WP9 Use Case 2: Overtaking

Driver Risk Awareness Prediction

HOLISTIC HUMAN FACTORS AND SYSTEM DESIGN
OF ADAPTIVE COOPERATIVE HUMAN-MACHINE SYSTEMS

Motivation

Literature asserts that physiological data such as Heart Rate (HR), Respirational Rate (RR), Non-specific Skin Conductance Fluctations (NSF) are linked to the affect and arousal state (McDuff et al, 2014; Healey & Picard,2005; Drachen et al., 2010). The main assumption behind the model is that arousal and risk awareness are linked together. The goal is to create a model which may detect whether the **driver's risk awareness** is adequate to the **potential danger** of a given traffic situation.

Such a model could be useful in building advanced driver assistance systems, since it could answer questions such as: is the driver's risk awareness adequate to the situation? If it is low in dangerous situations, assistance systems may take actions to raise risk awareness. Equally, assistance could be altered in the detrimental case of high risk awareness in harmless situations. Ultimately, such a model can be used to assert the human-in-the-loop requirement in manual driving or the adequate risk awareness in partial automated driving conditions.

The modelling uses Bayesian Belief Networks (BBN) to learn conditional probabilitic distributions from driving experiment data. BBNs (Koller & Friedman, 2009) have a few advantages over other techniques. As graphical models, they are easy to understand for humans; they are white-box mathematically plausible models of uncertainty. They can be used for diagnostic, predictive, and intercausal reasoning and combine weak evidence to strong hypotheses. In the driving domain, they have been used for stress detection (Rigas et al., 2008).

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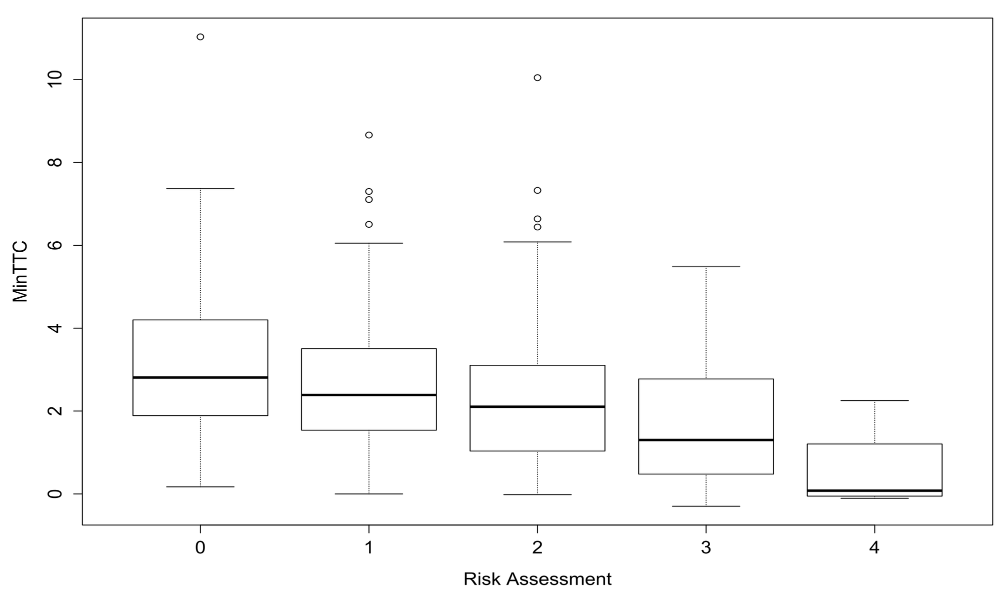
Results

		Distraction		
		Visual (SURT)	Acoustic / cognitive - easy condition (0-back)	Acoustic / cognitive - difficult condition (2-back)
HMI	Non-adaptive	1	4	5
	Adaptive	2		
	Adaptive automation	3		

This effort was run in conjunction with the TAK Use Case 9.2 Overtaking and the TAK AdCoS.
The experiment consisted of 5 conditions with different levels of automation and background tasks
Condition 3 was later removed from futher explorationfor automation was not activated in all cases.

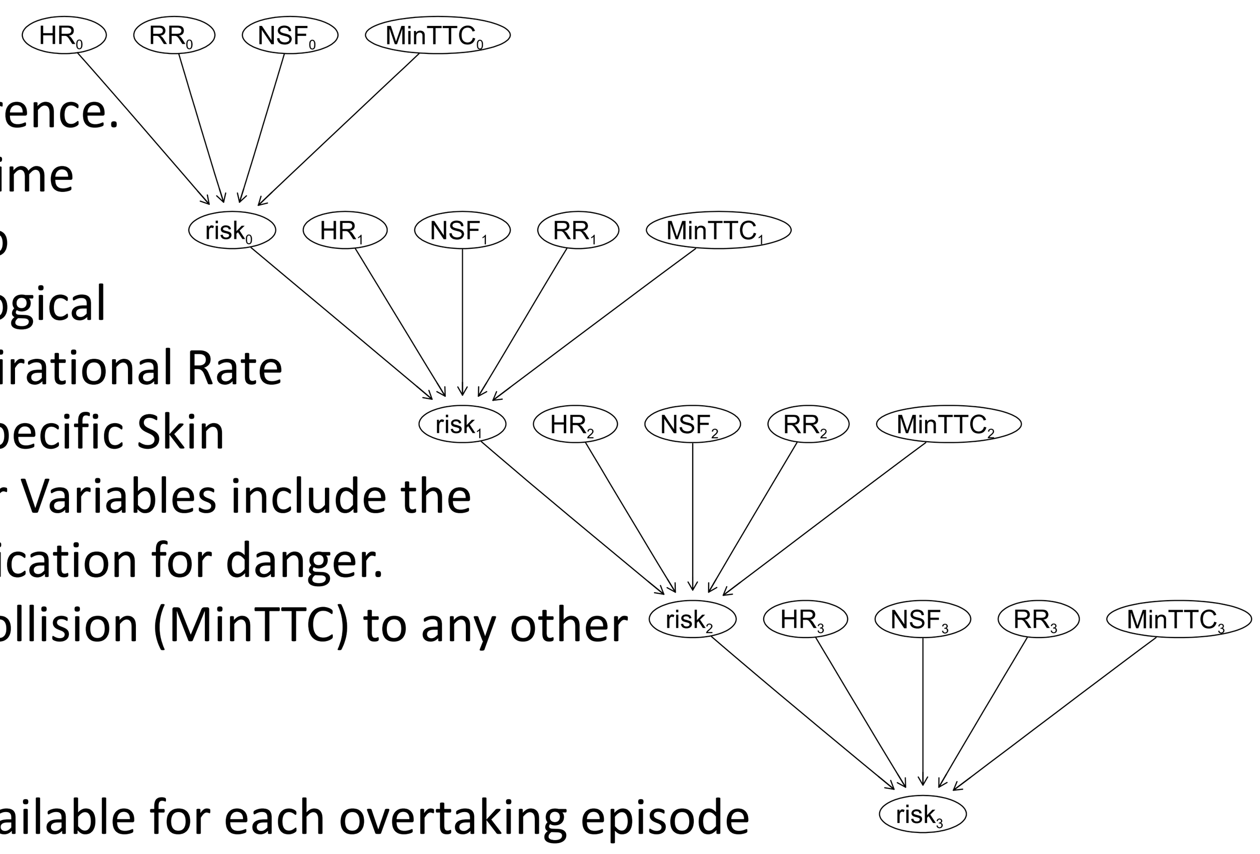
During each experimental run, several overtaking situations were enacted, which should result in a varying objective danger of the situation. **After each overtaking episode**, the subjects were asked to **assess the risk** of the situation according to the scale on the right.

Extremly dangerous and not controlable *[Extrem gefährlich und nicht kontrollierbar]*	10
Dangerous and difficult to control *[Gefährlich und schlecht kontrollierbar]*	9
	8
	7
Dangerous but controlable *[Gefährlich, aber kontrollierbar]*	6
	5
	4
Hardly dangerous and easy to control *[Gering gefährlich und sehr gut kontrollierbar]*	3
	2
	1
Absolutely no danger *[Absolut ungefährlich]*	0



As **indicator for the danger** in a given situation, we defined **MinTTC** as the minimum TTC to any other vehicle (rear or front) during an overtaking. The plot on the left shows indeed that Risk assessment and MinTTC correspond to each other.

The goal was to create a **Dynamic Bayesian Belief Network** for online risk awareness inference. The BBN consists of several time slices. Each time slice has a sensor model, which links a state to sensor variables. Sensor variables are physiological measurements such as Heart Rate (HR), Respirational Rate (RR) or Electro-Dermal Activity such as Non-Specific Skin Conductance Fluctuations (NSF). Other Sensor Variables include the objective traffic situation, which serves as indication for danger. In this case, we used the minimum Time-to-Collision (MinTTC) to any other vehicle during an overtaking episode.



The Risk assessment by the driver, which is available for each overtaking episode during the experiment, is used as state variable in the model. A transitional model between time slices connects the Risk Awareness state variables. Sensor and transitional models are described by conditional probability distributions.

The dynamic BBN spreads over four time slices. The data was time-homogenous, and as the latencies for Physiological response is at least 250 ms, we sampled the data with a frequency of 4 Hz. The above four-slice network such as in the figure above covers a full second of driving.

To validate the dynamic BBN, we performed a 10-fold cross validation of the data and compared the performance with the prediction error rate for the node Risk3, which means that the test set contained physiological data and traffic situation for the last second. For the conditions, the prediction error rate was around 10% or lower, which means that the **risk awareness was correctly predicted in 90% of the cases**. When all conditions are used for training and validation, the error rate is considerably higher.

The model can be used in an intelligent driver monitoring system to further assert if the risk awareness is adequate to the traffic situation.

	Total	Condition 1	Condition 2	Condition 4	Condition 5
Observations	34898	7561	9902	8320	9109
Prediction Error Rate ($risk_3$)	0.24	0.069	0.104	0.077	0.108

Consortium

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