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Kalman filter for turning rate estimation at signalized intersections, based on Floating Car Data

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Extended Abstract

This paper introduces two Kalman filter (KF) implementations for the estimation of turning rate at signalized intersections, assuming the availability of Floating Car Data (FCD). The developed filters are tested in microscopic simulation under various scenarios. The first filter is a typical (linear) KF that utilizes only real-time FCD. The second is an Extended (non-linear) Kalman filter that utilizes both real-time and offline (historical profiles) FCD. The aim of this paper is to demonstrate how Kalman filter can be used to estimate in real-time the total turning rate at an intersection, based on limited (and error-prone) measurements coming from FCD. Moreover, it is shown how to tune the filters to account for different errors in real-time measurements and in historical profiles, in order to use it in real-world applications.

The motivation of this paper is given in section 1 and the research objectives in section 2. The methodology is described in section 3. Finally, in section 4 the expected results are outlined and some preliminary results are presented.

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Nomenclature

$\boldsymbol{x}_k$	state vector at time step k
$\boldsymbol{u}_k$	control input vector at time step k
$\boldsymbol{z}_k$	measurement vector at time step k
$\boldsymbol{w}_k$	process noise vector at time step k
$\boldsymbol{v}_k$	measurement noise vector at time step k

1. Problem Statement

Traffic congestion and its numerous negative impacts (e.g. increased air and noise pollution, increased delays) is one of the biggest challenges in urban environments. Urban Traffic Control (UTC) systems, as part of dynamic traffic management, aim to reduce environmental impacts, increase traffic safety and efficiency of the road network. The more advanced UTC systems aim to optimize the signal timings real-time, based on traffic flow models (model-based traffic control). A very important ingredient for such an application is the traffic state estimation and prediction (van Lint & Djukic, 2012).

Urban traffic flow can be viewed as a dynamic process in terms of automatic control (Papageorgiou, 1998). As digitalization and connectivity in urban environments continue to grow, so do the potentially available data sources for improved traffic state estimation. The introduction of new data sources means an extension of the available sensors and measurements (Figure 1).

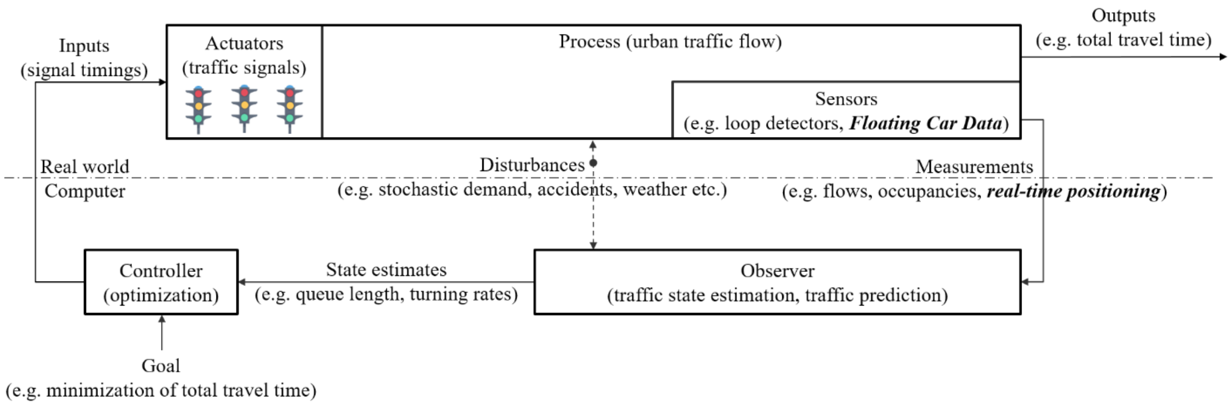

Figure 1. Basic elements of Urban Traffic Control

Even the most advanced UTC systems rely heavily on inductive loop detectors. Therefore, the traffic state estimation can typically utilize either measurements that come from loop detectors or measurements that emulate loop detectors (cameras for counting vehicles). In order to take full advantage of new data sources (new sensors), data fusion approaches are necessary that take into account measurement errors and disturbances. This paper deals in particular with the problem of turning rate estimation based on FCD.

2. Research Objectives

The research project **CENTAURO** (**C**onnected **E**nvironments for **N**egotiated **T**raffic Control **A**nd **UR**ban **O**ptimization) aims to reduce the dependency of UTC systems on loop detectors and develop a method that integrate various data sources for optimal traffic state estimation. To achieve that goal, a robust sensor and data fusion methodology is needed that offers the mathematical flexibility for extensions but is at the same time relatively easy to formulate for real traffic control systems. The Kalman filter (KF) is selected to be the foundation of our methodology (see section 3). In this paper, the new data sources that have to be integrated are the FCD and the parameters that has to be estimated are the turning rates. More specifically, two simple versions of Kalman filter (a linear KF and an Extended KF) are implemented in order to achieve the following research objectives:

- Integrate real-time measurements from FCD in the total turning rate estimation
- Integrate historical profiles from FCD in the total turning rate estimation
- Integrate information from more than one FCD provider (with different percentages and errors)
- Evaluate the performance of the filters under different traffic scenarios and filter parameters
- Evaluate the performance of the filters in comparison to turning rate estimation based on loop detectors
- Propose a simple method to tune the filters for real-world applications

3. Methodological Approach

Many successful applications of the (E)KF have been documented in the literature in the context of dynamic traffic management and control. Hans van Lint and Tamara Djukic (2012) provide an excellent literature overview and three practical and intuitive examples. In this paper two versions of KF are developed and tested in simulations. Section 3.1 describes the basic principles of the Extended Kalman Filter (EKF) and section 3.2 shows the two developed filters. For more details on the formulas of (E)KF see the very practical course pack "*An Introduction to the Kalman Filter*" by Welch and Bishop (2001).

3.1. The Extended Kalman Filter (EKF)

Kalman filter is one of the most widely used tools for stochastic estimation from noisy measurements. The filter is recursive (does not require storage of all previous data) and can be used to combine measurements from various sensors that are subject to noise (error). These attributes (and the fact that it can be intuitively tuned) make it very attractive for real-time, real-life applications. The Kalman filter applies a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance (Welch & Gary, 2001).

The EKF is the nonlinear version of the Kalman filter and is usually used if the process to be estimated and (or) the measurement relationship to the process is non-linear (which is typically the case for real-world applications). The EKF linearizes around the current mean and covariance and consequently the convergence to an optimal estimation is not guaranteed. Despite the loss of optimality due to the local approximation, EKF has proven to work surprisingly well in many applications (van Lint & Djukic, 2012).

Two equations are needed to define the mathematical models of the process to be estimated. The process equation (defines the process model) and the measurement equation (defines the measurement model). In the case of EKF these two equations take the following general form:

$$x_k = f(x_{k-1}, u_k, w_{k-1}) \qquad \text{(process equation)} \tag{1}$$

$$z_k = h(x_k, v_k) \qquad \text{(measurement equation)} \tag{2}$$

The non-linear function f relates the state at the previous time step $k\text{-}1$ to the state at the current time step k and includes as parameters the control input vector u_k and the zero-mean process noise w_{k-1}.

The non-linear function h relates the measurement at the current time step k to the state at the current time step k and includes as parameter the zero-mean measurement noise v_k.

3.2. Filters for turning rate estimation

For the sake of simplicity, for the formulation of the developed filters, we will focus on one approach and one intersection. The presented formulation can easily be extended to several turning rate, approaches and intersections, since x_k and $\mathrm{z_k}$ are vectors.

In the examined case of simulated FCD at signalized intersections, the state to be estimated is just the turning rate. We assume that the measurements come directly as FCD turning rate from the FCD provider at predefined time intervals (e.g. every 15 minutes). That means that the measurement equation becomes:

$$z_k = x_k + v_k \qquad \text{(linear measurement equation)} \qquad (3)$$

Now the question is how to set up the process equation. Two filter variations are tested in this paper:

Filter A (KF-random walk):

For this filter we assume that the turning rate can be modeled by means of a random walk:

$$x_k = x_{k-1} + w_{k-1} \qquad \text{(random walk process equation)} \qquad (4)$$

Considering that the measurement equation is also linear, the filter becomes a linear Kalman Filter.

Filter B (EKF-historical model):

For this filter we assume that the turning rate follow a certain non-linear historical model and evolve according to the relationship:

$$x_k = \alpha_{k-1} x_{k-1} + w_{k-1} \qquad \text{(non-linear process equation)} \qquad (5)$$

The process equation is not linear (since α is not constant but can change every time step) and therefore the resulting filter is an EKF.

4. Expected results

The developed filters are tested in a microscopic simulation. The FCD turning rates are aggregated and passed in the filter in 15 minutes' intervals as real-time measurements. The simulation period for every simulation run is 24 hours. That means that the filter runs for a total of 96 steps per simulation run. Figure 2 shows an example of the performance of Filter A (KF-random walk) for the first 56 steps of one simulation run for a signalized approach with two turning movements (only one turning ratio estimation is plotted). The estimated values from the filter follow the actual total turning rates (ground truth) even in cases of extremely inaccurate measurements (e.g. when the observed FCD turning rate equals zero, see Figure 2, second 2700). It has to be mentioned, that in the example of Figure 2 the assumption of the random walk is not far from the ground truth, since the actual total turning rates don't demonstrate extreme fluctuations (total turning rates remain around 40-60%).

The results of this paper will not focus only on the evaluation of the developed filters under different simulation scenarios and filter parameters. A very interesting outcome of this paper is to assess if the EKF outperforms the KF (and under which circumstances). Filter B (EKF-historical model) is expected to perform better than Filter A in cases where there are patterns of swift changes in the historical profiles. Therefore, emphasis should be given in building the historical profiles and the respective historical model in the process equation form (equation 5). In addition, the results of this paper will demonstrate how the filters perform in comparison to detector-based turning rate estimation. Last but not least, this paper proposes a simple method for tuning the filters for real-world applications.

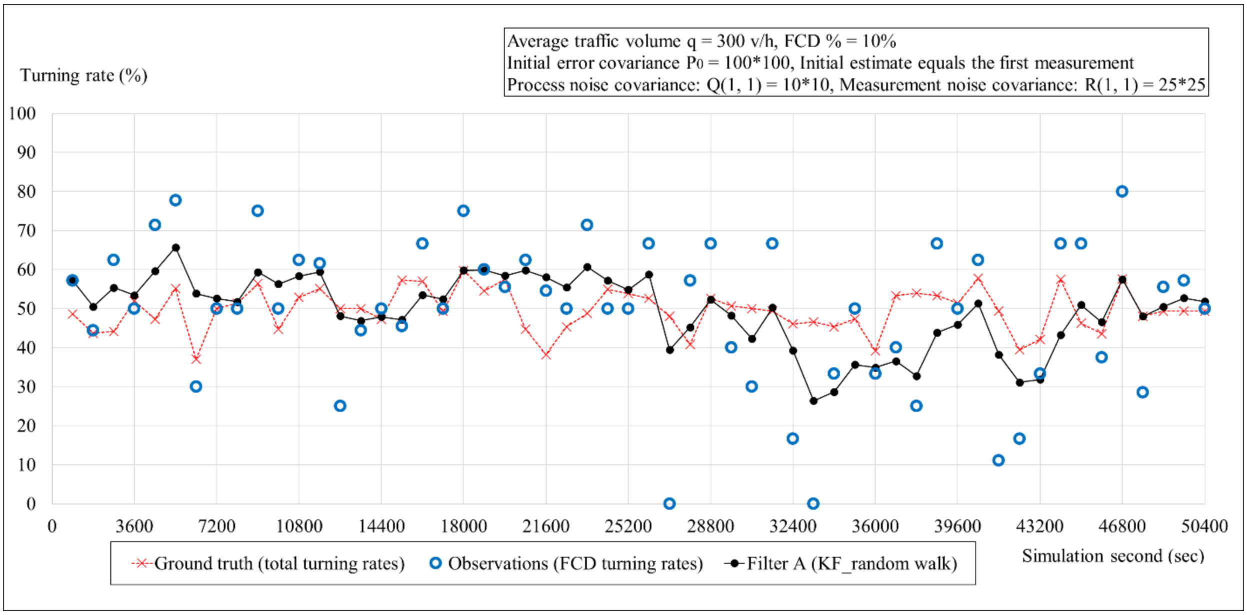

Figure 2. Performance of Filter A (preliminary results)

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