Title of Research: Extended Kalman filter and Unscented Kalman filter for Traffic State Estimation

1. INTRODUCTION:

The steadily increasing number and length of traffic jams on freeways has led to the use of several dynamic traffic management measures all over the world such as on-ramp metering, dynamic routing and the provision of congestion information. Usually these measures operate based on local data (occupancy, intensity or speed measurements).

However, considering the effect of the measures on the network level has many advantages compared to local control. E.g., solving a local congestion only, may have as consequence that the vehicles run faster into another (downstream) congestion, whereas still the same amount of vehicles have to pass the bottleneck (with a given capacity), and so the average travel time on the network level will still be the same. Another reason for considering the effects of control on the network level is that in a dense network a local control measure can have effects on more distant parts of the network: an improved flow may cause congestion somewhere else in the network or a reduced flow may prevent congestion somewhere else in the network. Furthermore, if dynamic origin-destination (OD) data is available, control on the network level can take advantage of the predictions of the flows in the network. Local controllers are not able to use OD information because the flows arriving at the local controller depend on the actions of other controllers elsewhere in the network, which are unknown. E.g., during peak hours the density on the mainstream (freeway) can be so high that the queue on an on-ramp spills back to the surface streets of the city, whereas (pro-active, coordinated) metering of upstream on-ramps could reduce the density of the main-stream flow and prevent spill back of the on-ramp queue. Another source of degraded network performance is that congestion may block traffic flows on routes that do not pass the bottleneck (or incident location), such as a freeway with a congested off-ramp where the vehicles that want to leave the freeway block the mainstream traffic.

Advanced Traveler Information Systems (ATIS) and dynamic traffic management (DTM) usually requires some estimate of the current traffic state as an input. The estimated state can also be used in a model predictive control (MPC) approach to optimize traffic conditions. In general, ATIS/DTM/MPC applications need the traffic states in real time. MPC is an optimal control method applied in a rolling horizon framework. Both optimal control and MPC have the advantage that the controller generates control signals that are optimal according to a user-supplied objective function.

Usually, the traffic state cannot be directly measured (everywhere) but needs to be estimated (interpolated) from in complete, noisy, and local traffic data. Commonly, volumes (flows) or average vehicle speeds are measured at certain locations in the traffic network, e.g., by double induction loop detectors or by floating car data.

In the current state of practice, often, very simple methods are used to perform such a task, such as the piecewise constant speed-based method and the piecewise linear speed-based method. These simple methods assume that the behavior of traffic is always equal under all
traffic conditions. In reality, the direction in which information travels through the network depends on the traffic conditions: under free-flow conditions, information travels downstream, but under congested conditions, information travels upstream. Therefore, these simple methods exhibit significant bias. One reason for their continuous use in practice is that the alternatives up to now have been too slow to perform in real time.

One way to take the information direction into account is using the spatio-temporal interpolation method. The adaptive smoothing method is such a method that is able to interpolate traffic conditions between detectors, taking the information direction into account. Because the ASM cannot predict the traffic state, for ATIS/DTM/MPC applications, it requires the results to be copied into a traffic flow model. An alternative approach is to directly use a traffic flow model for state estimation, such as the LWR model or second-order or higher order traffic flow models. The traffic flow models with increasing order are of increasing complexity, which comes at the cost of more parameters, which makes calibration more difficult, and at the cost of larger computation times. The choice for a model thus should be based on the balance between model complexity and model capabilities. In this present work, the LWR model is used with Extended Kalman filter (EKF).

The Extended Kalman filter not only provides a way to use traffic data to correct the model state but also allows for filtering of measurement noise. The latter is particularly important when dealing with induction loop data because these detectors are in famous for their noisy performance.

One disadvantage of the EKF is that it contains expensive matrix operations, which cause the computation time to become very high in large-scale applications. Therefore, until now, it has been very hard to apply the LWR model with the EKF in real time on large networks. Another disadvantage of the EKF is that it is at least theoretically sensitive to the nonlinearity of traffic. For the EKF, a Taylor expansion is used, which is inaccurate around capacity the derivative of the fundamental diagram that is used in the EKF shows a sudden sign change around this point, which potentially causes higher order errors (due to the so-called“flip-flop-behavior”). Alternatives exist, such as the unscented Kalman filter (UKF) or particle filters (PF). The UKF overcomes the problem of sign change not by using Taylor expansion but by numerically computing the covariance.

To study about an Extended Kalman filter and Unscented Kalman filter that are still fast enough for large-scale real-time applications, a new localization of filter for EKF and UKF are studied in this work, now a comparative study between these three filters needs to be validated, which of the filters can best be used.

**Keyword**- Extended Kalman filter (EKF), Lighthill-Whitham and Richards (LWR), Global Extended Kalman filter (G-EKF), Localized Extended Kalman filter (L-EKF), Unscented Kalman filter (UKF), Localized Unscented Kalman filter (L-UKF).