Using a Layered Algorithm to Detect Driver Cognitive Distraction

Yulan Liang[1], John D. Lee[2]

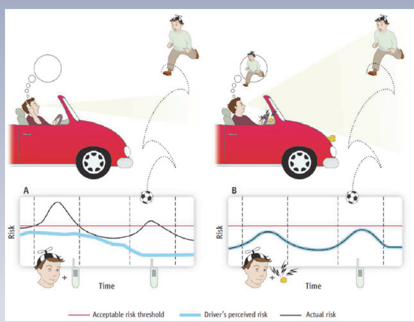
[1]Liberty Mutual Research Institute for Safety, Hopkinton, MA

yulan.liang@libertymutual.com

[2]University of Wisconsin, Madison, WI

Background

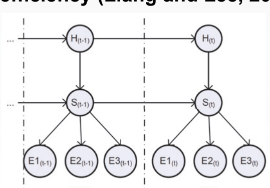
A promising strategy to minimize the effects of driver distraction is to develop the technology that can mitigate distraction based on the state of drivers as well as the traffic context or environment.



Attention and risk. Technology may mitigate distraction by helping drivers to distribute their attention and guiding them to engage distractions only when roadway demands are low. (Lee, 2009)

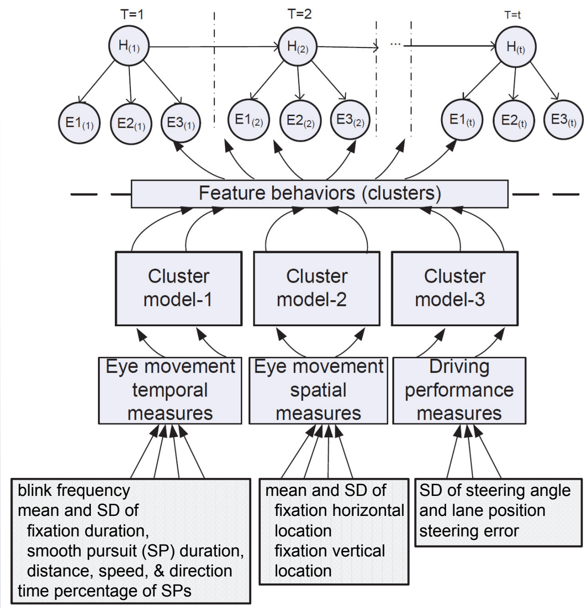
One challenge in building such a system is to accurately and efficiently detect driver cognitive distraction, which likely requires integrating a large number of indicators across relatively long periods of time and modeling for each individual driver.

In a previous study, Dynamic Bayesian Network (DBN) produced promising results with 86% accuracy, but lacked efficiency (Liang and Lee, 2008).



DBNs are a probability-based approach to present conditional dependencies between variables and can model a time-series of events according to a Markov process. For example, the arrow between variable nodes $H_{(t)}$ and $S_{(t)}$ indicates that $S_{(t)}$ is independent of all variables other than $H_{(t)}$.

The Layered Algorithm



DBNs infer driver cognitive state based on the feature behaviors and consider time dependency

Supervised clustering models classify feature behaviors in three performance perspectives

Distraction indicators are divided into three perspectives

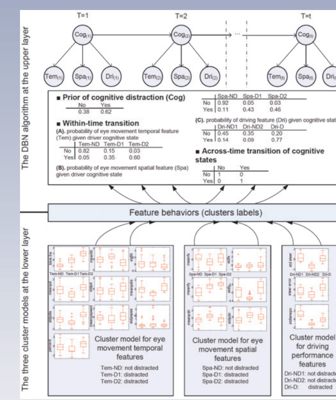
Methods

A simulator-based experiment
- 9 experienced drivers
- 4 distraction drives and 2 baseline drives
- eye movements and driving performance

Algorithm setups and training
- distraction drives = 1, baseline drives = 0
- 19 distraction indicators summarized across 30 seconds
- 2/3 for training and 1/3 for testing
- individual model for each driver

Results

Both algorithms achieved accuracy of 88%; however, the layered algorithm reduced training CPU time from an average of 19.1 minutes to 13 seconds and testing CPU time from 5.9 seconds to 1.0 second.



Interpretation of the models. The example showed that during cognitive distraction, the driver tended to 1) blink faster, 2) look closer to the vehicle instead of straight ahead, and 3) steer more abruptly than with no distraction.

Conclusion

The layered algorithm capitalizes on the best attributes of component data mining methods and can identify human cognitive states efficiently.

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