A real-time framework for dynamic estimation of traffic demand from floating car data

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Research Goal

• Research conducted within the Project “Pegasus”:
  – Granted by Italian Ministry of Economical Development (“Industria 2015” Initiative)
  – Partners: Octotelematics, ENEA, CTL, …

• Task of CTL: Develop an online tool for simulation and prediction of urban road traffic in urban areas

• Exploit floating car data as main source of information

• Industrial Research: develop innovative products
A real-time framework for dynamic estimation of traffic demand from floating car data
Dynamic OD Matrix Estimation

Formulation

- **Objective**: estimate a demand matrix $d_t$ for each time interval $t$ (with $t=1,\ldots,n$) using historical O-D estimates $d_t$, real-time traffic counts $v_i$ as well as other information like speed $s_i$ and travel times $u_i$. 
State of the art

Formulation (Cascetta et al., 1993)

- **Simultaneous approach** (Balakrishna et al., 2006; Cipriiani et al. 2011)

\[
\left( d_1^*, d_n^* \right) = \arg\min_{x_1, \ldots, x_n \geq 0} \left[ f_1 \left( x_1 K, x_n, d_1^* K, d_n^* \right) + f_2 \left( v_1 K, v_n, v_1 L, v_n \right) + f_3 \left( s_1 L, s_n, s_1 L, s_n \right) + f_4 \left( u_1 L, u_n, u_1 L, u_n \right) \right]
\]

- **Sequential approach** (Cremer & Keller, 1987; Ashok & Ben-Akiva, 1993; Barcelò et al., 2010; …)

\[
d_h^* = \arg\min_{x_h \geq 0} \left[ f_1 \left( x_h, d_h^* \right) + f_2 \left( v_h \left( x_h | d_1^* K, d_{h-1}^* \right), \hat{v}_h \right) \right]
\]
State of the art

Solution methods

• Off-line applications
  – Generalized Least Squares (Cascetta et al., Bierlaire&Crittin);
  – Evolutionary algorithms (Park&Zhu,’05; Kattan & Abdulhai,’06)
  – SPSA (Balakrishna et al.; Cipriani et al.2011)

• On-line applications
  – Generalized Least Squares (Cascetta et al.1993; Bierlaire & Crittin, 2004: LSQR)
  – Kalman Filter (Ashok & Ben-Akiva 1993; Ben-Akiva et al. 2001; Okutani & Stephanades 1984; Zhou & Mahmassani, 2007; Dixon & Rilett, 2002; van der Zijpp & Hammerslag 1994,…)

• Most applications on freeways or small size networks
  (largest have 60 zones Barcelò et al.; Zhou & Mahmassani)
Solution method

Kalman Filter

State evolution

\[ d(t + 1) = A(t|t + 1)d(t) + u(t) \]

Measures-State relationship (traffic model)

\[ d(t + 1) = A(t|t + 1)d(t) + F(t)
\begin{bmatrix} f_{FCD}(t) - H(t)d_{FCD} \end{bmatrix} \]

Kalman gain

\[ F(t) = r \Psi_e(t|t)H^T(t)\Psi_v^{-1}(t) \]

\( u = \) input errors  
\( A = \) transition matrix  
\( v = \) measure errors  
\( H = \) assignment matrix  
\( \Psi_e = \) estimation errors covariance  
\( \Psi_v = \) measure errors covariance  
\( r = \) average FCD sampling rate
Exploiting Floating Car Data (FCD)

**Opportunities**

- Information from (potentially) all links of the network on vehicle positions and speeds
- Large samples to derive updated information on:
  - OD matrices
  - Trip chains
  - Stop and parking
  - Route choices
  - Speed profiles
  - Road graph modifications
Application

Metropolitan area of Roma: May 2010

• 104 millions of records (positions and speeds)
• about 20 millions of data discarded (poor signal) or corrected (unrealistic values)
• Fleet: 103,000 floating vehicles; 80,000 vehicles in the study area
• Traffic: 9 millions trips
• Map matching: positions on TeleAtlas graph (300,000 links; 160,000 nodes); O-D on 1,300 zones

Problems:

• Huge amount of data
• High disaggregation of usual models
Exploiting Floating Car Data (FCD)

Questions

• Is it possible to exploit FCD for direct O-D matrix estimation?
• Secondarily, is it possible to apply FCD measures on links to well-known O-D estimation procedures from traffic counts?
Exploiting Floating Car Data (FCD)

Problems

• Destination is not detected in real-time, but after the vehicle has restarted
• Positions and speeds are detected with a given sampling interval (in time or in space)
• Link flows are not counted directly: estimation depends on penetration rate of equipped vehicles, on length of link, on the average sampling distance
• Actual sampling rates are variable and unknown
• Errors due to signal loss and map matching
Application

*Check reliability of FCD O-D matrix*

Comparison with the peak hour historical O-D matrix:

- About 16,000 trips vs. 340,000 trips (8:00-9:00)
- Disaggregate zoning (1,300 zones): very poor correlation
- Aggregate zoning (60 zones):
  - Better correspondence between intra-zonal trips ($R^2=0.70$)
  - Fair correspondence between inter-zonal trips ($R^2=0.45$)
FCD desire lines (peak hour, avg. day)

16,000 trips
1,300 zones
Application

• Aggregation of FCD O-D matrix from 1,300 to 60 zones
• On-line update through Kalman filter
• Refinement by disaggregating to 1,300 zones proportionally to generation
Application: observed data

Time profile of 10 largest O-D trips

![Time profile of 10 largest O-D trips](image)
Application: observed data

Time profile of 10 largest inter-zonal O-D trips
Application

*Link measurements from FCD*

- Map matching to road network model:
  - From TeleAtlas to ‘simplified’ graph: 93,000 links; 69,000 nodes (or: 15,000 links; 6,000 nodes)

- Traffic flows:
  - Link flows are estimated through inference of FCD positions
  - Only a subset of links is exploited for O-D estimation in order to:
    - Ensure statistical significant FCD link measures
    - Reduce the dimension of the assignment matrix

Flow and speed estimates from FCD measures on main roads
Application of O-D estimation and prediction procedure

*Off-line initialization:*

- Derive time-dependent O-D time series from historical FCD information
- Select optimal set of links to use in O-D matrix estimation
- Compute time-dependent assignment matrices
- Compute covariance matrices
Application of O-D estimation and prediction procedure

**On-line application**

- Update traffic flow estimates on links
- Update time-dependent assignment matrix by Dynamic Traffic Assignment
- Apply Kalman filter to update current O-D matrix estimate and predict the next 3 time intervals (rolling horizon)
- Disaggregate O-D estimate to 1,300 zones
Online Procedure (prototype in Matlab)

REAL TIME DATA

Database

O-D MATRIX ESTIMATION

DYNAMIC ASSIGNMENT

Flows, Speeds, Positions

Assignment matrix

Link flows

Forecasted O-D

Simulation period = 1h

Rolling horizon: \( \Delta t = 15\text{min} \)

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Preliminary results of O-D prediction

*Compare predicted and observed FCD O-D flows*

- Off-line simulation of real-time application
- Time slices: 15 minutes
- Every 1 hour, update current O-D matrix from real-time FCD link flows
- Predict O-D matrices for the next 3 time intervals
- Compare predicted O-D flows with observed ones
  - Mean Absolute Relative Error: $= 0.35$
  - Mean Relative Square Error: $= 0.517$

(Very preliminary results!)
Application: observed vs. predicted data

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Concluding remarks

- Research is still ongoing
- First applications highlighted cumbersomeness and complexity of the problem in time and space
- However, preliminary results are encouraging since:
  - the whole on-line framework seems to be feasible from a technical point of view
  - first results obtained are reasonable
- Research lines for improvements:
  - test alternative formulations of the estimation problem
  - exploit also travel time and speed information
  - enhance parallelization and hierarchy of the network