Development and evaluation of a hybrid travel time forecasting model

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Transportation Research Part C 8 - Emerging Technologies

Presented by Troels V. Larsen

AALBORG UNIVERSITY

Introduction

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- Department of Urban and Regional Planning
- University of Illinois at Urbana-Champaign
- Travel time estimation is hard using only a single forecasting method.
- Goal: Implement a hybrid travel time forecasting model
- Based on GIS technologies
  - *"...a computer system capable of integrating, storing, editing, analyzing, sharing and displaying geographically-referenced information."*

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- Historical database – road network integration
- Hybrid travel time forecasting model

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Architecture

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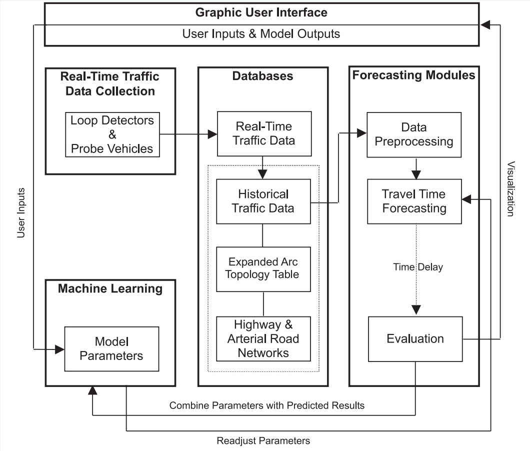

Scenario specifics

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- Recording intervals:
  - Highway data: 30 seconds
  - Arterial data: 5 minutes
- Computation time: Max 15 minutes, preferably less than 1-2 minutes.
- Usage: Predict travel times 15-60 minutes into the future.

Scenario specifics

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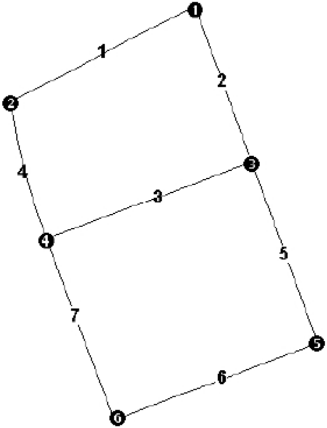
Network representation



Link_ID	From_Node#	To_Node#
1	1	2
2	1	3
3	3	4
4	2	4
5	3	5
6	5	6
7	4	6

Historical database

- Time and link are recorded
- Each link is stored twice, unless it is a one way street.
- (Link ID, Historical DB ID, From Node, To Node)

Time	Link				
	1	2	…	n-1	n
0:00	34	29	…	27	14
0:05	33	31	…	33	12
0:10	29	27	…	32	11
0:15	27	25	…	29	9
			⋮		⋱

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Forecasting

Forecasting modules

- Data preprocessing
- Travel time forecasting
- Evaluation

Forecasting modules

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- Travel time forecasting
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- Travel time forecasting
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Data preprocessing

- Screens and filters noise
  - Wavelet transformation technique
  - Outlier detection algorithm
- Remove noise from probe vehicles such as delivery trucks

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Forecasting through method learning

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- Parameter learning
- Relies on k-nearest neighbour

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Parameters

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Domains of model parameters

Parameters	Type	Domain	Unit
Forecasting range	Discrete	{15, 30, 45, 60}	Minute
Search data segment length	Discrete	{15, 30, 45, 60}	Minute
Day of the week	Binary	{Consider, Ignore}	–
Search range	Discrete	{1, 2, 3}	Hour
Large K	Discrete	{1, 2, 3, 4, 5, 6, 7, 8, 9, 10}	–
Small k	Discrete	{1, 2, 3, 4, 5, 6, 7, 8, 9, 10}	–
Local estimation method	Binary	{Local averaging, Local fitting}	–
Data preprocessing	Binary	{Wavelet, Outlier detection}	–

Evaluation

- Is activated as actual travel times arrives
- If the difference between actual and estimated travel time is too large, the parameters are readjusted using the ML module.
- ML Module:
  - Generates training samples
  - Identifies the lowest forecasting error from each parameter
  - Updates the hybrid model with the new parameters

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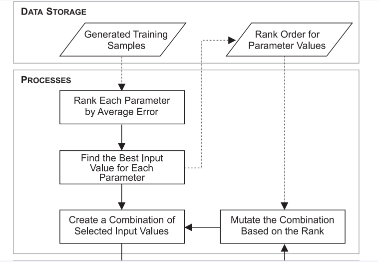
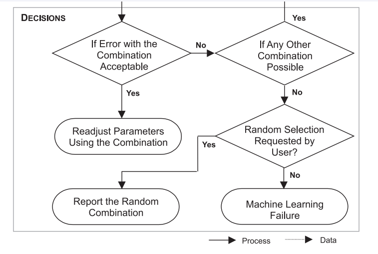
Parameter learning





Experimental Evaluation

Experimental evaluation

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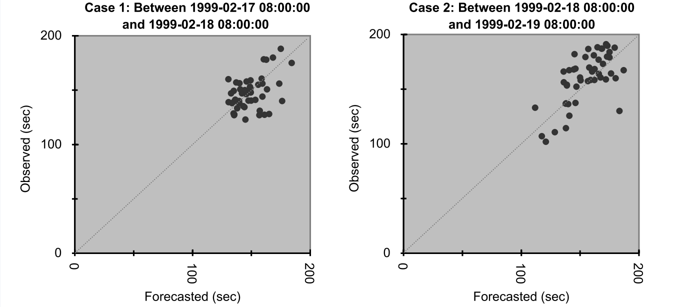
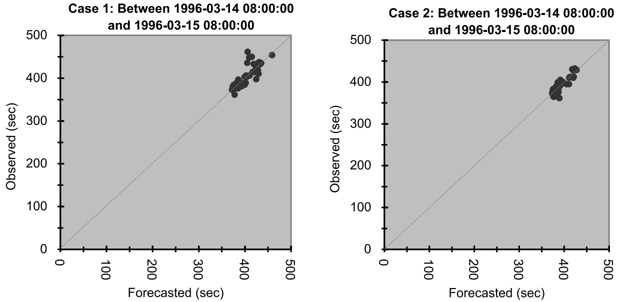
- Experiment:
    - 200 randomly selected points from the historical database
    - Seperated into arterial and highway data
    - Each experiment within 24 hours

Experimental evaluation



	RMSE (sec)	*MAPE (%)*	ρ	*Average Observed Travel Time*
Case 1	15.47	8.02	0.47	148.50
Case 2	19.63	9.88	0.66	161.67

Experimental evaluation



	RMSE (sec)	*MAPE (%)*	ρ	*Average Observed Travel Time*
Case 1	14.27	2.22	0.83	404.48
Case 2	8.46	1.67	0.90	390.52

Conclusion

Relation to our project

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- Travel time estimation
  - Offline / Online
  - Method learning
  - Evaluation of actual travel time
- GIS
  - Shape files
  - Software built on top of GIS
- Data storage
  - Relational database
  - Datawarehouse

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- Interesting ideas
- Sensible work
- Possibly a good average error rate

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Weaknesses

- Illogical structure
- Lacks a good overview
- Spends too much time discussing subjects that are irrelevant to the solution
- Figures are not used optimally - some should be explained better
- Inconclusive results
- Bad running time for highway data
- Nothing mentioned about time or space complexity. (Not a CS article)

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  - Travel-time prediction on freeways
  - Uses linear regression
- *Integration of GPS and GIS for traffic congestion studies* – Taylor, Wooley and Zito
  - Relies on several GIS layers
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