Application of an extended Kalman filter traffic estimation scheme to microsimulation

Anastasios Kouvelas*, Mohammadreza Saeedmanesh, Nikolas Geroliminis

École Polytechnique Fédérale de Lausanne
School of Architecture, Civil & Environmental Engineering
Urban Transport Systems Laboratory
GC C2 389-390, Station 18
CH-1015 Lausanne, Switzerland
{tasos.kouvelas, mohammadreza.saeedmanesh, nikolas.geroliminis}@epfl.ch

Extended abstract

In this work we study the problem of traffic state estimation for large-scale urban networks. Given a network that is partitioned in a number of regions, the aggregated traffic dynamics describe the vehicle accumulations in each region, as well as the transferring flows among neighbouring regions. Considering the fact that many such models have been extensively used for control in the literature recently, this work tackles the real-time estimation problem when limited data are available. Recently, there has been a lot of development with respect to methodologies for perimeter control that utilize the Macroscopic Fundamental Diagram (MFD) for multi-region urban networks. All these controllers are based on aggregated state-space modelling for the dynamics of the system. Nevertheless, from the viewpoint of field implementations of such approaches, there is a missing part (i.e. online state estimation) that is crucial to fill the gap between available data and the controller input requirements in order to close the real-time control loop.

As discussed above, traffic state estimation is a vital part of the online closed-loop traffic control system. It refers to estimating all traffic variables that are required by a controller as state feedback at the current time instant, given a set (e.g. output functions of a sub-vector of the state vector) of available real-time measurements. In most of online traffic control loop applications the whole state cannot be measured for different reasons, i.e., availability of sensors, communication issues, data dropouts, detector failures, and thus, an estimation engine that can reproduce the system state is deemed crucial for the controller performance. More precisely, for an urban network, the developed estimation algorithm should deliver the complete picture of the network (i.e. state vector) at the current time, given some incomplete information of available measurement data from loop detectors, GPS, and any other available sensor. It should be emphasized that the number of traffic variables to be estimated may be in general much greater than the number of variables that are directly measured. Moreover, the measurements may be noisy and this needs to be addressed within the estimation framework. The output of the “best state estimate” and the comparison with the real state (if available) is the essential contribution of the methodology.

Kalman filter is an optimal state estimator applied to linear dynamic systems that involves random (Gaussian) noise and incorporates a limited amount of noisy real-time measurements. Although it was originally derived for linear systems, Kalman filter can be also extended and be applied to nonlinear systems via specific online Taylor expansions of the originally nonlinear systems (i.e. the Taylor expansion needs to be calculated in real-time at every discrete time instant). This extended version that is utilized in the current work, is the so called Extended Kalman Filter (EKF). This methodology can be also viewed as a fusion between the real-time available measurements from the plant and the predefined nonlinear dynamic model that is derived for the process. Here, EKF is used to estimate traffic state

* *corresponding author*

variables (e.g. vehicle accumulations, flows), but also to estimate the exogenous signals of demands, and some states that are difficult to be measured and can be considered as time depended model parameters (i.e. regional turning ratios). More precisely, if some state variables are not measurable, we can reformulate the problem and denote them as model parameters (i.e. random walk processes) and then try to estimate their values in real-time.

Consider the following nonlinear state-space model

$$\mathbf{x}(k) = \mathbf{f}[\mathbf{x}(k-1), \mathbf{u}(k-1), \boldsymbol{\xi}(k-1)]$$

with the following output equation

$$\mathbf{y}(k) = \mathbf{h}[\mathbf{x}(k), \mathbf{u}(k), \boldsymbol{\psi}(k)]$$

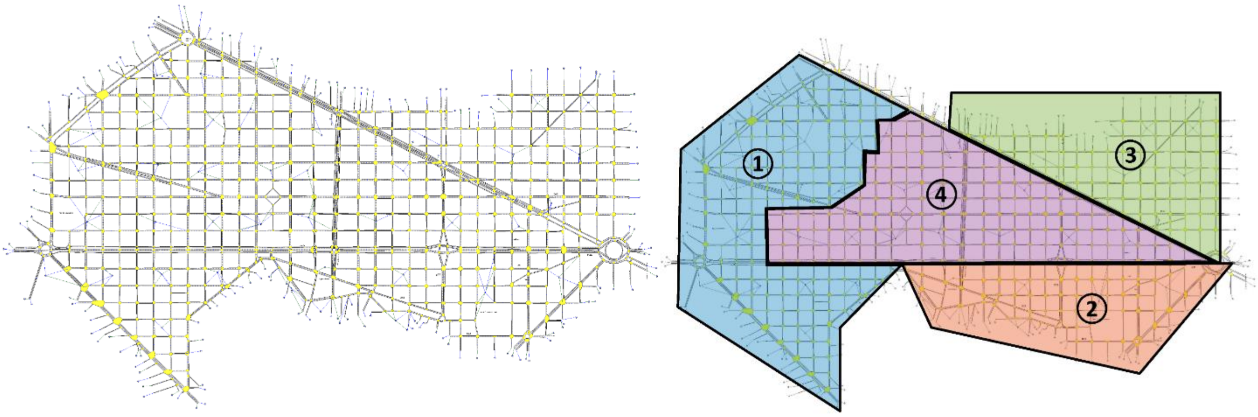
where $k = 1,2, \dots ,K$ is the discrete time index, $\mathbf{x}$ corresponds to the complete traffic state, $\mathbf{f}$ and $\mathbf{h}$ are nonlinear differentiable vector functions that reflect the process and the output, respectively, and $\boldsymbol{\xi}$, $\boldsymbol{\psi}$ correspond to zero-mean Gaussian random noises that reflect the modeling error and the error of the measurements respectively. At iteration k, given all the available measurements $\mathbf{y}(k-1), \mathbf{y}(k-2), \dots, \mathbf{y}(0)$ collected up to that point, the recursive equations that provide the prior $\hat{\mathbf{x}}(k|k-1)$ and posterior $\hat{\mathbf{x}}(k-1|k-1)$ estimates of the state vector according to EKF theory are as follows:

$$\hat{\mathbf{x}}(k|k-1) = \mathbf{f}[\hat{\mathbf{x}}(k-1|k-1), \mathbf{u}(k-1), \mathbf{0}]$$

$$\hat{\mathbf{x}}(k-1|k-1) = \hat{\mathbf{x}}(k-1|k-2) + \mathbf{K}(k-1)(\mathbf{y}(k-1) - \mathbf{h}[\hat{\mathbf{x}}(k-1|k-2), \mathbf{u}(k-1), \mathbf{0}])$$

where matrix $\mathbf{K}(k-1)$ is the so called Kalman gain, which is calculated online based on the first-order linear Taylor-expansion of $\mathbf{f}$ and $\mathbf{h}$ at the current point $\hat{\mathbf{x}}(k-1|k-1)$ and for the expected value of all noises which is $\mathbf{0}$, for each k. Note that as these calculations are recursive, $\mathbf{K}(k-1)$ actually depends on traffic measurements of all previous time instants $k-1$, $k-2$, … , 0. Due to lack of space, the reader is referred to [1] for the analytical derivations of the EKF methodology. In [1] the authors have presented a generic estimation framework that is based on the seminal methodology of Kalman filtering [2] and its extensions for nonlinear systems (see, e.g. [3]), and can be used in practice for many different configurations of aggregated state vectors and real-time measurements. The presented EKF estimation scheme is based on a simple aggregated model of the system dynamics and some real-time measurements. The accuracy of the estimations is investigated through macrosimulation by studying a realistic configuration of real-time availability of measurements. The output of EKF are the resulting estimated traffic states (i.e., regional accumulations, demands, and distribution of outflows), which are compared to the real ones that are obtained from the stochastic plant. Note that the developed algorithm can be utilized by closed-loop online urban traffic management strategies (see e.g. [4]) to feed back to the controller the estimated traffic state.

In this work we apply the estimation framework described above to microsimulation in order to evaluate its performance. For the plant of the traffic process we utilize the commercial software simulation Aimsun. Note that this software is based on a car-following microscopic model and a complicated lane-changing model, and thus, this is essentially quite different than the aggregated model utilized by EKF for the urban multi-region traffic dynamics. By combining this model with measurements from the microsimulator we aim to test the performance of the estimation scheme. For our simulation experiments, we use as a case study network a replica of the CBD of Barcelona in Spain. For this network, we have a well calibrated microsimulation model in Aimsun (Figure 1(a)). Figure 1(b) presents the test network partitioned in 4 homogeneous regions. For the partitioning the algorithm presented in [5] has been used. The result of this algorithm is to get 4 clusters (zones) that are as homogeneous as possible and with compact shapes.



(a) (b)

Figure 1: (a) Aimsun microsimulation model for the CBD of Barcelona, (b) network partitioned in 4 homogeneous regions.

Consider now that we have available (noisy) measurements from an urban network. If traffic loop detectors are installed and perhaps also some real-time GPS data are available, it is reasonable to assume that we can get measurements for the total accumulation of any region n_i, and also the aggregated transfer flows from any region i to any region j (but not detailed route choices, trip endings, and demand data). Given these real-time measurements every T=90sec, it is the purpose of EKF to try to estimate other state variables (needed by the controller), which are (a) the regional turning ratios α_{ij} (that correspond to the distribution of outflow to neighbouring regions), and (b) the aggregated demands d_i for every region. Moreover, EKF provides estimates for the complete state, i.e. even for the accumulations n_i that are directly measured we get an estimate that will filter out the measurement noise.

After applying the EKF methodology to microsimulation we are able to compare the estimated values to the real values of the state variables. Figure 2 presents the time-series of demands for the four regions of Barcelona. The estimated value (red) is compared to the real value (blue) that is obtained by the simulator. We can observe that the estimation scheme can follow quite well the signal of the unknown demand even though the plant and EKF aggregated model are quite different in nature. We are able to provide quite accurate online estimates that can be utilized for control purposes. Similarly, Figure 3 presents the estimated (red) and real (blue) trajectories for the regional turning ratios α_{ij}. The estimates are also reasonably accurate, following quite well the real trajectories. Note that in region 4 the estimation results are better than in regions 1, 2, and 3, and this is because the MFD model incorporated within EKF has more information about the dynamics of this region. Overall, the estimation results can be deemed satisfactory in order to be used for real-time control purposes (e.g. model predictive control).

References

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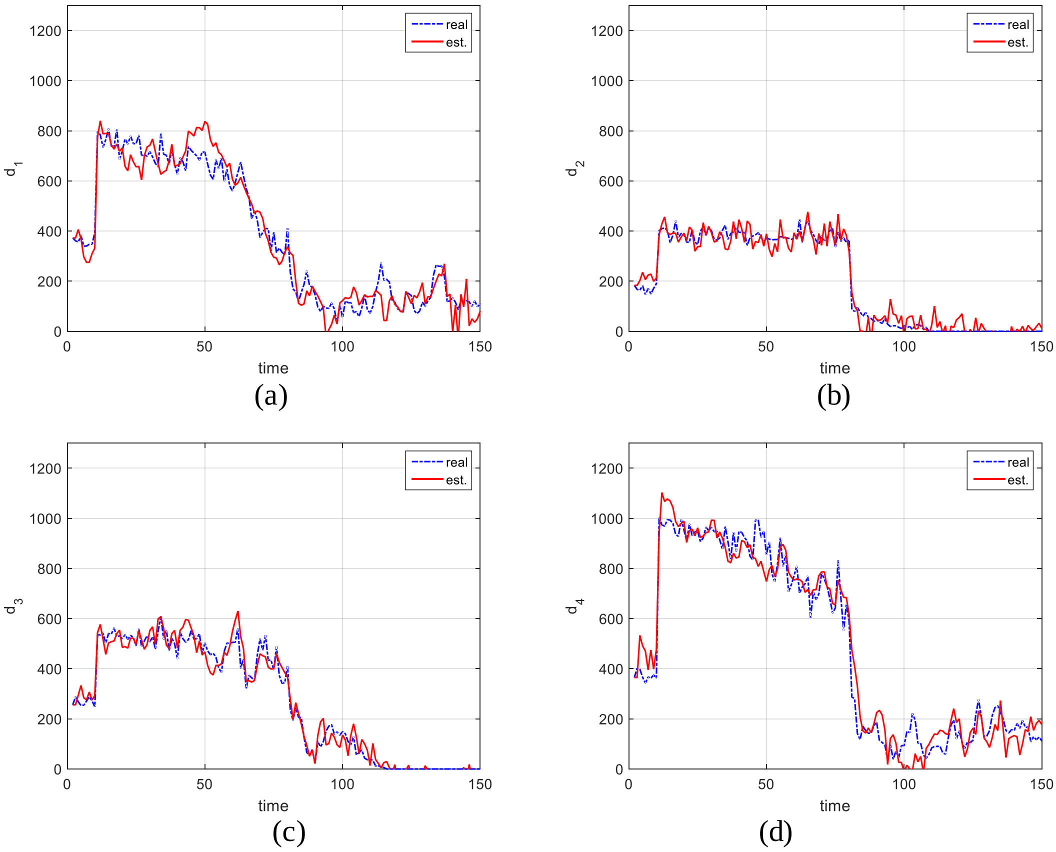

Figure 2: Estimated and real trajectories for the exogenous demands (a) d_1, (b) d_2, (c) d_3, and (d) d_4.

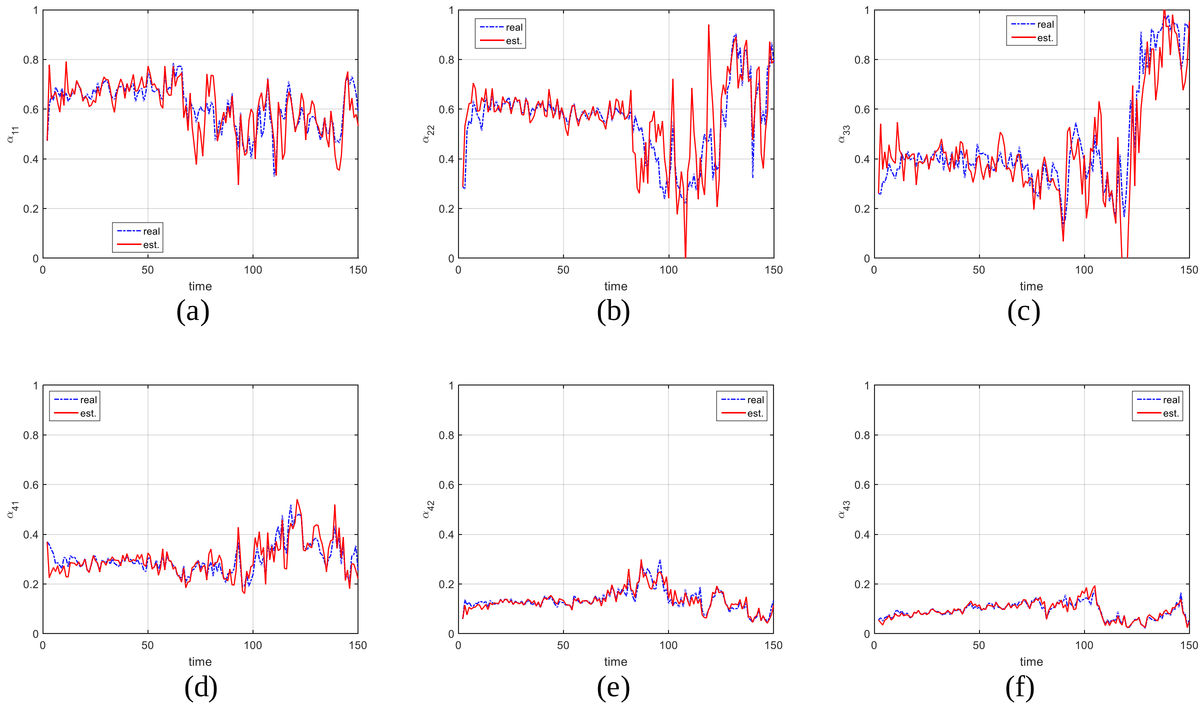

Figure 3: Estimated and real trajectories for the regional turning ratios (a) α_{14}, (b) α_{24}, (c) α_{34}, (d) α_{41}, (e) α_{42}, and (f) α_{43}.