Traffic state estimation at signalized intersections based on connected vehicles

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Research goal

Optimal traffic state **estimation and prediction** for traffic **signal control** by capitalizing on the new sensing and communication capabilities from **connected environments** in urban areas.

Data: Connected Environments

Measurements from new data sources: e.g. Connected Vehicles, Cameras etc.

Extended Observer: Urban Traffic State Estimation and Prediction

Extended Traffic State Estimation and Prediction:
- Queue length
- Arrivals
- Departures
- Turnings

Controller: Urban Traffic Control
Methodology
Extended Observer based on (Extended) Kalman Filter

**Time Update ("Predict")**

- \( \hat{x}_k^{\text{predicted}} \) (a priori state estimate)

**Measurement Update ("Correct")**

- \( \hat{x}_k^{\text{corrected}} \) (a posteriori state estimate)

**State vector:**

\[
\hat{x}_k = \begin{bmatrix}
    x_k^{\text{queue length}} \\
    x_k^{\text{arrival rate}} \\
    x_k^{\text{departure rate}} \\
    x_k^{\text{turning rate}}
\end{bmatrix}
\]

**Measurement vector:**

\[
\hat{z}_k = \begin{bmatrix}
    z_k^{\text{queue length}_{V2X}} \\
    z_k^{\text{arrival rate}_{loop}} \\
    z_k^{\text{departure rate}_{camera}} \\
    z_k^{\text{turning rate}_{rawFCD}}
\end{bmatrix}
\]

**Example:**

- \( x_k^{\text{queue length}} = x_{k-1}^{\text{queue length}} + \text{arrivals} - \text{departures} \)

- \( x_k^{\text{turning rate}} = a_{k-1}^{\text{turning rate}} \times x_{k-1}^{\text{turning rate}} \)

- \( a_{k-1}^{\text{turning}} \): changes every time step according to the historical profile.
Filter step ("Predict" and "Correct")

\[
\hat{x}_{k} = \hat{x}_{k-1} - (\hat{x}_k \text{departure rate} \times u_k \text{effective green}) + (\hat{x}_k \text{arrival rate} \times u_k \text{effective red})
\]

\[
\hat{x}_{k} = \hat{x}_{k} \times K_k \times \text{queue length}_{cv} - \hat{x}_{k} \text{predicted queue length}
\]

\[
\text{queue length}_{cv}
\]

\[
\text{corrected queue length}
\]

\[
\text{predicted queue length}
\]

\[
\text{time}
\]

\[
x_K: \text{traffic states (queue length, arrival rate, departure rate)}
\]

\[
u_K: \text{control input (signal timings)}
\]

\[
z_K: \text{traffic measurements (from Connected Vehicles)}
\]

\[
K_K: \text{Kalman gain}
\]
Measurement Update ("Correct")

**Input needed from Connected Vehicles and signal control:**
- timestamp \(t_i\)
- position \(x_i\)
- speed \(v_i\)
- last cycle red duration \(R\)
- last cycle green duration \(G\)

**Intermediate parameters for the calculation of \(\ddot{z}_k\):**
- time joining the queue \(t_{\text{joining\_queue}}\)
- time crossing the stopline \(t_{\text{crossing\_stopline}}\)
- position in the queue \(l\)
- number of CVs in the queue \(m\)

**Measurement vector:**
\[
\ddot{z}_k = \begin{bmatrix} z_k^{\text{queue\_length\_cv}} & z_k^{\text{arrival\_rate\_cv}} & z_k^{\text{departure\_rate\_cv}} \end{bmatrix}^T
\]

| Research goal | Methodology | Contributions | Conclusions | Outlook |

Contributions
Potential of new data
Simulations with **limited and imperfect** measurements

- Demonstrate the **working principles** of the developed Extended Observer
- Demonstrate the **potential and limitations** of the developed Extended Observer
Simulation example

Queue length estimation

*Measured queue length -1: there are no measurements available for this cycle

RMSE_queue_measurements = 9.14
RMSE_queue_filtered_estimations = 7.5
Saturation degree: 100%
Penetration rate: 10%
Cycles without measurements: 37.50%

\[
\begin{align*}
Q_{\text{queue}} &= R_{\text{queue.cv}} \\
Q_{\text{arrival}} &= R_{\text{arrival.cv}} \\
Q_{\text{departure}} &= R_{\text{departure.cv}} \\
Q \text{: process noise covariance} & \quad R \text{: measurement noise covariance}
\end{align*}
\]
Simulation example

*Measured queue length -1: there are no measurements available for this cycle*
Preliminary simulations results

\[ Q_{\text{queue}} = R_{\text{queue cv}} \]
\[ Q_{\text{arrival}} = R_{\text{arrival cv}} \]
\[ Q_{\text{departure}} = R_{\text{departure cv}} \]

\( Q \): process noise covariance
\( R \): measurement noise covariance

\( \text{RMSE change}(\text{-7.781 \%}) \)
\( \text{RMSE change}(\text{-18.13 \%}) \)
\( \text{RMSE change}(\text{-13.69 \%}) \)
\( \text{RMSE change}(\text{-15.34 \%}) \)

*statistically significant (paired t-test)
Simulation example

“What if the quality of the measurements and the state variates strongly?”

平均交通量: q = 50-600 v/h
渗透率 p = 5%
RMSE-Connected Vehicles = 23.12
RMSE-Extended Observer = 10.56

平均转率 (%)
Simulation example

„What if there is a specific historical profile that we want to trust more than the measurements?“

Methodology

Average traffic volume: q = 50-600 v/h
Penetration rate p = 5%
RMSE-Connected Vehicles = 23.12
RMSE-Extended Observer = 5.22

Turning rate (%)

Simulation second (sec)
Conclusions
Conclusions

Extended Observer (based on Extended Kalman Filter):

- Utilizes **imperfect measurements** from low number Connected Vehicles (**low penetration rates**)
- Provides **improved estimation** in comparison to relying solely on the measurements
- Provides an **intuitive way for tuning** the filter (“should I trust the measurements or the model more?”)

But:

- **Tuning (Q, R)** is very critical in Kalman filtering
- **Biased measurements** or **biased model** can lead to reduced performance
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Outlook
Outlook

- Compare with estimation from loop detectors
- Test different data availability combinations
- Evaluate the impact on signal control
- Derive requirements for connected environments
- Add another layer: “Continuous” filter (every 3 seconds)
Thank you for your attention

„Science fiction is sexier than science facts“  
(Dr. S. Shladover, UC Berkeley,  
MFTS 2018, Ispra, 11.06.2018)

Thank you for your attention