Introduction

We propose a general framework for aggressive driving prediction (ADP) at intersections in a connected vehicle environment:

1. The proposed framework uses time series k-means to categorize multi-dimensional time series trajectories into several driving patterns.
2. We train an unsupervised learning model on the connected vehicle dataset to identify anomalous trajectories and apply this model to clusters to provide an aggressiveness score for each driving pattern.
3. We use real-world connected vehicle trajectories obtained from the Ann Arbor Safety Pilot project to implement our framework, and discuss how safety-focused warning systems, both at the individual vehicle- and system-level, can be developed using this framework.
4. It is part of our closed-loop control framework as shown below:

Results and Discussion

The clustering results are shown in Figure 2. It shows six driving patterns generated by the framework.

- Based on isolation forest, we identify the aggressive trajectories in the dataset and compute the probability of aggressiveness in each cluster.
- Figure 3 visually validates the premise of this study that different clusters represent different driving patterns, and that each driving pattern has a different aggressiveness score within a different context.
- The aggressiveness score of a cluster can be interpreted as the probability that a trajectory belonging to that driving pattern being anomalous (i.e., risky/aggressive).

Figure 2: Time series K-Means results with dynamic time warping

Figure 3: Isolation forest aggressive trajectory detection results visualized for the acceleration dimension. Aggressive driving trajectories are determined by the anomaly detection method and are colored in red.

Figure 5: Aggressiveness profile of the example intersection

Figure 5 demonstrates an overview of driver aggressiveness as vehicles approach the intersection under study. It shows the total percentage of trajectories in each cluster within the 10 second time period during which vehicles approach the intersection stop line. The information can be used to by transportation management agencies to create safer intersections.

Conclusions

We propose a scalable framework to learn, detect, and predict aggressive driving in a connected vehicle environment without human intervention (e.g., subjective data labeling). The proposed framework is based on unsupervised learning, and uses a multi-dimensional time series feature space, constructed based on vehicle trajectories, to compute and predict aggressiveness scores to vehicles approaching an intersection.

Impacts

1. Enhancing safety by predicting aggressive driving in real time in a connected vehicle environment.
2. Providing context for informed control measures through identifying driving patterns. Anomalous driving behaviors under different driving patterns require distinct control measures.
3. An automated framework for identifying risky behavior that does not require resource-intensive and subjective human labeling of data (i.e., subjective identification of aggressive driving)
4. A transferable model that can be implemented at any intersection
5. Providing a safety profile for intersections, which can be utilized by traffic management agencies

Acknowledgement

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References

USDOT, Intersection Safety, 2018

Materials and Methods

We provide a methodology based on unsupervised learning to cluster multi-dimensional connected vehicle trajectories.

1. Construct a physics-based feature set for quantifying measures of aggressiveness in driving. The features include the relative location, vehicle motion, energy, force, and signal phasing and timing (SPAT).
2. Use a time series k-means algorithm with a dynamic time warping (DTW) similarity measure to cluster multi-dimensional trajectories into groups of driving patterns.
3. Use isolation forest to compute aggressiveness scores of clusters.
4. Online assessment by assigning real-time trajectories into clusters.

Figure 1: ADP in the closed-loop control framework

Figure 4: Online assessment of incoming trajectories

Figure 4 demonstrates the results of online assessment of sample trajectories at the intersection of interest. In this figure, we re-assess the clustering assignments of vehicles every second. In Figure 4, when vehicle 7 enters the 10-second cordon encompassing the intersection, it is assigned an aggressiveness probability of 41.2%. As it approaches the intersection stop line, its risk is reduced substantially.

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