DYNAMIC ODME FOR AUTOMATED VEHICLES MODELING USING ‘BIG DATA’

Dr. Jaume Barceló, Professor Emeritus, UPC-Barcelona Tech, Strategic Advisor to PTV Group

Shaleen Srivastava, Vice-President/Regional Director (PTV Group Americas)
INTRODUCTORY REMARKS

Connected vehicle systems and autonomous vehicles likely to be major game changers in traffic and mobility. No longer a question of if, but of when, in what form, at what rate. And through what kind of evolution path…

… operational regimes in which vehicles are connected to each other and to the infrastructure, and augmented with autonomous capabilities.

CONNECTED & AUTONOMOUS VEHICLES

- Adaptive Cruise Control
- Traffic Sign Recognition
- Emergency Braking
- Pedestrian Detection
- Collision Avoidance
- Lane Departure Warning
- Park Assist
- Cross Traffic Alert
- Rear Collision Warning
- Park Assist
- Blind Spot Detection
- Surround View

Legend:
- Long-Range Radar
- LiDAR
- Camera
- Short-/Medium Range Radar
- Ultrasound

www.ptvgroup.com
AUTONOMOUS VS CONNECTED VEHICLES

Transformational Shift No. 7: From Hands Free to Mind Free: Future Will See Fully-automated Vehicles

- **Drive and Let Drive Concept**: Can be manually driven or self-driven by the vehicle.
- **Predetermined A-to-B**: Ideally suitable for Personal Rapid Transit (PRT).
- **Personal Mobility with Route Inputs**: Ideally suitable for urban commuters and people with special mobility needs.

**Autonomous Adaptive Mobility Vehicles**

Fully-automated vehicles hold the potential for fundamental rethinking of vehicle designs. For instance, partially collapsible vehicles also save parking space when not in motion.

Source: Frost & Sullivan
SINGLE VEHICLE APPLICATIONS & COOPERATIVE APPLICATIONS
WILL AV REPLACE CURRENT AUTOMOTIVE TECHNOLOGIES FOR INDIVIDUAL MOTORIZED MOBILITY? OR, WILL MOSTLY BE USED FOR COLLECTIVE MOBILITY?

GATEway experts and partners reveal how trialed pods are set to improve mobility in London

The GATEway Project: This is just the beginning.

VISUALIZATION OF SHARED SELF-DRIVING CAR SIMULATION FOR LISBON
A SELF-ORGANIZING SYSTEM OR BETTER EXTERNALLY ASSISTED?
COOPERATIVE DRIVING WITH THE HELP OF V2X COMMUNICATIONS


Macroscopic simulation of traffic flow (spatio-temporal evolution of traffic density) close to an on-ramp using the GKT model, combined with a novel ACC/CACC modeling approach. Left: manual cars; Middle: ACC-equipped cars; Right: CACC-equipped cars.

• Connect VACS and TM communities for maximum synergy
• TM remains vital while VACS are emerging
• Overlapping link controllers?
• Share of control tasks?

Autonomous vehicles rely on knowing the roadway they are traveling on, changes to the roadside such as new development or construction will require the type of real-time exchange of information that CV technology provides including valuable information about the road ahead—allowing rerouting based on new information such as a lane closures, or congestion growing.

ATKINS “Autonomous vs connected vehicles – what’s the difference?” (Suzanne Murtha | 02 Oct 2015 |)
Each of the vehicles measures each half second and stores its position, heading, speed, and acceleration, as well as distances and relative speeds to “visible” surrounding vehicles captured by the radars.
V2V TRACKED EQUIPPED VEHICLES “AWARE” OF SURROUNDING VEHICLES ⇒ TRAJECTORY RECONSTRUCTION & TRAFFIC STATE ESTIMATION

- The relative distance $d_{eo}$ between the equipped and the observed car
- The relative speed $v_{eo}$ between the equipped and the observed car
- The map-matched position $(x_e, y_e)$ and speed $v_e$ of the equipped car.

TRAFFIC DATA ANALYTICS

(Extracting the most useful & valuable information from traffic measurements)

Dealing with heterogeneous traffic data from varied technological sources (conventional detectors, Bluetooth, GPS, cooperative & autonomous vehicles...):
- Data filtering, completion and fusion techniques
- Processing huge amounts of data (Big Data ⇒ Ad hoc Data Base Management Techniques)

Kernel Smoothing Methods, Kalman Filter & traffic flow based models to identify and remove outliers
And to supply missing data

Data Fusion Techniques

Kernel Smoothing Methods
Machine Learning
Traffic Models
Dynamic Flow Models
OD Estimation
CONCEPTUAL APPROACH TO AN ADAPTIVE AREA WIDE CONTROL STRATEGY BASED ON THE NETWORK FLOW DIAGRAM

Figure 6 Potential use of the Network Fundamental Diagram to support Active Area Wide Traffic Management Strategies

Identification of time-dependent mobility patterns in terms of Origin-Destination (OD) Matrices Exploiting ICT measurements

State equations AR(r) on deviates:
\[ \Delta g(k+1) = \sum_{i} D(w) \Delta g(k-1) + w(k) \]

D(w) transition matrices describing the effects of previous OD path flow deviates \( \Delta g_{ij}(k-w+1) \) on current flows \( \Delta g_{ij}(k+1) \)

Observation equations:
\[ \Delta z(k) = A_{\Delta}U_{ij}(k)^{T} \Delta g(k) + \epsilon(k) \]

Kalman recursive dynamics

\[ \begin{align*}
\Delta z(k) &= \begin{pmatrix} \Delta z_1(k) \end{pmatrix} \\
A_{\Delta}U_{ij}(k)^{T} \Delta g(k) &= \begin{pmatrix} \Delta g_{ij}(k) \end{pmatrix} \\
\epsilon(k) &= \begin{pmatrix} \epsilon_1(k) \end{pmatrix}
\end{align*} \]

First block: deviates of observations at sensor locations

Second block: conservation flows for each time interval k

MLU OD Path id | OD path links | OD pair | ICT sensor id | Entry id | MLU OD Path id | OD path links | OD pair | ICT sensor id | Entry id
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1-6-11</td>
<td>1=(1,8)</td>
<td>6,1,5</td>
<td>1</td>
<td>6</td>
<td>3-6-11</td>
<td>3=(2,8)</td>
<td>7,1,5</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>2-7-9-11</td>
<td>1=(1,8)</td>
<td>6,2,3,5</td>
<td>1</td>
<td>7</td>
<td>4-7-9-11</td>
<td>3=(2,8)</td>
<td>7,2,3,5</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>2-8-13</td>
<td>1=(1,8)</td>
<td>6,2,4</td>
<td>1</td>
<td>8</td>
<td>4-8-13</td>
<td>3=(2,8)</td>
<td>7,2,4</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>1-5-10-14</td>
<td>2=(1,9)</td>
<td>6,1,3,4</td>
<td>1</td>
<td>9</td>
<td>3-5-10-14</td>
<td>4=(2,9)</td>
<td>7,1,3,4</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>2-8-14</td>
<td>2=(1,9)</td>
<td>6,2,4</td>
<td>1</td>
<td>10</td>
<td>4-8-14</td>
<td>4=(2,9)</td>
<td>7,2,4</td>
<td>2</td>
</tr>
</tbody>
</table>

PTV GROUP
www.ptvgroup.com

DATA COLLECTION FROM AUTONOMOUS/CONNECTED VEHICLES

Assumption: travel times $T_{rq}$ of drivers departing from origin $r$ during time interval $t$ going through POI $q$ follow a distribution (not stationary under congestion), no matter the selected path.

Approximate travel time distributions by discrete distributions with bin proportions updated according to collected on-line ICT data.

$N(t, r, s)$ Number of trips starting at time interval $t$ from $r$ to $s$

$h_k(t)$ Number of trips starting at time interval $t$ from $r$ to $s$ using path $k$

$\tau_k(t)$ Average travel time from $r$ to $s$ on path $k$ at time interval $t$
EKF APPROACH FOR NETWORKS (III) : FLOW ESTIMATES AND ERROR CORRECTIONS (SHALEEN SRIVASTAVA, 2010)

- Traffic flow at a location
- Flows \( y(t) \)
- Assume Gaussian distributed measurements

- Model simulation (virtual detectors) – traffic flow
- Measurement (real detectors) – traffic flow

- Flows measurement from the model at \( t_1 \):
  Mean = \( z_1 \)
  Variance = \( \sigma z_1 \)
- Optimal estimate of traffic flows: \( \hat{y}(t_1) = z_1 \)
- Variance of error in estimate: \( \sigma^2 x (t_1) = \sigma^2 z_1 \)
EKF APPROACH FOR NETWORKS (III) : FLOW ESTIMATES AND ERROR CORRECTIONS (SHALEEN SRIVASTAVA, 2010)

- So we have the prediction \( \hat{y}(t_2) \)
- Detector data measurement at \( t_2 \): Mean = \( z_2 \) and Variance = \( \sigma z_2 \)
- Need to correct the prediction by model due to measurement to get \( \hat{y}(t_2) \)
- Closer to more trusted measurement – linear interpolation

- Corrected mean is the new optimal estimate of traffic flows (basically we have ‘updated’ the predicted flows by model using detector data)
- New variance is smaller than either of the previous two variances
If measurement is preferred:
- Measurement error covariance decreases to zero
- Weights residual more heavily than prediction

If prediction is preferred:
- Prediction error covariance decreases to zero
- Weights prediction more heavily than residual
MEASURING THE QUALITY OF THE ESTIMATES ESTIMATED (KF APPROACH) VS TARGET FLOWS IN OD PAIRS FOR A 15 MINUTES INTERVAL

Barcelona’s Central Business District (CBD), Eixample, 2111 sections, 1227 nodes 120 generation centroids, 130 destination centroids (877 non-zero OD pairs) 116 Loop detector Stations & 50 Bluetooth Antennas