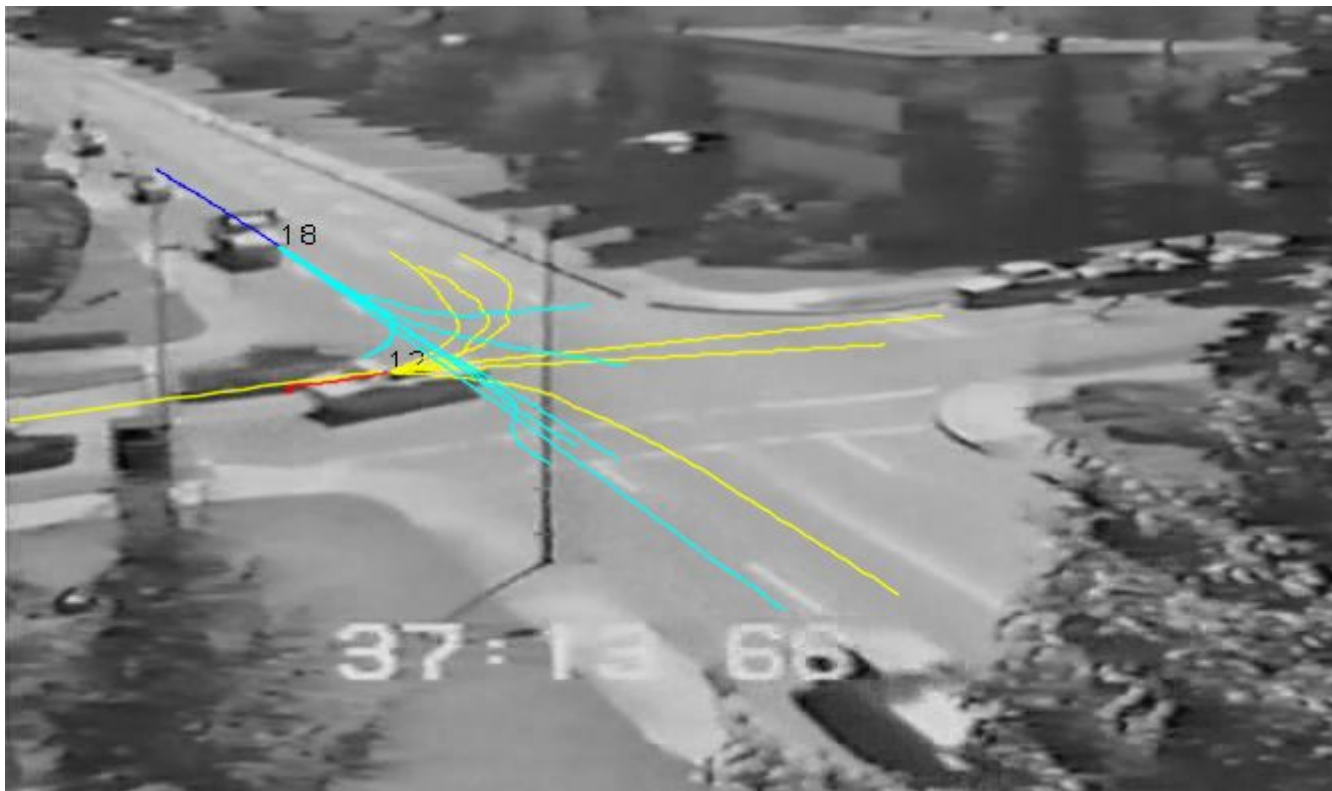
58 prototype trajectories
(138009 trajectories)

128 prototype trajectories
(88255 trajectories)



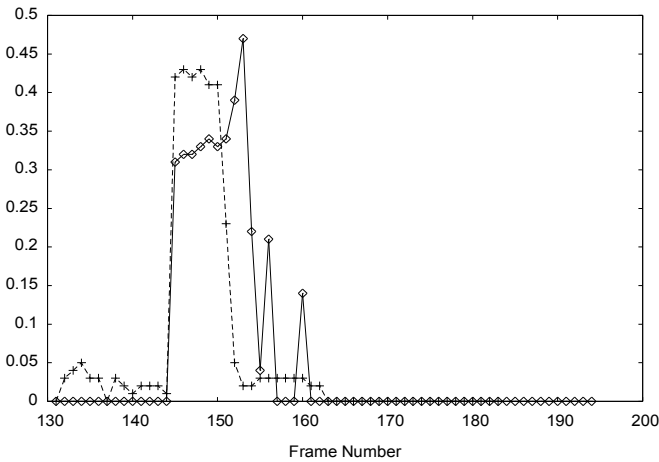
58 prototype trajectories
(2941 trajectories)

3. Traffic Conflicts

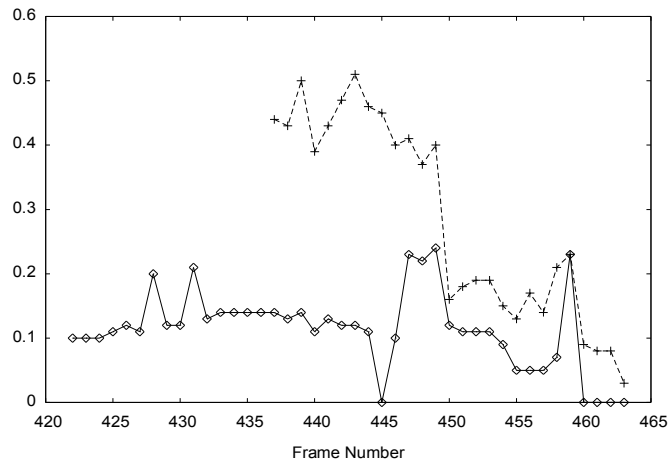


3. Collision Probability

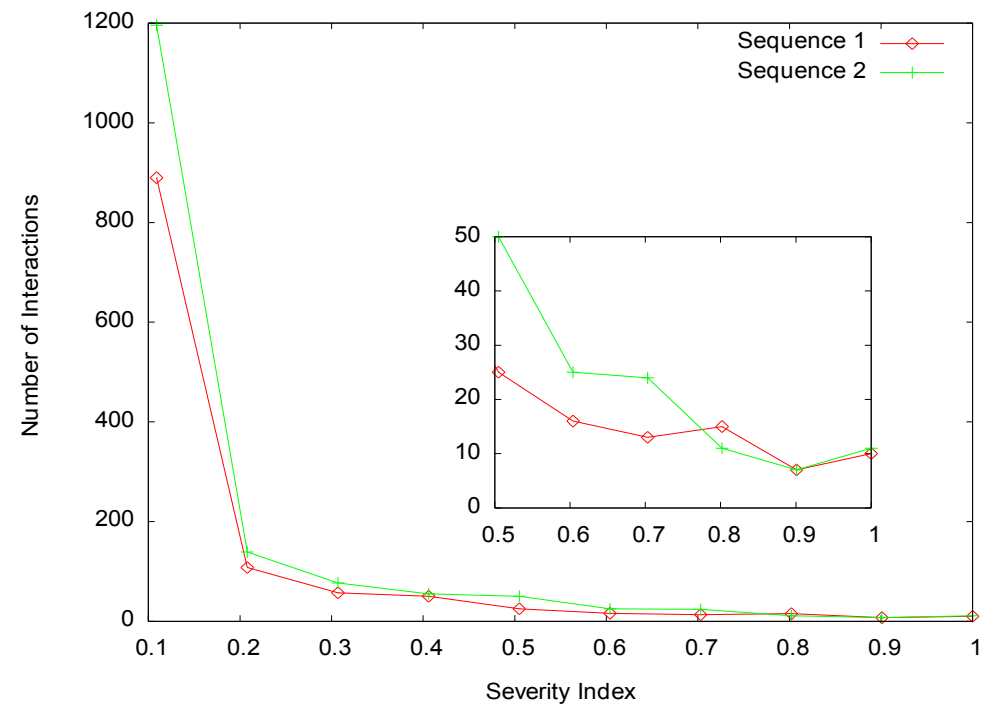
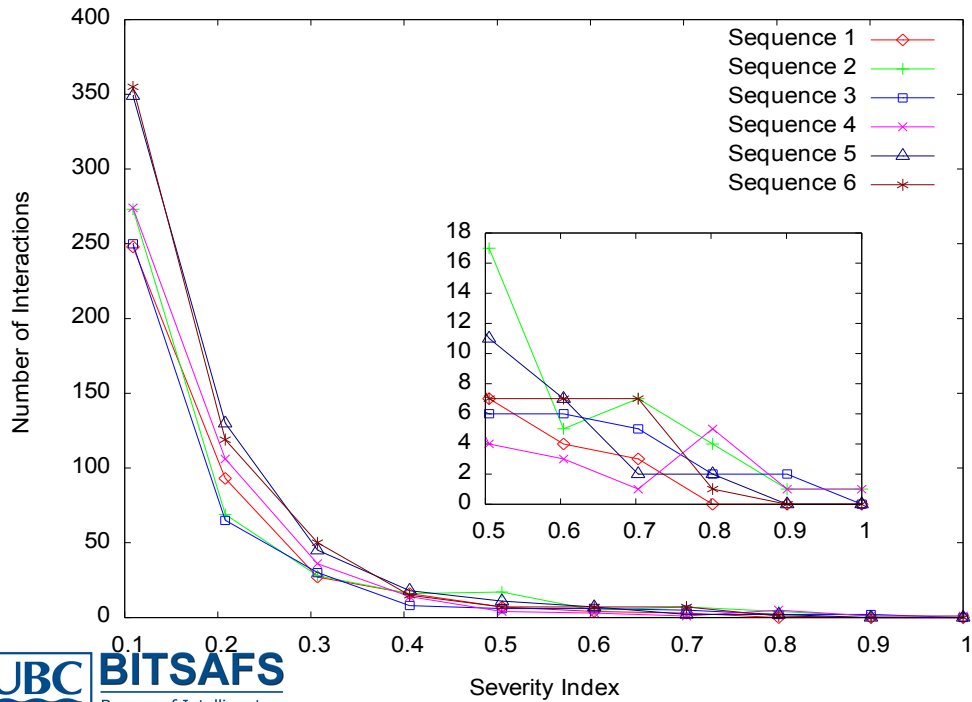
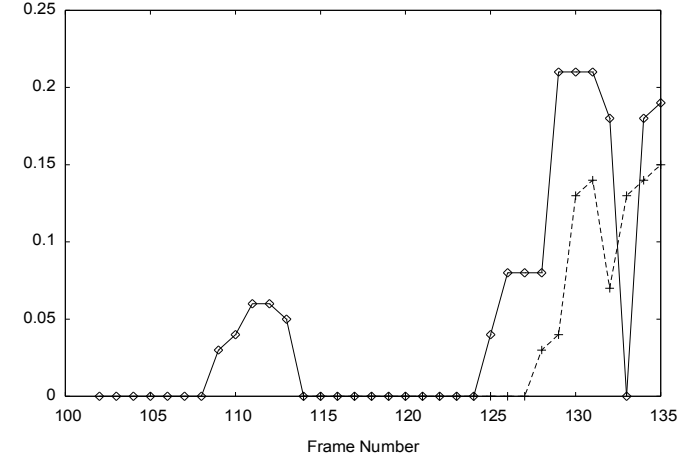
Collision Probability (Sequence 1)



Collision Probability (Sequence 2)



Collision Probability (Sequence 3)



Conclusion

- Probabilistic framework for automated road safety analysis.
- Complete system for automated traffic data collection: traffic intelligence.
- Robustness and versatility of feature tracking.
- Make the program available.

Future Work

- Improve vehicle detection and tracking: detect shadows, estimate vehicle size.
- Extensions:
 - Road user identification: trucks, buses, vehicles, two-wheels and pedestrians.
 - Pedestrian tracking and modeling.

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THANK YOU !