Design of Real-time Transition from Driving Assistance to Automation: Bayesian Artificial Intelligence Approach

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AMAA 2014

Berlin, Germany

Presentation structure

- Necessity of Cognitive Features in Driving Assistance System Design
- Bayesian Artificial Intelligence
- Transition from Human Control to Automation
- Conclusions

Technological Forecasts & How to Overcome Shared Authority Concerns

- Autonomous vehicles in the long term

- Driving assistance in the short term

- But, no clear definition of how to integrate human and technology factors in order to make human control and automation seamless

- Need to overcome shared authority concerns in increasing automation in driving

Necessity of Cognitive Features in Driving Assistance System Design

Cognitive vehicle features	Required for human control	Required for adaptive longitudinal & lateral control
❑Situational awareness (position and surroundings)	X	X
❑Gather, send & process data	X	X
❑Cooperate/collaborate	X	X
❑Communication for active safety		X
❑Warnings and advice	X	
❑Diagnostic capability	X	X
❑Crash situation: send and receive information	X	X
❑Non-distractive user interface	X	X
❑Infotainment capability	*NA	*NA

Driving Assistance Design Features

Multifunctional advanced driver assistance system (ADASS) design

- Open architecture & algorithms
- Natural interface of driver and automation features
- Interface with portable device
- Sensor network for data capture
- Integrated sensing for state estimation
- Communication systems
- Mechatronics/Microelectromechanical systems (MEMS)

Role of Bayesian Artificial Intelligence (AI)

AI:

“Intelligence developed by humans, implemented as an artefact”

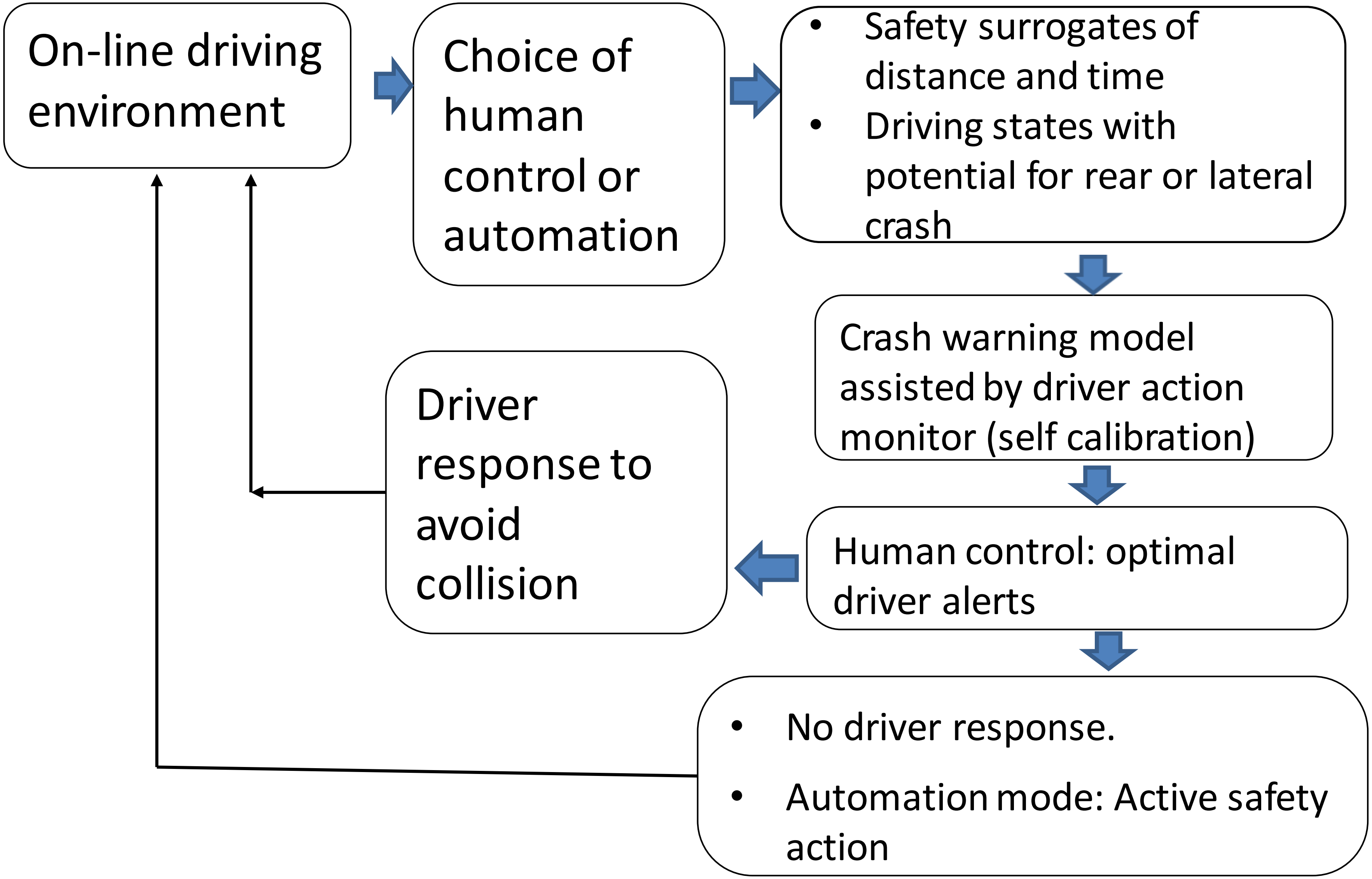
Bayesian AI:

Algorithms that enable driving as well or in certain situations better than humans can (e.g. non-distracted non-aggressive driving) while adapting to stochastic and changing driving environment states.

Implementation Steps:

I. Algorithm for driving missions.
II. Compute expected gains/utilities
III. Optimal course of action

High Level Architecture of Driver Assistance System’s Advanced Safety Function



On-line driving environment

Choice of human control or automation

- Safety surrogates of distance and time
- Driving states with potential for rear or lateral crash

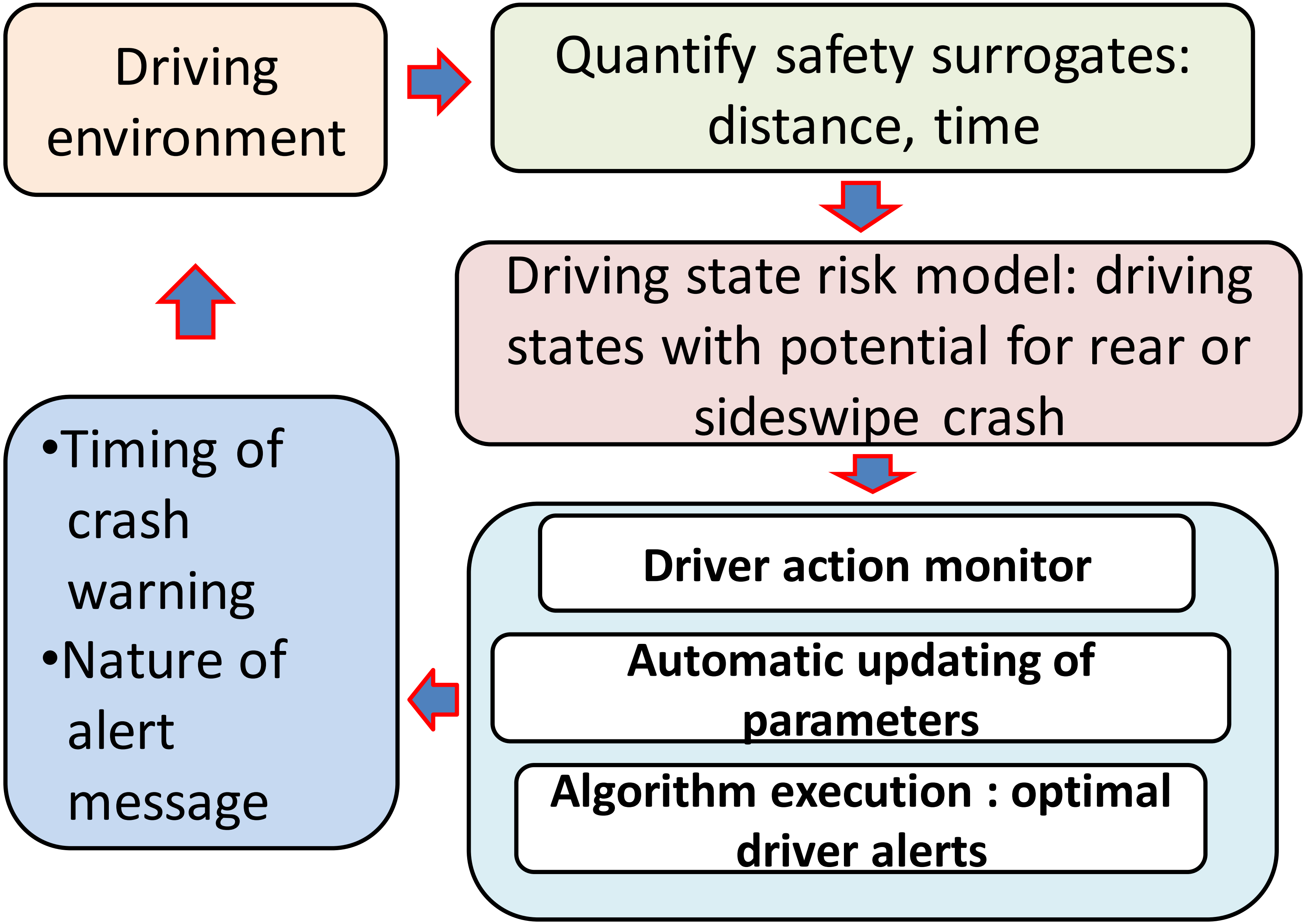
Crash warning model assisted by driver action monitor (self calibration)

Human control: optimal driver alerts

Driver response to avoid collision

- No driver response.
- Automation mode: Active safety action

Major functions of the crash warning system



Driving environment

Quantify safety surrogates: distance, time

Driving state risk model: driving states with potential for rear or sideswipe crash

Driver action monitor

Automatic updating of parameters

Algorithm execution : optimal driver alerts

- Timing of crash warning
- Nature of alert message

Variables (Human Control)

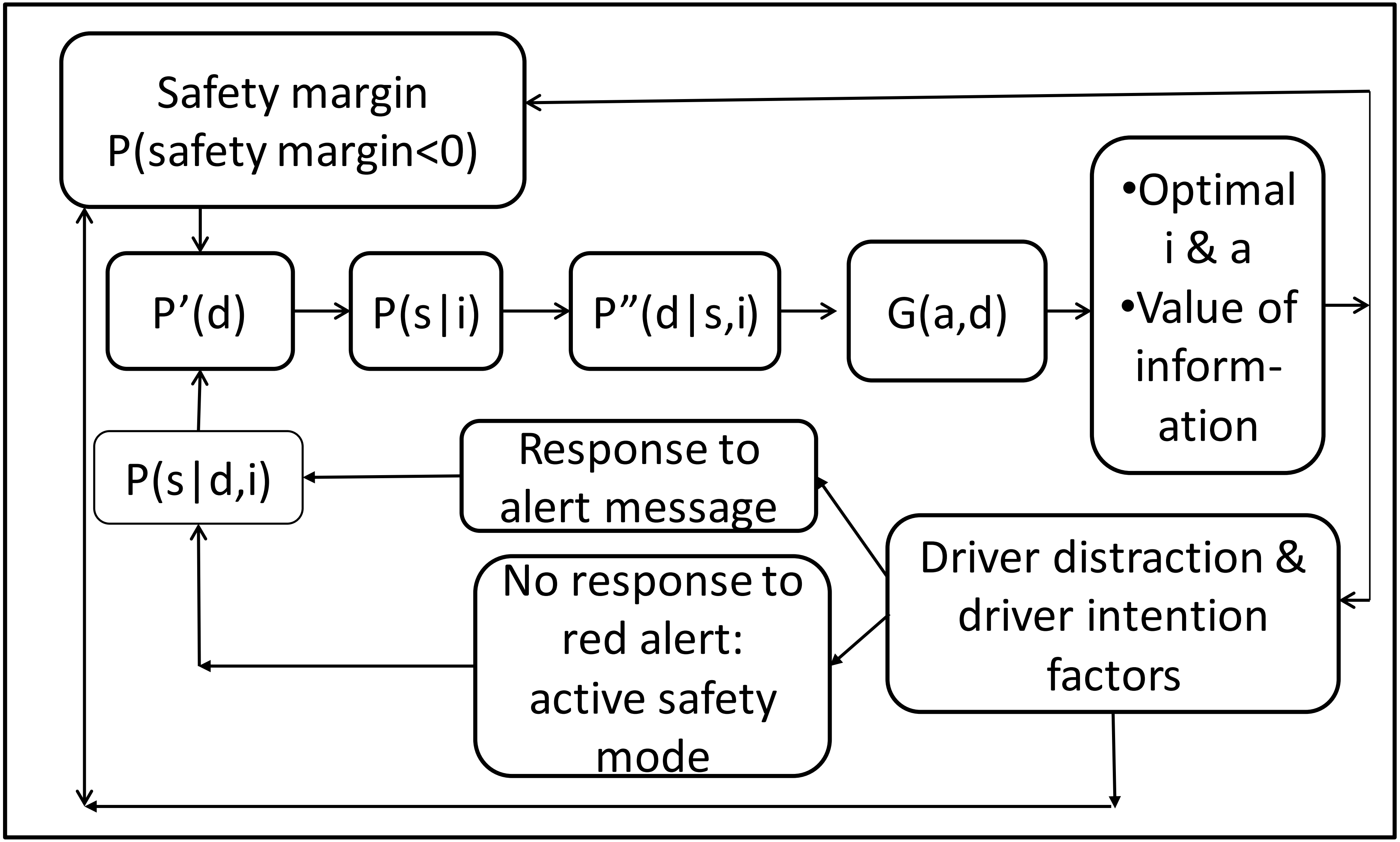
d	distance between vehicles
d_c	critical distance

s	reading on d
s_c	corresponds to d_c

i_0	do not wait, immediate action
i_w	acquire and analyze additional data

a_0	no action
a_a	amber alert
a_r	red alert

Operation of Collision warning and Active Safety System



Safety margin
P(safety margin<0)

P'(d)

P(s|i)

P"(d|s,i)

G(a,d)

- Optimal i & a
- Value of inform-ation

P(s|d,i)

Response to alert message

No response to red alert: active safety mode

Driver distraction & driver intention factors

Components of the Transition Algorithm

Location & distance; Montecarlo simulation of safety margins

Priors P’(d) & self calibration for updating probabilities

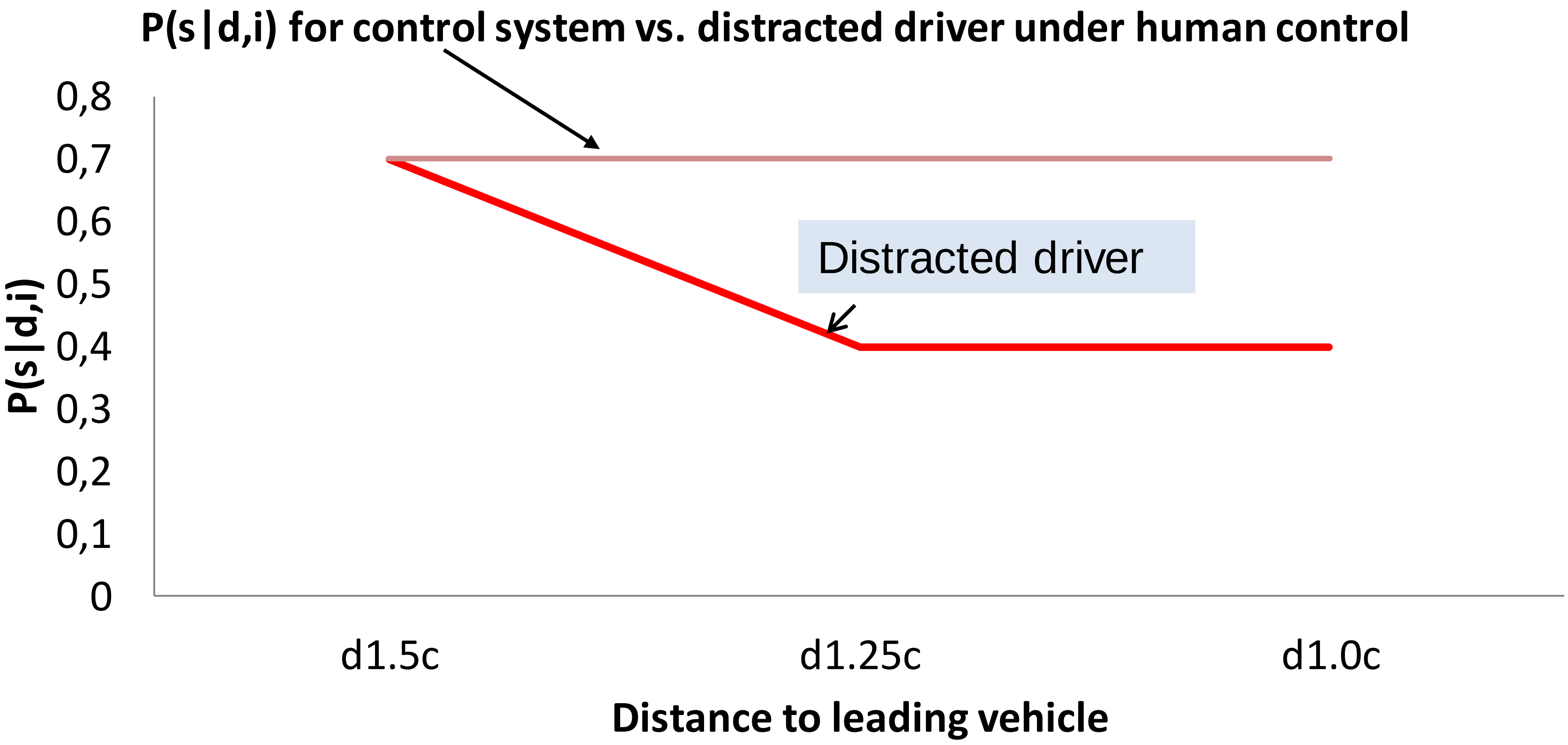
Conditional P(s|d,i) & self calibration

Posteriors P”(d|s,i)

Gain (utility) G(a,d)
Expected gain, value of information & optimal i & a

Bayesian

Comparison of distracted driving and automation



P(s|d,i) for control system vs. distracted driver under human control

Optimal Courses of Action for Avoiding Rear Crashes and Transition to Automation

Location of vehicle & prior probabilities	$d_{1.5c}$	$d_{1.25c}$	$d_{1.0c}$
	$P'(d_{1.0c}) = 0.1$ $P'(d_{1.25c}) = 0.2$ $P'(d_{1.5c}) = 0.7$	$P'(d_{1.0c}) = 0.15$ $P'(d_{1.25c}) = 0.7$ $P'(d_{1.5c}) = 0.15$	$P'(d_{1.0c}) = 0.7$ $P'(d_{1.25c}) = 0.2$ $P'(d_{1.5c}) = 0.1$
Driver distraction	**Not distracted**	**Somewhat distracted**	**Distracted**
Optimal course of action	i_w & a_0	i_w & a_a	i_0 & a_r . ***If no action is taken, launch automated braking.***

Optimal Courses of Action for Avoiding Lateral Crashes and Transition to Automation

Separation distance & prior probabilities	s_{2c} $P'(s_{1.0c}) = 0.1$ $P'(s_{1.5c}) = 0.2$ $P'(s_{2c}) = 0.7$	$s_{1.5c}$ $P'(s_{1.0c}) = 0.15$ $P'(s_{1.5c}) = 0.7$ $P'(s_{2c}) = 0.15$	s_c $P'(s_{1.0c}) = 0.7$ $P'(s_{1.5c})= 0.2$ $P'(s_{2c})= 0.1$
Driver distraction	**Not distracted**	**Somewhat distracted**	**Distracted**
Optimal course of action	i_w & a_0	i_w & a_a	i_0 & a_r . ***If no action is taken, launch automated braking.***

Driving Environment and Optimal Actions under Automation

Driving environment	**Deceleration** case optimal actions
$d_{1.0c}$ $d_{1.25c}$ $d_{1.5c}$	$i_{0\,\&}\,a_E$ $i_{w\,\&}\,a_N$ $i_{w\,\&}\,a_0$

NOTES: a_o is no action. a_E is emergency deceleration. a_N is normal speed change.

Driving Environment and Optimal Action under Automation

Driving environment	**Acceleration** case optimal actions
$d_{1.5c}$ $d_{1.75c}$ $d_{2.0c}$	$i_{w\,\&}\,a_0$ $i_{w\,\&}\,a_N$ $i_{w\,\&}\,a_H$

NOTES: a_o is no action. a_N is normal speed change. a_H is high acceleration.

Conclusions

- Importance of a well-designed transition
- Research attention is drawn to the complexity of modeling the transition from human control to machine control under traffic states that involve high degrees of collision risk.
- Characterization of driving states that require real-time transition from driver-in-the loop to the automated function.

Conclusions (Continued)

- The Bayesian approach to meeting the requirements of the emergency transition has merits
- The example cases illustrate the integration of intelligent technology, Bayesian artificial intelligence, and abstracted human factors

Sponsors

- Natural Sciences and Engineering Research Council of Canada (NSERC)
- Ministry of Transportation, Ontario (MTO)