Linking Roadway and Naturalistic Data to Study Driver Route Choice and Car-following Behavior

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Funded: VDOT and MAUTC

Modeling Driver Heterogeneity in Route Choice Behavior Based on a Real-Life Naturalistic Driving Experiment

Co-authors: Aly Tawfik, Ph.D. and Jianhe Du, Ph.D.

Funded by: VDOT and MAUTC

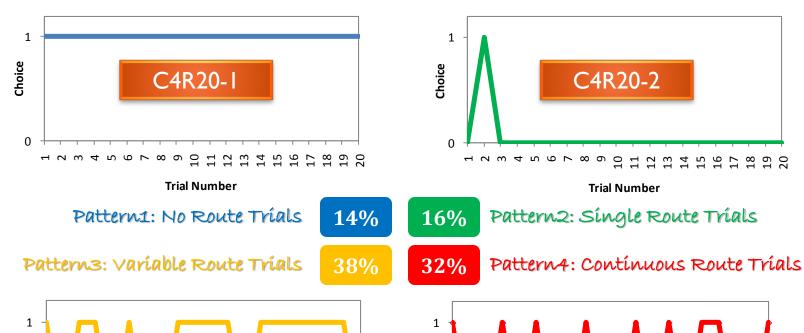
Motivation

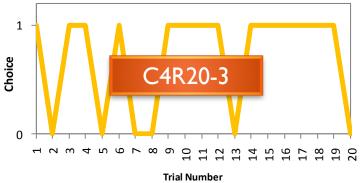
- Equilibrium: Nakayama et al ('01), "Drivers do not become homogeneous and rational, as equilibrium analyses presuppose; rather, there are fewer rational drivers even after a long process of learning, and heterogeneous drivers make up the system"
- ➤ **Driver Rationality:** Bogers et al ('05), "studies that focus only on a rather rational description of day-to-day learning cover only a limited part of the way route choices are made over time"
- ➤ Driver Heterogeneity: Iida et al ('92), "it is desirable to develop a model which is disaggregated by a type of driver because the route choice behavior varies by individual"
- Experiment Medium: Prato ('09) and Papinski ('11) "four main challenge areas: i) experiment medium, ..."

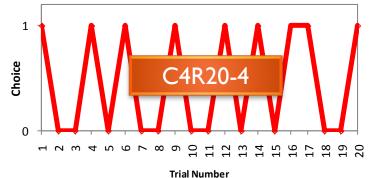
100-Car Naturalistic Driving Data

- Geocoded home and work address in ArcGIS
- Identified commuting trips by comparing the O-D with home/work locations
- Exported route maps and removed drivers without regular commuting behavior
- Sample
 - 39 Drivers with a total of 68 choice situations and an average 85 Trials
- Procedure
 - Pre-task questionnaires, I-Year real-life data, and Personality Inventory

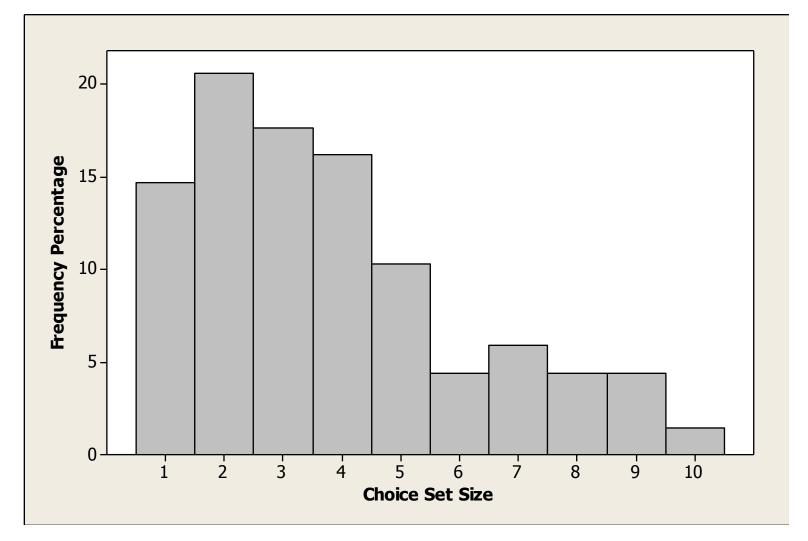
Disaggregate Findings







Driver Choice Set



Variables Considered

#	Variable Name	Variable Description	Variable Values							
Var	Variables of Driver Demographics									
	Age _i	Age of driver i	19 to 57							
2	Gender _i	Gender of driver i	F or M*							
3	Ethnicity _i	Ethnicity of driver i	W or NW*							
4	Education _i	Education level of driver i	G or NG*							
7	Dr Years _i	Number of years driver i has been licensed to driver	2 to 42							
6	Dr Miles _i	Number of miles driver i drives per year (in thousands)	15 to 40							
Var	Variables of Driver Personality Traits									
1	N _i	Neuroticism of driver i	7 to 75							
2	E _i	Extraversion of driver i	17 to 66							
3	O _i	Openness to experience of driver i	14 to 53							
4	A_{i}	Agreeableness of driver i	12 to 66							
5	C_{i}	Conscientiousness of driver i	19 to 62							
Var	iables of C	hoice Situation								
1	TT _c	Expected travel time of choice situation c (in minutes)	8 to 95							
2	TS _c	Expected travel speed of choice situation c (in km/h)	24 to 90							
3	TD _c	Expected travel distance of choice situation c (in km)	6 to 108							
Var	Variables of Driver-Choice Combination									
4	Obs _{ic}	Number of trips observed for driver i in choice situation c	25 to 216							
* M:	* M: male, F: female, W: white, NW: non-white, NG: no post-graduate degree, G: have a post-graduate degree									

Driver Choice Set and Switching

Significant Variables	Route Switching Model (Beta)	Choice Set Size Model * (Gamma)
(Intercept)	-1.38	- 0.284
University Education	-0.81	- 0.098
Driven Miles	-0.30	n/s
Neuroticism	n/s	0.049
Extraversion	0.56	n/s
Openness to Experience	-0.97	- 0.25
Conscientiousness	0.46	0.079
Expected Travel Time	0.35	n/s
Expected Travel Speed	-0.55	- 0.058
Number of Observations	n/s	0.001

Findings

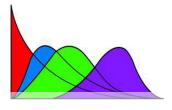
Choice Set

- Smaller choice set:
 - Drivers without post-graduate degrees and higher scores of openness to experience
- Larger choice set:
 - Higher values of neuroticism and conscientiousness, lower travel speeds
 - Finally, it is satisfying that the number of observations was found to marginally increase the choice set size.

Route Switching

- Personality trait variables seem were as important as variables of travel experience (travel speed).
 - Drivers' openness to experience was the most important variable

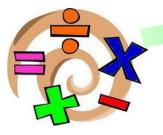
Application



Population Distributions

- Personal Variables
- Personality Traits





Transportation

Models







Choice Situation Characteristics







Model



Past Experience



Road Network



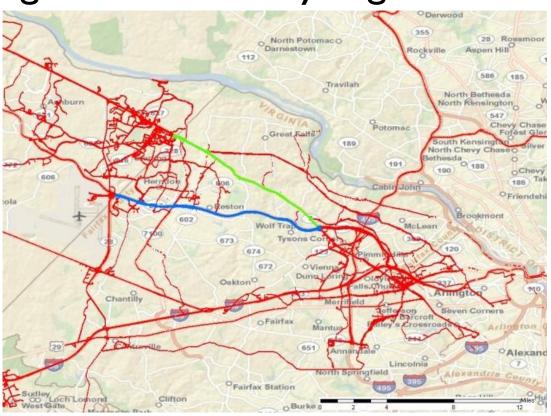
Modeling Driver Carfollowing Behavior using Naturalistic Driving Data

Co-authors: John Sangster, MS and Jianhe Du, Ph.D.

Funded by: MAUTC

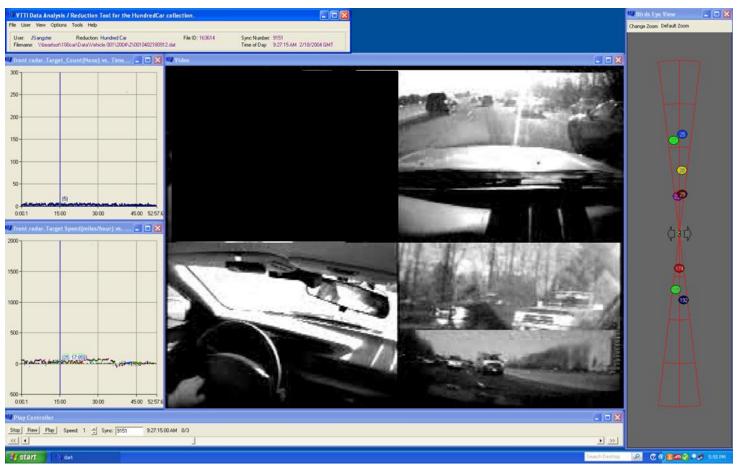
Data Reduction

 Multiple drivers identified using GIS; homogeneous roadway segment.



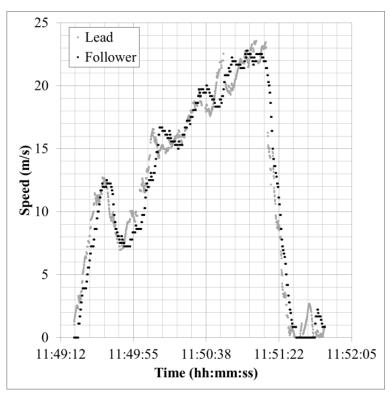
Data Reduction

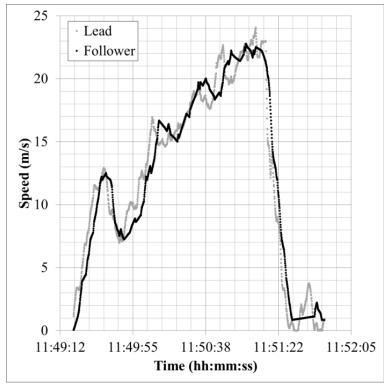
Car-following events verified visually



Data Reduction

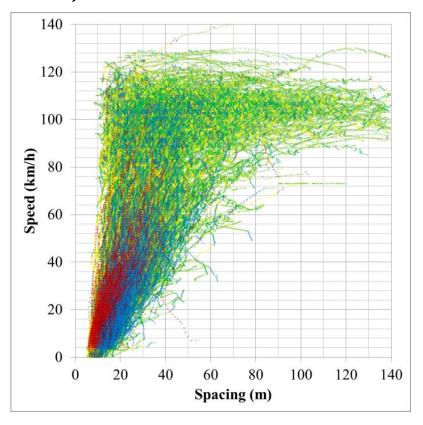
Interpolation of data feeds





Dataset Extracted from Database

 Green indicates steady-state travel, red for deceleration, and blue for acceleration.



Dataset Extracted from Database

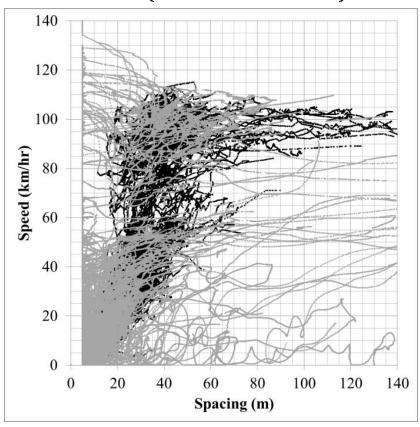
- Full database (Hundred Car Study) includes 108 drivers, 337,000 hours of data, 207,000 trips.
- GIS identified 15 drivers commuting on Dulles Airport Access Road.
- Validated data available for 7 drivers.
- Final dataset includes 7 drivers, 1,732 carfollowing events totaling 789 minutes.

Car-following models analyzed

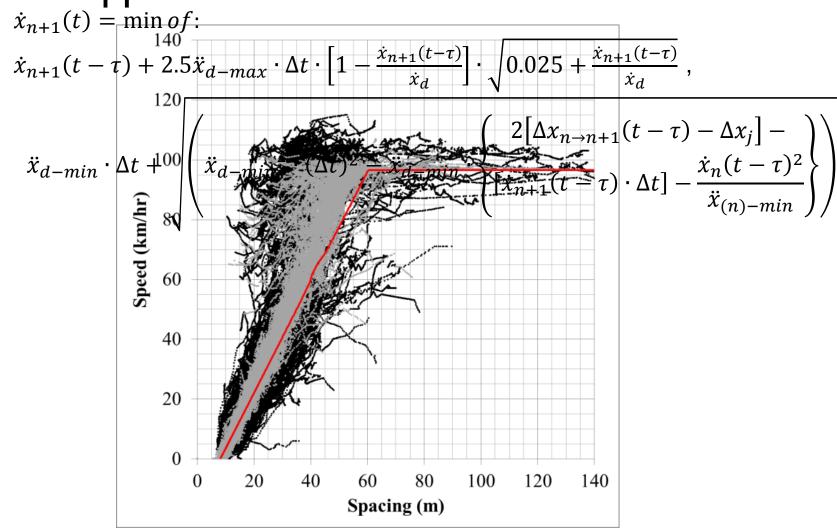
- Gaxis-Herman-Rothery (GHR) Model
 - GHR-I model incorporated in ACC systems
- Gipps Model
 - Incorporated in the AIMSUN software
- Intelligent Driver Model (IDM)
 - Extension of the Gipps model
- Rakha-Pasumarthy-Adjerid (RPA) Model
 - Van Aerde steady-state model
 - Vehicle dynamics acceleration constraints and collision avoidance constraints

Gaxis-Herman-Rothery (GHR) Model

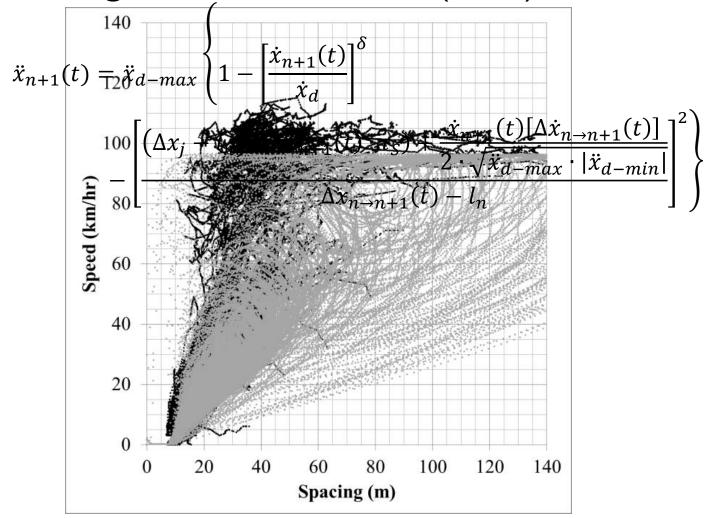
$$\ddot{x}_{n+1}(t) = \left\{ \frac{\alpha [\dot{x}_{n+1}(t)]^z}{[\Delta x_{n\to n+1}(t-\tau)]^l} \right\} \cdot [\Delta \dot{x}_{n\to n+1}(t-\tau)]$$



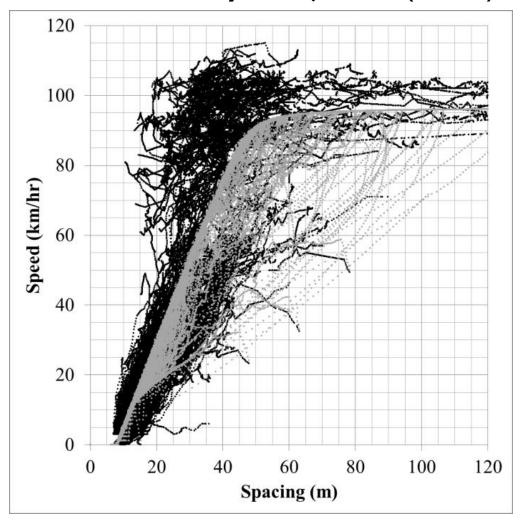
Gipps Model



Intelligent Driver Model (IDM)



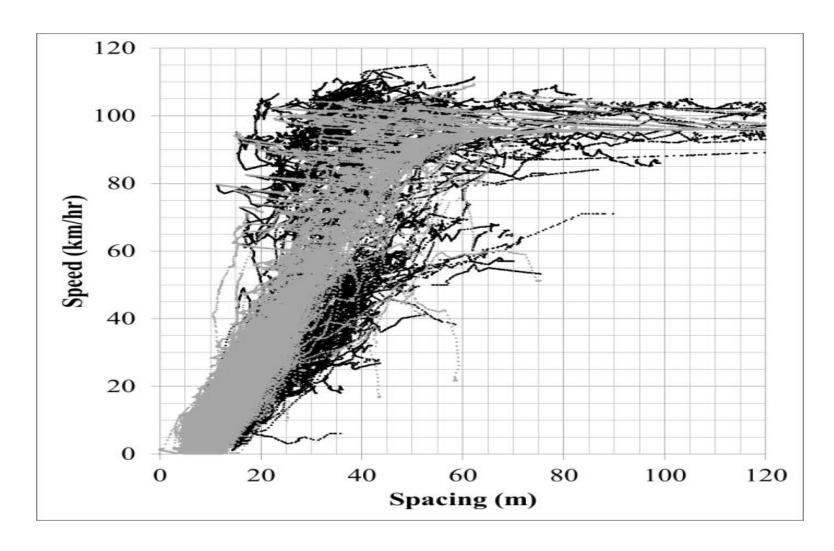
Rakha-Pasumarthy-Adjerid (RPA) Model



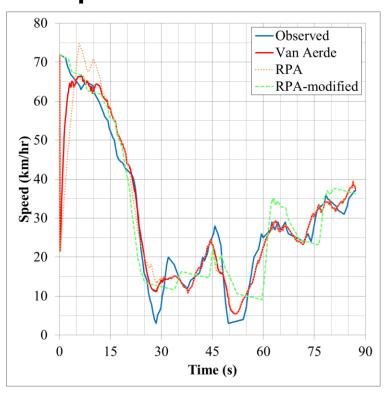
Comparison of Error Measures

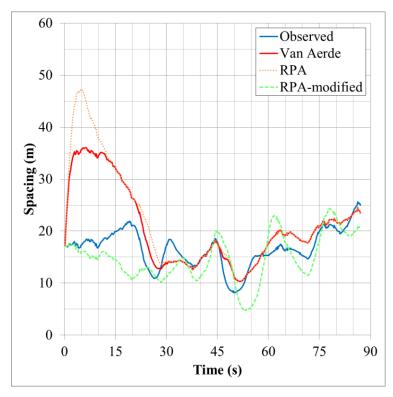
Model	D124	D304	D316	D350	D358	D363	D462	Aggregate
GHR Model	0.00079	0.00082	0.00096	0.00080	0.00104	0.00046	0.00069	0.00033
Gipps Model	0.00064	0.00033	0.00030	0.00094	0.00028	0.00019	0.00055	0.00014
IDM	0.00142	0.00172	0.00101	0.00181	0.00069	0.00068	0.00328	0.00026
RPA Model	0.00086	0.00037	0.00044	0.00118	0.00034	0.00019	0.00087	0.00021

Results of Comparative Analysis



Sample Event





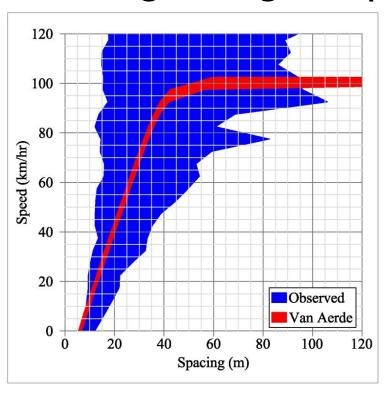
Comparison of Error Measures

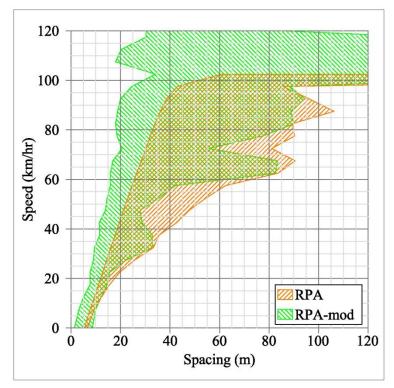
Model	D124	D304	D316	D350	D358	D363	D462	Aggregat e
Van Aerde Model	0.00073	0.00037	0.00036	0.00105	0.00030	0.00017	0.00052	0.00018
RPA Model	0.00086	0.00037	0.00044	0.00118	0.00034	0.00019	0.00087	0.00021
Revised RPA Model	0.00065	0.00032	0.00029	0.00088	0.00029	0.00015	0.00036	0.00015

Parameter	D124	D304	D316	D350	D358	D363	D367	D462	Aggrega te
GHR	0.00079	0.00082	0.00096	0.00080	0.00104	0.00046	0.00104	0.00069	0.00033
Gipps	0.00064	0.00033	0.00030	0.00094	0.00028	0.00019	0.00040	0.00055	0.00014
IDM	0.00142	0.00172	0.00101	0.00181	0.00069	0.00068	0.00057	0.00328	0.00026
RPA	0.00063	0.00031	0.00026	0.00082	0.00026	0.00015	0.00038	0.00035	0.00012

Model Coverage

Coverage using 90th percentile range.





Conclusions

- Naturalistic data provides a wealth of data for use in studying traveler behavior:
 - Departure time trends
 - Route set size
 - Route choice behavior
 - Car-following behavior
- Augmentation with other data sources to give larger picture can also be beneficial