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Enhanced Queue Length Estimation in Oversaturated Conditions for Adaptive Signal Control based on Aggregated Floating Car Data

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Extended Abstract

This paper presents a method that fuses travel time measurements from aggregated Floating Car Data (FCD) and queue measurements from loop detectors in order to improve the queue length estimation in cases of oversaturation. The algorithms are based on the widely used Extended Kalman Filter and are tested in a microscopic simulation of a real intersection in various scenarios (e.g. different saturation degrees and penetration rates) based on the real detector and FCD availability. Even though aggregated travel times may not be able to capture minor cycle-to-cycle variations of queue length, this paper shows that they could be used to identify major queue length jumps that remain undetected by inductive loops. Furthermore, the enhanced queue length estimation is tested with the adaptive Urban Traffic Control System Utopia/Spot with promising results in terms of delay reduction even in oversaturated conditions.

Keywords:

Extended Kalman Filter, Data Fusion, Queue Length Estimation, Floating Car Data, Connected Vehicles, Adaptive Signal Control

Problem Statement

Traffic congestion in urban areas remains one of the major challenges for traffic planners and engineers. Traffic signal control, as part of dynamic traffic management, aims to mitigate the negative impacts of traffic congestion, such as increased emissions and delays, by optimizing the signal timings of signalized intersections [1]. To achieve that goal, the state of the art Urban Traffic Control (UTC) systems utilize loop detector data in order to estimate (and in some cases predict) the traffic state in the urban network. In the case of signal control, queue length estimation in oversaturated conditions has proven to be both challenging and critical for signal optimization [2].

Considering the latest sensor and communication developments (e.g. image recognition in cameras, Car-to-Infrastructure, 5G communication), fusion of diverse data sources for queue length estimation becomes essential for UTC systems. In theory, it is expected that information from individual Connected Vehicles (CV), such as speed, position and acceleration will improve the queue length estimation coming from loop detectors [3]. But in practice, traffic data providers such as TomTom, Inrix and Here provide currently mainly aggregated travel times for road segments (or average speeds) based on Floating Car Data (FCD) through their open APIs [4].

Research Objectives

This paper focuses on the potential of currently available aggregated FCD as an extra data layer in addition to loop detectors based on simulations of a real signalized intersection in Verona, Italy. More specifically, the objectives of this paper are the following:

- Mathematical formulation of the developed filter for queue length estimation based on fusion of aggregated FCD and loop detectors.
- Evaluation of the queue length estimation with simulations (in comparison to estimation based solely on loop detectors).
- Evaluation of the resulting signal control with simulations (in comparison to the control based only on loop detectors).

Methodological Approach

In the scope of the research project CENTAURO, a prototypical module for sensor fusion has been developed in order to reduce the dependency of current UTC systems on loop detectors. The developed Extended Observer (EO) is based on the Extended Kalman Filter (EKF) and allows the fusion of diverse data sources (e.g. cameras, FCD, CV) for traffic state estimation at signalized intersections. The EKF (nonlinear version of the Kalman Filter) is a predictor-corrector type estimator that allows for stochastic estimation from noisy measurements (see Figure 1).

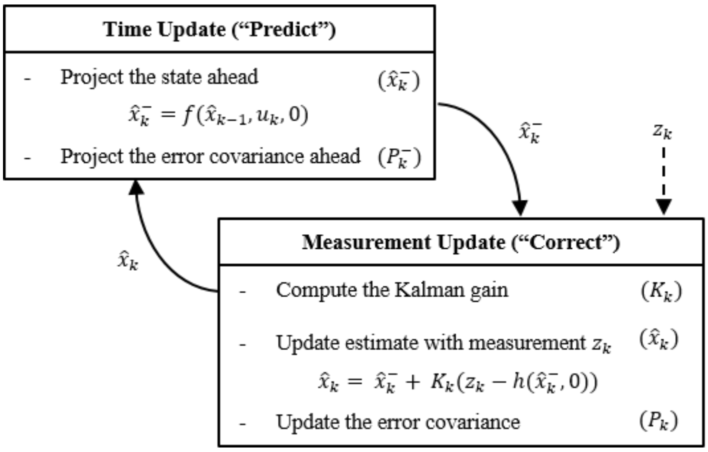

Figure 1 – The Extended Kalman Filter

The process equation is utilized to predict the state (a priori estimate, $\hat{x}_k^-$) and the measurement equation is utilized to correct the state (a posteriori estimate, $\hat{x}_k$) based on the incoming measurements.
These two equations take the following general form in the case of EKF:

- Process equation: $x_k = f(x_{k-1}, u_k, w_{k-1})$
- Measurement equation: $z_k = h(x_k, v_k)$

The non-linear function f relates the state at the previous time step k-1 (x_{k-1}) to the state at the current time step k (x_k) . The non-linear function h relates the measurement (z_k) at the current time step k to the state at the current time step k. The Kalman gain (K_k) is updated every time step and can be viewed as a weighting factor that decides how much we are willing to trust the model or the measurements. The vector v_k indicates the error in the measurement, the vector w_{k-1} indicates the error in the model and the vector u_k indicates the control input [5].

In the case of queue length estimation with the EO, the process equation becomes:

Process equation:

$$x_k^{queue} = x_{k-1}^{queue} - u_k^{dep} + u_k^{arr} + w_{k-1}^{queue}$$

with:

x_k^{queue}: number of queued vehicles at the end of red time of signal cycle k (veh).

x_{k-1}^{queue}: number of queued vehicles at the end of red time of signal cycle k-1 (veh).

u_k^{dep}: vehicles that departed during signal cycle k (veh).

u_k^{arr}: vehicles that arrived during signal cycle k (veh).

w_{k-1}^{queue}: queue process noise (veh).

Since the measurements used in this paper are coming from two different data sources the measurement equation becomes:

Measurement equation:

$$\vec{z}_k^{queue} = \begin{bmatrix} z_k^{queue\_aggFCD} \\ z_k^{queue\_loop} \end{bmatrix} = \begin{bmatrix} \alpha \times (x_k^{queue})^{\beta} \\ x_k^{queue} \end{bmatrix} + \begin{bmatrix} v_k^{queue\_aggFCD} \\ v_k^{queue\_\_loop} \end{bmatrix}$$

with:

$z_k^{queue\_aggFCD}$: travel time for road segment leading to the stop line, measured from FCD (sec).

$z_k^{queue\_loop}$: number of queued vehicles, measured from loop detector (veh).

α, β: factors depending on the travel time measurement points.

$v_k^{queue\_aggFCD}$: queue measurement noise from FCD (veh).

$v_k^{queue\_loop}$: queue measurement noise from loops (veh).

Expected Results

The developed algorithms are programmed in C++ and tested in a microscopic simulation (PTV Vissim) of an existing intersection in Verona, Italy through the COM interface. The flows are based on real detector data and the travel time measurements are based on the real data availability from a global traffic data provider for the specific intersection. The examined intersection is controlled from the state-of-the-art adaptive UTC system Utopia/Spot from Swarco AG. The queue length measurement from the loop detectors comes from the emulated Utopia/Spot controller. The EO can then feed the existing controller from Utopia/Spot with the new filtered estimation. In the specific intersection, one signalized approach is typically oversaturated (beyond the existing loop detector), resulting in reduced performance of the control. In this paper we investigate if the developed EO can improve the queue length estimation and the resulting signal control in various simulation scenarios (e.g. different penetration rates and different saturation degrees). In the following, some preliminary results are presented.

Evaluation of queue length estimation

Figure 2 shows an indicative 2-hour simulation run with the measurements from aggregated FCD and loop detector, as well as the resulting estimation for the examined oversaturated approach. The measurements ($z_k^{queue\_loop}$) from the loop detector (100m from the stop line) point to the correct queue for low queue values (undersaturated cycles) but they are naturally not able to capture longer queues for oversaturated cycles. The FCD measurements ($z_k^{queue\_aggFCD}$) however can point to the correct queue for oversaturated cycles. Therefore, the filtered estimations from the EO ($\hat{x}_k$) that fuses both data sources are closer to the ground truth in comparison to just relying on the loop measurements. The ground truth for the back end indicates the theoretical position of the last stopped vehicle due to the oversaturated red signal and the resulting stop-and-go. The preliminary results show that the Root Mean Square Error (RMSE) of the EO is around 15% lower than the RMSE from the queue measurements coming from the loop detectors.

Evaluation of signal control

Moreover, to evaluate the potential of the aggregated FCD measurements, we feed the new estimation from the EO to the existing Utopia/Spot controller and we compare the results with the original control (i.e. only with loop measurements). The new estimation leads to new green time distribution among signal groups (maximum cycle and green times are the same in both scenarios). The preliminary results show that the average vehicle delay at the oversaturated approach is 16% lower for the controller that uses the EO estimations. This comes of course at the expense of the competing approach (18% increase of the average vehicle delay) since the intersection runs above capacity from all directions. Nevertheless, the average vehicle delay for the complete intersection is 4% lower. This indicates that aggregated FCD can be used to mitigate the congestion at a specific approach in oversaturated conditions without affecting the overall level of service of the intersection.

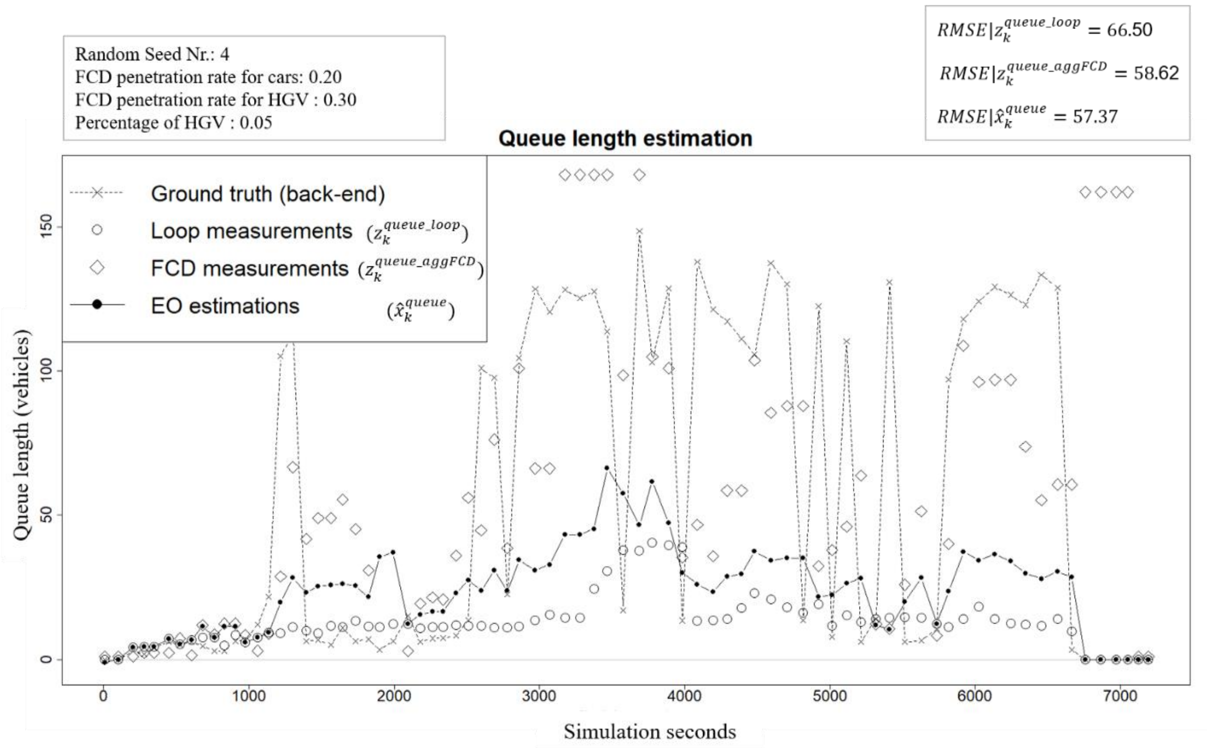

Figure 2 – Example of queue length estimation

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