Validation of the Driving by Visual Angle car following model

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Why modelling car following?
Examples of models

Box-and-Arrow

\[ \text{Attitudes/personality} \rightarrow \text{Task demand (workload)} \]
\[ \text{Driver state} \rightarrow \text{Intention} \]
\[ \text{Experience} \rightarrow \text{Situation awareness} \]

Long-term
Medium-term
Short-term

Carsten (2007)
Examples of models

Cognitive architecture, production rules

\[(p \text{ decide-lc-lane1}}
\begin{align*}
=\text{goal}\rangle \\
\quad \text{isa drive} \\
\quad \text{stage decide-lc} \\
\quad \text{task lk} \\
\quad \text{lane lane1} \\
\quad v =v \\
\quad \text{fkind car} \\
\quad \text{fthw } =\text{thw} \\
\quad \text{!eval! (}< =\text{thw *thw-pass*})
\end{align*}
\]

\[=\text{subgoal}\rangle
\begin{align*}
=\text{check-lc} \\
\quad \text{lane lane1} \\
\quad v =v \\
\quad \text{result } =\text{result} \\
\quad \text{!push! } =\text{subgoal} \\
=\text{goal}\rangle \\
\quad \text{stage } =\text{result}
\end{align*}

(Salvucci, e.g. 2005)
Examples of models

Psychophysical controller for car following behavior

\[ a_{t+1} = j \left( \frac{1}{\alpha_t} - \frac{1}{\alpha'} \right) + k \frac{d}{dt} \alpha_t \]

Anderson and Sauer (2007)
Some properties of driver models
Some properties of driver models

Formalization

- qualitative (verbal)
- quantitativ (computational)

Properties
Some properties of driver models

Formalization

- qualitative (verbal)
- quantitative (computational)

Properties

Scope

- micro
- macro
Some properties of driver models

- Formalization
  - qualitative (verbal)
  - quantitative (computational)

- Properties
  - micro approach
  - macro approach

- Machine learning
- Rules
- Controller (open / closed loop)
Some properties of driver models

Descriptive

Explicative

Psychological claim

Formalization

Qualitative (verbal)

Quantitative (computational)

Properties

Machine learning

Rules

Controller (open / closed loop)

Approach

Scope

Micro

Macro
Some properties of driver models

- cognition
- evaluation
  - descriptive
  - explicative
  - machine learning
  - rules
  - controller (open / closed loop)

Purpose
- Psychological claim
  - qualitative (verbal)
  - quantitative (computational)

Formalization
- approach

Scope
- micro
- macro
Some properties of driver models

- **Purpose**
  - qualitative (verbal)
  - quantitative (computational)

- **Formalization**
  - qualitative
  - quantitative

- **Psychological claim**
  - descriptive
  - explicative

- **Properties**
  - cognition
  - evaluation
  - descriptive
  - explicative
  - machine learning
  - rules
  - controller (open / closed loop)

- **Scope**
  - micro
  - macro

- **Approach**
  - open / closed loop

- **Machine learning**
Some properties of driver models

Purpose
- formalization
  - qualitative (verbal)
  - quantitative (computational)

Properties
- scope
  - micro
  - macro

Psychological claim
- descriptive
- explicative

Approach
- machine learning
- rules
- controller (open / closed loop)

Purpose
- cognition
- evaluation
Why modelling car following?

basic driving task
- essential for higher cognition driver models
- comparatively easy modelling of a driving task

extremely useful for design of assistance systems

lacking so far
- good data on individual car-following behavior
- systematic evaluation of models on this data

we contribute to close that gap
- data for individual drivers
- from real traffic with instrumented vehicle
- systematic variation of road type (city, highway, country)
Basic driving tasks

from Hakuli et al. (n.d.) according to Donges (1982)
Control level of driving

road and traffic situation

- trajectory / maneuver level
  - anticipatory open loop
  - task irrelevant steering behavior
  - compensatory closed loop

- stabilizing / control level

steering angle

vehicle dynamics

output feeds back

adapted from Donges (1978)
A very simple car following model

\[ a_t = s(v_{VF_{t-T}} - v_{FF_{t-T}}) \]

with
\[ a(t) = \text{acceleration at time } t, \]
\[ v_{VF_{t-T}} = \text{velocity lead vehicle one timestep ago}, \]
\[ v_{FF_{t-T}} = \text{velocity following vehicle one timestep ago}, \]
\[ s = \text{free parameter} \]
A very simple car following model

\[ a_t = s (v_{VF_{t-T}} - v_{FF_{t-T}}) \]

basic algorithm
1. choose a start parameter for \( s \)
2. take values for leading vehicle from data
3. take first value for following vehicle from data
4. compute prediction for the next time step by using the predicted \( a \)
5. do so until the end of the vector
6. compute error metric
7. test next parameter, until the error metric is at a minimum
A very simple car following model

empirical vs predicted velocity, s = 1

predicted velocity vs lead car, s = 1
A very simple car following model

all together, $s = 1$

all together, $s = 9.22$
The Gipps model

\[ \nu_{t+\tau} = b^{max} \]

\[ + \sqrt{(b^{max})^2 \cdot \tau^2 - b^{max} \cdot (2 \cdot [d_t + d^{min}] - \nu_{FF_t} \cdot \tau - \frac{\nu_{V_{FF_t}}^2}{b^{est}}) } \]

with

- \( b^{max} \) = most severe braking of the driver,
- \( b^{est} \) = estimated braking of the leading vehicle,
- \( d^{min} \) = safety distance,
- \( d_t \) = velocity of leading vehicle at time \( t \),
- \( \tau \) = apparent reaction time, a constant for all vehicles,
- \( \nu_{V_{FF_t-\tau}} \) = velocity lead vehicle one timestep ago,
- \( \nu_{FF_{t-\tau}} \) = velocity following vehicle one timestep ago

Gipps (1981)
The Helly model

\[ a_t = j \cdot (d_{t-T} - d'_t) + k \cdot (v_{VF_{t-T}} - v_{FF_{t-T}}) \]

with

\[ d'_t = s + r \cdot v_{FF_t}, \]
\[ s = \text{safety distance}, \]
\[ v_{VF_{t-T}} = \text{velocity lead vehicle one timestep ago}, \]
\[ v_{FF_{t-T}} = \text{velocity following vehicle one timestep ago}, \]
\[ r = \text{weight factor}, \]
\[ T = \text{time step} \]

Helly (1959)
The Driving-by-Visual-Angle model

\[ a_{t+1} = j \cdot \left( \frac{1}{\alpha_t} - \frac{1}{\alpha'} \right) + k \cdot \frac{d}{dt} a \]

with

\[ \alpha' = 2 \cdot \arctan \left( \frac{w}{THW \cdot v_{FF_t}} \right) \]

and

\[ \alpha_t = \text{visual angle}, \]
\[ \alpha' = \text{desired visual angle}, \]
\[ w = \text{width of lead car}, \]
\[ THW = \text{timegap}, \]
\[ v_{FF_t} = \text{velocity lead car} \]
The Driving-by-Visual-Angle model

\[
\alpha = 2 \times \arctan \left( \frac{\text{width}}{2 \times \text{distance}} \right) \approx \frac{\text{width}}{\text{distance}}
\]
Helly’s model vs. DVA

Helly

\[ a_{t+1} = j(d_t - d'_t) + k(v_{LV_t} - v_{FV_t}) \]

DVA

\[ a_{t+1} = j \left( \frac{1}{\alpha_t} - \frac{1}{\alpha'_t} \right) + k \frac{d}{dt} \alpha \]

\[ = j \frac{1}{w} (d_t - d'_t) + (-k)(w \left( \frac{d_{t-1} - d_t}{d_t^2} \right)) \]
Validation methods

driving simulator: often sinusoidal speed profiles
  • disadvantage: might be too artificial
real driving data: cameras, induction loops etc.
  • disadvantage: dirty data, absolutely no control over situation
Methods

12 participants over 8 weeks, on Sundays / public holidays only

road types:
• highway
• city (straight and curved road)
• country

70 km, 2 hours drive
Methods
Predictions unoptimized

DVA unoptimized, subj 2, city ring

DVA is unstable!
Predictions unoptimized

Gipps unoptimized, subj 2, city ring

- empirical
- predicted
- lead car

RMSD = 1.8152
Predictions unoptimized

Helly unoptimized, subj 2, city ring

- empirical
- predicted
- lead car

RMSD = 0.7337
Results constrained, distance

**DVA**

**Gipps**

<table>
<thead>
<tr>
<th>Region</th>
<th>DVA</th>
<th>Gipps</th>
</tr>
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<tbody>
<tr>
<td>hway</td>
<td></td>
<td></td>
</tr>
<tr>
<td>city</td>
<td></td>
<td></td>
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<tr>
<td>cityRing</td>
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<td>cityStrt</td>
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</tbody>
</table>

RmSD [m/s]

RMSD [m/s]
Results constrained, distance

**DVA**

- Region: hway, ctry, city, cityRing, cityStrt
- RMSE [m/s]

**Helly**

- Region: hway, ctry, city, cityRing, cityStrt
- RMSE [m/s]
Results unconstrained, speed

DVA

Gipps

RMSD [m/s]

region

hway  cty  city  cityRing  cityStrt

region

hway  cty  city  cityRing  cityStrt
Results unconstrained, speed

DVA

Helly

RMSD [m/s]

region

hway cty city cityRing cityStrt

hway cty city cityRing cityStrt

0.0 0.5 1.0 1.5 2.0

0.0 0.5 1.0 1.5 2.0
Discussion

DVA does not hold its promises
• a few psychophysical additions doesn’t make it psychologically plausible!
• unstable controller?

degree of psychology in car following controllers
• non-trivial question
• depends a lot on handling of parameters

interaction of parameters and optimization algorithm
• some algorithms are more sensitive to starting parameters than others
Outlook and Lessons Learned

systematic evaluation
• more models
• different driving simulators
• possibly new data collection in the field with better sensors

parameter
• other optimization algorithms
• windowing
• maximum likelihood methods
• bootstrapping
• grid search

more computational power / less precision
• more efficient code
• cluster
• less optimized parameters
Literature


