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Kalman Filter Applications for Traffic Management

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1. Introduction

Traffic congestion is a major problem in urban areas that has a significant adverse economic impact through deterioration of mobility, safety and air quality. As a result, the importance of better management of the road network to efficiently utilize existing capacity is increasing. To that end, many urban areas build and operate modern Traffic Management Centers (TMCs), which perform several functions, including collection and warehousing of real-time traffic data, as well as utilization of this data for various dynamic traffic control and route guidance applications. In order to be effective, these applications—which include Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS)—require traffic models that provide, in real-time, estimation and prediction of traffic conditions.

The complexity of transportation systems often dictates the use of detailed simulation-based Dynamic Traffic Assignment (DTA) models (Ben-Akiva et al., 1991, 2002, Mahmassani, 2001) for this purpose. Dynamic Traffic Assignment (DTA) systems support both planning and real-time applications. Planning applications may include the off-line evaluation of incident management strategies, the evaluation of alternative traffic signal and ramp meter operation strategies and the generation of evacuation and rescue plans for emergencies (e.g. natural disasters) that could affect the traffic network. Real-time applications make use of the traffic prediction capabilities of DTA systems and may include on-line evaluation of guidance and control strategies, real-time incident management and control, support of real-time emergency response efforts and optimization of the operation of TMCs through the provision of real-time predictions.

Real-time DTA systems typically comprise two main functions: traffic state estimation, and traffic prediction (Ben-Akiva et al., 2002). An overview of the state-of-the-art Dynamic Traffic Assignment framework is shown in Fig. 1. DTA functionality is supported by two main modules: a demand simulator and a supply simulator. The demand simulator fuses surveillance information with historical information for the estimation and prediction of the evolving demand patterns. This is achieved through a combination of aggregate predictive


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models and disaggregate behavioral models (Antoniou et al., 1997). The supply simulator is usually based on high-level (mesoscopic or macroscopic) models that represent traffic dynamics using speed-density relationships, kinematic representation of traffic elements of queueing theory, etc. A detailed treatment of the demand-supply interactions within a state-of-the-art DTA system can be found in Ben-Akiva et al. (2002).

Fig. 1. Dynamic traffic assignment framework overview

In the current DTA framework, only the OD flows are calibrated on-line: one of the key components of dynamic traffic assignment is the Origin-Destination (OD) estimation and prediction process (Ashok & Ben-Akiva, 1993, Ashok, 1996, Ashok & Ben-Akiva, 2000, 2002). OD estimation combines historical and real-time information to obtain dynamic demand matrices. However, a number of other parameters are used by models in the demand simulator and the supply simulator. On the supply side parameters include speed-density relationship parameters and output capacities of network links and intersections. On the demand side, additional parameters (besides the OD flows) include behavioral model parameters.

In most cases, the approach to the problem of calibration of these parameters has been to perform off-line calibration of the simulation models using a database of historic information. The calibrated parameter values are then used in the on-line simulations. The calibrated model parameters therefore represent average conditions over the period represented in the data. Models that were calibrated this way may produce satisfactory results in off-line evaluation studies, which are concerned with the expected performance of various traffic management strategies. However, this may not be the case in real-time applications, which are concerned with the system performance on the given day. If the model calibrated off-line is used without adjustment, the system is not sensitive to the variability of the traffic conditions between days, which are the result of variations in the parameters of the system, such as weather and surface conditions. Such variations may cause traffic conditions to differ significantly from the average values. Thus, the predictive power of the simulation model may be significantly reduced.

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Speed–density relationships may depend on location–specific parameters, such as type of facility, number of lanes, lane width, slope, surroundings, as well as exhibit temporal variations, i.e. they may vary by season, day of the week, or even time of day, reflecting different driving behaviors (e.g. experienced drivers during commute periods). Off-line calibration could, in principle, deal with these situations, through the generation of a historical database of different speed-density relationships, categorized by the conditions. Based on the prevailing conditions, the “appropriate” relationship could then be retrieved and used. However, traffic dynamics also depend on factors that cannot always be anticipated or observed, such as weather conditions, incidents, unscheduled maintenance work, traffic mix. Even when these factors can be predicted, it would be impractical to calibrate traffic dynamics models for each possible scenario. Minor incidents (such as a car slowing down in the break-down lane) that are not reported or captured otherwise in the system may also impact the traffic dynamics.

The output capacity of the network links and intersections is another example. Average values could in general be obtained during an off-line calibration phase. However, capacities are affected by several phenomena (including weather and lighting conditions, traffic composition, etc.) and may therefore change as prevailing conditions change. To overcome this problem, real-time data can be used to re-calibrate and adjust the model parameters on-line, so that prevailing traffic conditions can be captured more accurately. The wealth of information included in the off-line values can be incorporated into this process by using them as a priori estimates.

The remainder of this chapter is organized as follows. Section 2 presents a review of relevant literature, Section 3 presents a formulation of the on–line calibration problem as a state–space model, and Section 4 presents applicable solution approaches. Section 5 presents an application of the methodology to a network in Southampton, U.K., and Section 6 concludes the chapter with a summary and directions for further research.

2. Literature review

The topic of on-line calibration of traffic simulation models has received only limited attention in the literature. This section presents a review of prior on-line calibration research. System–level approaches are presented first, followed by research focused on individual components.

2.1 System–level approaches

Doan et al. (1999) outline a framework for periodic adjustments to a traffic management simulation model in order to maintain an internal representation of the traffic network consistent with that of the actual network. The authors categorize the error sources as demand estimation, path estimation, traffic propagation, internal traffic model structure, and on-line data observation and propose a system of on-line and off-line adjustment modules. A similar approach is proposed in Peeta and Bulusu (1999), where consistency is sought in terms of minimizing the deviations of the predicted time–dependent path flows from the corresponding actual flows. He et al. (1999) develop a combined off–line and on–line calibration process to adjust the analytical dynamic traffic model’s output to be consistent with real–world traffic conditions by periodically detecting inconsistencies between model outputs and real–world data, and actuating the correction model to correct the errors.
2.2 Supply parameters

van Arem and van der Vlist (1992) developed an on-line procedure for the estimation of current capacity at a motorway cross-section. The procedure is based on the combination of an on-line estimation of a “current” fundamental diagram with a maximum occupancy that may be achieved under free-flow conditions. The capacity is estimated by substituting the current maximum occupancy into the current fundamental diagram.

Tavana and Mahmassani (2000) use transfer function methods (bivariate time series models) to estimate dynamic speed-density relations from typical detector data. The parameters are estimated using the past history of speed-density data; no predetermined parameters or shape for the model are assumed. The method is based on time series analysis, using density as a leading indicator. Hyunh et al. (2000) extend the work of Tavana and Mahmassani (2000) by incorporating the transfer function model into a DTA simulation-based framework. Furthermore, the estimation of speeds using the transfer function model is implemented as an adaptive process, where the model parameters are updated on-line based on the prevailing traffic conditions. Qin and Mahmassani (2004) evaluate the same model with actual sensor data from several links of the Irvine, CA, network. In this chapter, determination of system input and output is derived from the higher-order continuum model. From the numerical results, the performance and the robustness of the transfer function model is in general found to be superior to the static model.

Van Lint et al. (2002) develop a state-space formulation of the travel time prediction problem and use it to derive a recurrent state-space neural network (SSNN) topology that captures the highly non-linear characteristics of the freeway travel time prediction problem. Van Lint et al. (2005) extend the model with preprocessing strategies based on imputation in order to achieve accuracy and robustness with respect to missing or corrupt data. Liu et al. (2006) present two distinct ways of using Extended Kalman Filters to address the problem of short-term urban arterial travel time prediction. Van Lint (2006) proposes a delayed EKF method for the online incremental training of a data driven travel time prediction model (a state-space neural network) for the prediction of travel times.

Antoniou et al. (2005) formulate the problem of on-line calibration of the speed-density relationship as a flexible state-space model and present applicable solution approaches. Three of the solution approaches [Extended Kalman Filter (EKF), Iterated EKF, and Unscented Kalman Filter (UKF)] are implemented and an application of the methodology with freeway sensor data from two networks in Europe and the U.S. is presented. The EKF provides the most straightforward solution to this problem, and indeed achieves considerable improvements in estimation and prediction accuracy. The benefits obtained from the —more computationally expensive— Iterated EKF algorithm are shown. An innovative solution technique (the UKF) is also presented.

Wang and Papageorgiou (2005) present a general approach to the real-time estimation of the complete traffic state in freeway stretches. They use a stochastic macroscopic traffic flow model, and formulate it as a state-space model, which they solve using an Extended Kalman Filter. The formulation allows dynamic tracking of time-varying model parameters by including them as state variables to be estimated. A random walk is used as the transition equations for the model parameters. A detailed case study of this methodology is presented in Wang et al. (2007).

Boel and Mihaylova (2006) present a stochastic model of freeway traffic suitable for on-line estimation. The model is estimated using a recursive filter based on Monte Carlo techniques (called also particle filters). Ben Aissa et al. (2006) use sequential Monte-Carlo or particle filter methods for the estimation and prediction of travel time.
2.3 Behavioral parameters
Peeta and Yu (2006) propose a behavior-based consistency-seeking modeling approach to bridge the functional gaps between route choice models and dynamic traffic assignment models vis-a-vis predicting the time-dependent network traffic flow patterns. The approach consistently addresses day-to-day learning and within-day dynamics using a single hybrid probabilistic-possibilistic behavioral model (Peeta & Yu, 2004, 2005) through intuitive if-then rules that are based on the findings of past studies in the literature. The approach avoids rigid assumptions on driver behavioral tendencies and a priori knowledge of driver behavior class fractions, and enables the classification of information characteristics and the consistent modeling of information effects. The proposed approach uses currently available data and achieves computational tractability by obviating a search procedure to predict the dynamically evolving traffic flow pattern.

2.4 Demand parameters
Ashok and Ben-Akiva (Ashok & Ben-Akiva, 1993, Ashok, 1996, Ashok & Ben-Akiva 2000, 2002) formulate the real-time OD estimation and prediction problem as a state-space model and solve it using a Kalman Filtering algorithm. One interesting characteristic of this approach is the use of deviations of OD flows (instead of the OD flows themselves) as variables. The use of deviations incorporates the wealth of structural information about spatial and temporal relationships between OD flows contained in the historical estimates into the OD estimation framework. The real-time OD estimation and prediction framework has been implemented in the DynaMIT DTA system (Antoniou et al., 1997, Ben-Akiva et al., 2002). An efficient solution algorithm for the OD estimation problem has been presented by Bierlaire and Crittin (2004). Zhou and Mahmassani (2004) develop a similar Kalman-filter based adaptive OD estimation and prediction procedure using a polynomial trend filter to recursively capture demand deviations from a priori demand estimates.

2.5 Conclusion
The problem of on-line calibration of DTA systems has received some attention in the literature. Most existing methodologies, however, impose serious constraints and make restrictive assumptions. In particular, the components of a DTA system are considered in a sequential approach and iterative/heuristic approaches are proposed to estimate the appropriate parameters on-line. Individual approaches for the on-line calibration of subsets of the parameters have also been developed. Such approaches update only a subset of the parameters in a DTA system. Therefore, all error or uncertainty is attributed to one source, which is unrealistic. Instead, an approach is needed that jointly estimates demand and supply parameters simultaneously and captures the complex demand and supply interactions (Ben-Akiva et al., 2002), thus ensuring consistency between the estimated parameters.

3. State-space formulation
A classical technique for dealing with dynamic systems is state-space modeling. In this section, the on-line calibration problem is formulated as a state-space model, comprising:

- Transition equations that capture the evolution of the state vector over time, and
• Measurement equations that capture the mapping of the state vector on the measurements.

Given that state–space models have been extensively studied and efficient algorithms have been developed to solve them, this formulation will lead us naturally to Section 4 where solution approaches are discussed.

The first step in developing a state–space model is to define the state vector. In this context, the parameters and inputs that need to be calibrated define the state. Measurement and transition equations are developed next, followed by a reformulation of the problem in terms of deviations.

3.1 State vector

The concept of the state (or state vector) is fundamental in the description of a state–space model. The state vector $x_h$ is defined as the minimal set of data that is sufficient to uniquely describe the dynamic behavior of the system at time interval $h$ (the assumption of a discrete, stochastic, dynamic system is made). The state vector includes the parameters $\pi_h$ that need to be calibrated during time interval $h$. The main parameters for the on–line calibration problem for a DTA system include:

• OD flows,
• Behavioral model parameters, such as route, departure and mode choice model parameters,
• Speed–density relationship parameters, and
• Segment capacities.

It should be noted, however, that the approach is general and can easily incorporate a different set of parameters.

3.2 Measurement equations

Available information is associated with the unknown parameter values through measurement equations. A priori values of the model parameters provide direct measurements of the unknown parameters. Surveillance information, on the other hand, can be used to formulate indirect measurement equations, where the output of the simulator model $S$ (when the unknown set of parameter values is used as input) would match the surveillance information.

By definition, a direct measurement provides a preliminary estimate of a parameter. Within the context of on–line calibration, preliminary estimates of the parameters are provided by the off–line calibration. Therefore, the vector of off–line calibrated parameter values $\pi_h^{\alpha}$ can be used as an a priori estimate of the true parameter vector $\pi_h$. The a priori values of the input parameters can be expressed as a function of the “true” parameters:

$$\pi_h^{\alpha} = \pi_h + v'_h$$  \hspace{1cm} (1)

where $v'_h$ is a vector of random error terms.

Direct measurements of some OD flows could also be available from advanced surveillance technologies, such as Automated Vehicle Identification (AVI) systems or probe vehicles. Such technologies allow the tracking of equipped vehicles as they move through the network, thus obtaining detailed surveillance information (based on a sample of the population). When the vehicles can be detected close to their origin and their destination, it
The duration of the estimation and prediction intervals was set to fifteen minutes. OD estimation requires that the count measurements are aggregated to the duration of the interval (i.e. fifteen minutes in this case study). To maintain consistency between the various algorithms, this level of aggregation has been maintained for the counts in the on-line calibration approach. Furthermore, minute-by-minute speed and density surveillance information was used.

Therefore, the measurement vector for each fifteen-minute interval consisted of 390 elements:
- 15-minute count measurements: 10 count measurements in total
- Minute-by-minute speed measurements: 150 speed measurements
- Minute-by-minute density measurements: 150 density measurements
- *A priori* state vector: 80 elements comprising 20 OD flows, 45 capacities, and 15 speed-density relationship parameters (3 groups of 5 parameters each).

The transition fractions that were estimated during the off-line calibration were used for the OD flows. The degree of the autoregressive process for the OD flows was found to be equal to two. For the supply parameters, a degree of one was used for the autoregressive process. Furthermore, variance/covariance matrices were estimated based on the output of the off-line calibration (Ashok, 1996, Balakrishna et al., 2005).

The period of analysis comprises six intervals of fifteen minutes (i.e. from 16:15 to 17:45). A warm-up period of 75 minutes (from 15:00 to 16:15) is used to ensure that the network is adequately loaded.

### 5.2 Results

Tables 1 and 2 summarize the obtained fit for estimated and predicted speeds and counts. The *base* row provides the performance when only demand parameters are estimated on-line. The next three rows show the results obtained when demand and supply parameters are jointly estimated (each row corresponds to one of the considered algorithms). RMSN values are provided, as well as percent improvement over the base case; in particular, the results for the cases where demand and supply parameters are estimated jointly are shown as percent improvement over the *base* case (i.e. when only demand parameters are estimated on-line).

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Estimated RMSN (%)</th>
<th>One-step pred. RMSN (%)</th>
<th>Two-step pred. RMSN (%)</th>
<th>Three-step pred. RMSN (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>0.1286</td>
<td>---</td>
<td>0.1540</td>
<td>---</td>
</tr>
<tr>
<td>EKF</td>
<td>0.1039 (19.2%)</td>
<td>0.1318 (14.4%)</td>
<td>0.1550 (7.0%)</td>
<td>0.2008 (-5.4%)</td>
</tr>
<tr>
<td>LimEKF</td>
<td>0.1091 (15.1%)</td>
<td>0.1321 (14.2%)</td>
<td>0.1702 (-2.2%)</td>
<td>0.2036 (-6.9%)</td>
</tr>
<tr>
<td>UKF</td>
<td>0.1293 (-0.6%)</td>
<td>0.1505 (2.3%)</td>
<td>0.1756 (-5.4%)</td>
<td>0.2221 (-16.6%)</td>
</tr>
</tbody>
</table>

Table 1. Case study results (counts)

These results indicate that the joint calibration of demand and supply parameters can improve the ability of the system to accurately estimate and predict the traffic conditions. The EKF algorithm exhibits the best performance with considerable improvements in estimation and prediction accuracy (except for three-step predicted counts).
A small decrease in performance (compared to the EKF) —but still an improvement— is obtained when the LimEKF algorithm is used. It is interesting to note that while the LimEKF algorithm has order(s) of magnitude lower computational complexity (than the EKF or UKF algorithms), it still provides a significant improvement over the base case. Improvements of more than 10% are obtained in estimated and one–step predicted speeds and counts. Furthermore, the LimEKF algorithm provides a 7% improvement in two–step predicted speeds and close to a 9% improvement in three–step predicted speeds. However, there is a small deterioration (-2.2%) in the two–step predicted counts and almost a 7% deterioration in three–step predicted counts.

The UKF algorithm seems to have the least desirable performance in this application. While in general this algorithm provides improvement over the base case, its two–step and three–step predicted counts deteriorate (-5.4% and -16.6). Furthermore, (with the exception of two–step and three–step predicted speeds) this algorithm is generally outperformed by the LimEKF, which has vastly better computation properties.

One observation that is applicable to all algorithms is that the approach shows a superior performance in prediction of speeds over prediction of counts. The source of this phenomenon may be traced to the surveillance data that have been used for this case study. In particular, sensor counts have been aggregated in 15–minute intervals, while minute–by–minute speeds and densities have been used (resulting in a larger number of observations and hence a larger "weight" on these measurements). Counts have been aggregated to 15–minute intervals in order to be as compatible and comparable as possible with the base case where only OD flows are estimated on–line. For more details on the OD estimation procedure used in DynaMIT, cf. Antoniou et al. (1997).

The third measure of effectiveness (besides the fit of speed and counts) is the computational complexity of each algorithm. As discussed above, the computational performance of the on–line calibration approach for a simulation–based DTA system is determined largely by the number of function evaluations required. The EKF and the UKF algorithms require $2n$ and $2n+1$ function evaluations (and thus runs of the simulator) respectively (where $n$ is the dimension of the state vector). Therefore, the two algorithms have similar computational requirements (converging as the dimension of the problem increases).

The LimEKF algorithm, on the other hand, requires a single function evaluation irrespective of the dimension of the problem. Therefore, the computational performance of this algorithm is vastly superior to that of the other two algorithms (EKF and UKF). The *constant* computational requirements of the LimEKF algorithm (i.e. the fact that a single function evaluation is required irrespective of the application) makes it easy to obtain some further insight into the scalability of the approach to larger networks.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Estimated RMSN (%)</th>
<th>One-step pred. RMSN (%)</th>
<th>Two-step pred. RMSN (%)</th>
<th>Three-step pred. RMSN (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>0.1266</td>
<td>0.1494</td>
<td>0.1448</td>
<td>0.1494</td>
</tr>
<tr>
<td>EKF</td>
<td>0.1107 (12.6%)</td>
<td>0.1209 (19.1%)</td>
<td>0.1303 (10.0%)</td>
<td>0.1331 (10.9%)</td>
</tr>
<tr>
<td>LimEKF</td>
<td>0.1121 (11.5%)</td>
<td>0.1249 (16.4%)</td>
<td>0.1346 (7.0%)</td>
<td>0.1362 (8.8%)</td>
</tr>
<tr>
<td>UKF</td>
<td>0.1156 (8.7%)</td>
<td>0.1249 (16.4%)</td>
<td>0.1315 (9.2%)</td>
<td>0.1346 (9.9%)</td>
</tr>
</tbody>
</table>

Table 2. Case study results (speeds)
For example, assuming that an estimation interval of fifteen minutes is used, this approach can be used for any application (i.e. combination of DTA system and network) that allows for one function evaluation (for the on-line calibration) and another run of the simulator (for the prediction of the state using the on-line calibrated parameters within that time-frame). A related observation is that using the LimEKF and the on-line calibration approach to jointly estimate all inputs and model parameters is computationally equivalent to the base case (i.e. only using OD estimation to calibrate OD flows on-line).

The impact of the on-line calibration on the parameters is discussed next, using the results from the EKF algorithm. Fig. 4 shows the estimated capacities for all segments over time. The capacity in several mainline segments has been increased (from the original 2200 vehicles per hour per lane), sometimes close to 2400 vehicles per hour per lane. A capacity of 2400 veh/hr/lane for a motorway such as M27 is reasonable. The capacity for a few mainline segments, which include weaving and/or merging, is reduced to less than 1800 vehicles per hour per lane. The location of these four segments with reduced on-line calibrated capacity is indicated in Fig. 5. The distribution of the other segment capacities is fairly uniform around the off-line calibrated mean capacity (obtained through the general guidelines of the HCM, which could not capture the subtle -geometrical or other- variations among the segments). On-line calibration, on the other hand, is able to estimate individual capacities for each segment, based on the traffic dynamics of these segments, thus capturing these variations. Ramp capacity is generally stable, with the exception of three (out of sixteen in total) ramp segments, in which small decreases (of less than 125 vehicles per hour per lane) are observed.

Fig. 4. Estimated capacities (EKF)

Fig. 5. Mainline segments with lower capacities (due to weaving and merging)
Fig. 6 and 7 show the evolution of the on-line calibrated speed–density relationships over time for mainline segments and ramp segments respectively. Each curve in these figures corresponds to a time interval, for which the on-line calibration was performed. One general observation is that on the day, for which the on-line calibration took place, the observed speeds and densities were higher than those observed during the off-line calibration (as indicated by the off-line calibrated speed–density relationship, also shown in these figures). The on-line calibrated speed–density relationships have changed in a way that captures this behavioral shift, indicating that the on-line calibration performs as intended. This shift is clearer for ramp segments (Fig. 7) and the second mainline segment group (Fig. 6(b)), while smaller changes (still in the right direction) are obtained for the other group of mainline segments (Fig. 6(a)).

(a) Group A

(b) Group B

Fig. 6. On-line calibrated speed–density relationships (Mainline segments – EKF)

Fig. 7. On-line calibrated speed–density relationships (Ramp segments – EKF)

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6. Conclusion

An on–line calibration approach for dynamic traffic assignment systems has been developed. The approach is general and flexible and makes no assumptions on the type of the DTA system, the models or the data that it can handle. Therefore, it is applicable to a wide variety of tools including simulation–based and analytical, as well as microscopic and macroscopic models.

The objective of the on–line calibration approach is to introduce a systematic procedure that will use the available data to steer the model parameters to values closer to the realized ones. The output of the on–line calibration is therefore a set of parameter values that — when used as input for traffic estimation and prediction – minimizes the discrepancy between the simulated (estimated and predicted) and the observed traffic conditions. The scope of the on–line calibration is neither to duplicate nor to substitute for the off–line calibration process. Instead, the two processes are complementary and synergistic in nature.

The on–line calibration problem is formulated as a state–space model. State–space models have been extensively studied and efficient algorithms have been developed, such as the Kalman Filter for linear models. Because of the non–linear nature of the on–line calibration formulation, modified Kalman Filter methodologies have been presented. The most straightforward extension is the Extended Kalman Filter (EKF), in which optimal quantities are approximated via first order Taylor series expansion (linearization) of the appropriate equations. The Limiting EKF is a variation of the EKF that eliminates the need to perform the most computationally intensive steps of the algorithm on–line. The use of the Limiting EKF provides dramatic improvements in terms of computational performance. The Unscented Kalman Filter (UKF) is an alternative filter that uses a deterministic sampling approach. The computational complexity of the UKF is of the same order as that of the EKF.

Empirical results suggest that joint on–line calibration of demand and supply parameters can improve estimation and prediction accuracy of a DTA system. While the results obtained from this real network application are promising, they should be validated in further empirical studies. In particular, the scalability of the approach to larger, more complex networks needs to be investigated.

The results also suggest that — in this application — the EKF has more desirable properties than the UKF (which may be expected to have superior performance over the EKF), while the UKF seems to perform better in terms of speeds than in terms of counts. Other researchers have also encountered situations where the UKF does not outperform the EKF, e.g. LaViola, J. J., Jr. (2003) and van Rhijn et al. (2005).

The Limiting EKF provides accuracy comparable to that of the best algorithm (EKF), while providing order(s) of magnitude improvement in computational performance. Furthermore, the LimEKF algorithm is that it requires a single function evaluation irrespective of the dimension of the state vector (while the computational complexity of the EKF and UKF algorithms increases proportionally with the state dimension). This property makes this an attractive algorithm for large–scale applications.

7. References


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The Kalman filter has been successfully employed in diverse areas of study over the last 50 years and the chapters in this book review its recent applications. The editors hope the selected works will be useful to readers, contributing to future developments and improvements of this filtering technique. The aim of this book is to provide an overview of recent developments in Kalman filter theory and their applications in engineering and science. The book is divided into 20 chapters corresponding to recent advances in the field.

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