PARAMETER CALIBRATION OF MICROSCOPIC TRAFFIC MODELS IN ONLINE SIMULATIONS

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Abstract. This paper discusses the continuous parameter calibration of microscopic traffic models in online simulations. An algorithm is described which uses a recent development in filter theory, the Unscented Kalman Filter. The algorithm is supplied with data of loop detectors and, of course, with the model. It adapts continuously the model parameters to the incoming data in order to keep the online simulation as realistic as possible. The parameters to be filtered have to be chosen carefully, considering their probability density function, which should be roughly Gaussian-distributed.

Numerical experiments in a simple non-real scenario was carried out using the "SK-Model" proposed by Stefan Krauss. The results show the ability of the filter algorithm to calibrate at least three of the four model parameters online.

Introduction

The online simulation of road traffic is a promising approach to provide network-wide traffic information. By continuously supplying a simulation model with actual observation data the traffic situation in the whole net, particularly in unobserved parts, can be estimated.

Up to now, macroscopic modelling approaches have been used for online traffic simulation (e.g. (Papageorgiou et al., 1989), (Kim, 2002)). Recently the online application of microscopic traffic models is gaining acceptance. With the traffic information system OLSIM Wahle et al. (2001) a research implementation of a large-scale microscopic online simulation has been developed and is simulating the highway network of a state of Germany.

The challenge in using microscopic models traffic for online simulations is beside higher requirements in computing power the difficulty to calibrate these models. That is partly due to the fact that the observed data do not directly relate to the model parameters. Furthermore some of the parameters (e.g. acceleration, top speed, headway, gap acceptance and propensity to change lane) depend on weather conditions, nightfall and darkness as well as driver- and vehicle-population characteristics. The influences of these factors onto highway traffic have been investigated in a lot of studies. For example in (Kockelman, 1998) higher flows was observed for more mature and more male traveler groups, as well for non-rainy conditions with fewer long vehicles. In (Prevedouros and Kongsil, 2003) for heavy rain on highways an average speed reduction of about 30 km/h was determined. Obviously, these influences are subject to spatiotemporal changes. Thus, a continuous and spatially separated calibration of the appropriate model parameters is required to keep an online simulation as realistic as possible.

The idea of online calibration of microscopic traffic models was mentioned in (Jayakrishnan et al., 2001), but no algorithm to do that has been proposed so far. For macroscopic models the use of the Kalman Filter approach to solve the parameter calibration problems was investigated ((Cremer, 1979), (Poschinger, 1999)) and showed encouraging results. Here we investigate the use of the Unscented Kalman Filter to calibrate microscopic traffic models in online applications. We concentrate on highway traffic, where inductance double loop detectors are used as data sources. Numerical experiments using the proposed approach are described in the second part of this paper.

Methodology

Any microscopic traffic flow model has a set of parameters, denoted as w. Besides simple models with a few parameters (e.g. "Optimal Velocity Model" (Bando et al., 1995), 5 parameters), there are also highly complex "high-fidelity" models like MITSIM (about 15 parameters), which try to reproduce traffic as realistic as possible, but at the cost of a large number of parameters and increased numerical efforts.

Typically the parameters in w are unknown and can be considered as continuous random variables, represented by their probability density function $p(w)$. Online calibration requires a continuous tracking of $p(w)$. The appropriate technique for parameter tracking of dynamic systems is filtering.

Parameter estimation with filters. Filters are recursive estimators. Besides state estimation, they are used for parameter estimation of dynamic systems. Therefore the following state space representation is formed:

$$w_{k+1} = w_k + r_k, \tag{1}$$

$$d_k = G(x_k, w_k) + e_k. \tag{2}$$

It is common to model the dynamics of a vector of parameters w_k corresponding to a stationary process with identity state transition matrix, driven by a noise term r_k. The nonlinear function $G(x_k, w_k)$ provides the data measured in the online simulation, when the traffic model is applied to the system state x_k for the timespan Δt, using the parameter set w_k. The desired output d_k is equivalent to the real-life traffic data, observed at time $t = k\Delta t$.

Despite recent development efforts in many other advanced traffic surveillance systems, inductance loops are still the most widely used traffic sensors. Loop detectors usually deliver aggregated data only, containing average speed $\bar{v}$ and average time headway $\overline{T}$ as well as their standard deviations $\sigma^{(v)}$ and $\sigma^{(T)}$. So the observations in the real world d_k respective in the simulation $G(x_k, w_k)$ are described by these four values $\left\{\bar{v}, \overline{T}, \sigma^{(v)}, \sigma^{(T)}\right\}$. However, sometimes single event data are available for further processing. Then the observation in the simulation $G(x_k, w_k)$ can be extended by another value δ, representing the absolute deviation between the event sequences measured in the real world $V_{Real}(t)$ and in the simulation $V_{Sim}(t)$, where $V(t)$ is the sum of all detected speeds between t_0 and t :

$$V(t) = \sum_{(t_i, v_i) | t_0 \le t_i \le t} v_i \tag{3}$$

For a time span $[t_0, t_0 + \Delta t]$ the deviation δ is calculated as:

$$\delta = \frac{\sqrt{\int_{t_0}^{t_0+\Delta t} (V_{Real}(t) - V_{Sim}(t))^2 \, dt}}{\int_{t_0}^{t_0+\Delta t} V_{Real}(t) \, dt} \tag{4}$$

The desired output d_k for δ is zero, because here the error e_k is observed directly.

There are different filtering algorithms to estimate $\hat{w}_k$ and its covariance P_{w_k}. The application of particle filters would allow to estimate parameters with non-Gaussian distributions $p(w)$. However, for microscopic traffic models the calculation of $G(x_k, w_k)$ demands extensive computing, so it is too costly to do that in real-time for thousands of particles (parameter sets).

The Kalman filter and its derivates require a roughly Gaussian distribution of $p(w)$. That limits the choice of parameters to be filtered, but seems to be inevitable. The basic Kalman filter is not feasable because of the non-linearity of $G(x_k, w_k)$. The Extended Kalman Filter (EKF) was the standard technique for performing recursive nonlinear estimation so far. However, it provides only an approximation to optimal nonlinear estimation and turns out to be numerically unstable. An alternative with performance superior to that of the EKF is the Unscented Kalman Filter (UKF).

Parameter Estimation with the Unscented Kalman Filter. The UKF was first proposed by Julier and Uhlmann (Julier et al., 1995) and further developed by Wan and van der Merve (Wan and Merve, 2001). It offers a better performance then the EKF and is simpler in implementation. As in the EKF the probability density functions of the parameters $p(w)$ are represented by Gaussian random variables, but are now specified using a minimal set of carefully chosen sample points.

The algorithm starts with an initial expectation of $\hat{w}_0 = E[w]$. Here a default parameter set can be used. The initial covariance matrix $P_{w_0} = E\left[(w - \hat{w}_0)(w - \hat{w}_0)^T\right]$ should reflect the confidence in the initial parameter estimation $\hat{w}_0$.

The equations of the UKF for parameter estimation are presented in Table 1. A description with regard to the present application follows below.

In (5) the propagated parameter set $\hat{w}_k^-$ is equated with the previous parameter set estimation $\hat{w}_{k-1}$, because no information about the parameter's dynamics is available.

In (6) the covariance matrix P_{w_k} is propagated by adding the noise term R_k^r. Higher noise values lead to an increase of error, but ensure a faster adaption to the changing of parameters. So R_k^r has to be chosen as trade-off between a good convergence rate and tracking performance. For solving optimization problems there are algorithms to gradually reduce R_k^r. However, for the present tracking problem a constant R^r gave satisfying results. R_k^r also sets a lower bound for the parameter covariance $P_{w_k}^-$ what prevents the algorithm from stalling. This is important for present application, because the error e_k can indeed fall to zero.

TABLE 1. Unscented Kalman Filter for parameter estimation (Wan and Merve, 2001)

For $k \epsilon \{1, \ldots, \infty\}$ with increment Δt, the time update and sigma-point calculation are given by

$$\hat{w}_k^- = \hat{w}_{k-1}, \tag{5}$$

$$P_{w_k}^- = P_{w_{k-1}} + R_{k-1}^r, \tag{6}$$

$$\mathcal{W}_{k|k-1} = \left[\hat{w}_k^- \quad \hat{w}_k^- + \gamma\sqrt{P_{w_k}^-} \quad \hat{w}_k^- - \gamma\sqrt{P_{w_k}^-}\right], \tag{7}$$

The sample weights are calculated as $W_0^{(m)} = \frac{\lambda}{L+\lambda}$, $W_0^{(c)} = \frac{\lambda}{L+\lambda} + 1 - \alpha^2 + \beta$ and $W_i^{(m)} = W_i^{(c)} = \frac{\lambda}{2(L+\lambda)}$ for all $i = 1, ..., 2L$.

$$\mathcal{D}_{k|k-1} = G\left(x_k, \mathcal{W}_{k|k-1}\right), \tag{8}$$

$$\hat{d}_k = \sum_{i=0}^{2L} W_i^{(m)} \mathcal{D}_{i,k|k-1}. \tag{9}$$

And the measurement-update equations are

$$P_{\tilde{d}_k \tilde{d}_k} = \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{D}_{i,k|k-1} - \hat{d}_k\right)\left(\mathcal{D}_{i,k|k-1} - \hat{d}_k\right)^T + R_k^e, \tag{10}$$

$$P_{w_k d_k} = \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{W}_{i,k|k-1} - \hat{w}_k^-\right)\left(\mathcal{D}_{i,k|k-1} - \hat{d}_k\right)^T, \tag{11}$$

$$\mathcal{K}_k = P_{w_k d_k} P_{\tilde{d}_k \tilde{d}_k}^{-1}, \tag{12}$$

$$\hat{w}_k = \hat{w}_k^- + \mathcal{K}_k\left(d_k - \hat{d}_k\right), \tag{13}$$

$$P_{w_k} = P_{w_k}^- - \mathcal{K}_k P_{\tilde{d}_k \tilde{d}_k} \mathcal{K}_k^T, \tag{14}$$

where $\gamma = \sqrt{L+\lambda}$, λ is a composite scaling parameter, L is the dimension of vector w resp. the number of parameters to be calibrated, $\alpha = 1$ determines the spread of the sigma points and $\beta = 2$ incorporates prior knowledge of $p(w)$.

In (7) the $2L+1$ sample points specifying $p(w)$ are calculated and stored in the columns of the matrix $\mathcal{W}$. To calculate the matrix square root of $P_{w_k}^-$ the Cholesky factorization is used.

It may happen that a parameter in $\mathcal{W}_{k|k-1}$ exceeds its valid range. For this parameter the simulation would not deliver reasonable results or even not run. A way to handle this problem is to shift the value of this parameter into its valid range. Obviously then the arrangement of the samples does not accurately capture the known statistics anymore. However, it seems to be a proper way to ensure a stable algorithm, as tests showed.

To calculate $G\left(x_k, \mathcal{W}_{k|k-1}\right)$ in (8), for each sample parameter set (each column) in $\mathcal{W}_{k|k-1}$ a copy of the simulation is created, initialized with the actual traffic state estimation and run for the time span Δt. In the simulations traffic data are observed in the same way like in the real road net. The data are stored in $\mathcal{D}_{k|k-1}$, and the mean $\hat{d}_k$ is given by their weighted average (9).

In (10) the transformed covariance $P_{\tilde{d}_k \tilde{d}_k}$ is calculated as the weighted outer product of the observations, added by the observation noise covariance R_k^e. The observation noise is here assumed to be a Gaussian, uncorrelated, white sequence with constant covariance.

In (11) and (12) the cross correlation matrix $P_{w_k d_k}$ and the Kalman gain $\mathcal{K}_k$ are calculated according to the well established Kalman Filter measurement update equations.

In (13) the predicted parameter set $\hat{w}_k^-$ is adjusted according to the deviation of the real observation d_k from the predicted observation $\hat{d}_k$. The Kalman gain $\mathcal{K}_k$ determines the degree to which $\hat{w}_k^-$ is adjusted. The covariance P_{w_k} is updated according to (14).

The algorithm works recursively with time increment Δt. In general a short Δt ensures a good tracking behaviour. However, to get reliable data from a detector a considerable number of vehicles should have passed it during Δt. Furthermore it has to be taken into consideration, how fast temporal changes of the external conditions influencing the road traffic occur. Probably an increment in range of a few minutes is recommendable and was used in the following experiments.

EXPERIMENTS

To validate the efficacy and robustness of the proposed algorithm, it was implemented and tested. For these tests the car following model proposed by Stefan Krauss (Krauss, 1998) was used. This "SK-Model" contains just four parameters with intuitive meaning. Furthermore it is robust, accident-free, numerically efficient, and in good agreement with empirical data.

In the "SK-Model" the velocity of a vehicle in the next time step is assumed by a function of its actual velocity v, the net (bumper to bumper) gap s and the velocity of the leading vehicle V. The model is defined by the following equations:

$$v_{safe}\left(t\right) = V\left(t\right) + \frac{g\left(t\right) - V\left(t\right)}{\frac{v(t)+V(t)}{2b} + 1}, \tag{15}$$

$$v_{des}\left(t\right) =| \; min\left\{v_{max}, v\left(t\right) + a\Delta t, v_{safe}\left(t\right)\right\}, \tag{16}$$

$$v\left(t + \Delta t\right) =| \; max\left\{0, v_{des}\left(t\right) - \eta\right\}. \tag{17}$$

The random pertubation $\eta = rand\left[0, \varepsilon a\right]$ is a random number between 0 and εa that allows for deviations from optimal driving. The model is parameterized by the maximum speed v_{max}, the acceleration a, the comfortable deceleration b, and the noise factor ε, which is between 0 and 1.

The filter algorithm was tested in a simple virtual scenario. Two parallel simulations of a straight 5 km long single-lane road segment with open boundaries was set-up. A detector located 4.5 km from the upstream end supplied observation data from both simulations. Cars were inserted simultaneously in both simulations with identical speed. The time headway was selected stochastically according to a given Gaussian distribution with mean 2 s (equivalent to 1,800 vehicles per hour) and a standard deviation of 1 s. Both simulations used the "SK-Model" with a time increment of 1 s.

The first simulation was used to produce traffic data at the detector as a substitute to real measurements. Its parameter set $w^{(real)}$ is unknown to the second simulation. The second simulation represented an online simulation, supplied only with the data measured at the detector in the first simulation. Its parameter set $w^{(sim)}$ was calibrated to minimize the deviation between the data measured at the detector in both simulations.

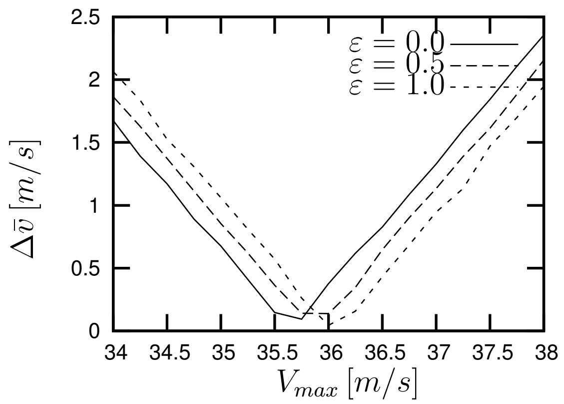
Before the filter algorithm was tested, the parameters to be filtered had to be chosen. Therefore the distribution of the error e (see (2)) in relation to $w^{(real)}$ and $w^{(sim)}$ was determined. For $w^{(real)}$ a typical parameter set for highway traffic was used (see Table 2).

TABLE 2. Typical parameter set of the SK-Model for highway traffic

Parameter	Typical Value
maximum velocity v_{max}	36 m/s
noise parameter ε	0.85
acceleration a	0.8 m/s^2
deceleration b	4.5 m/s^2

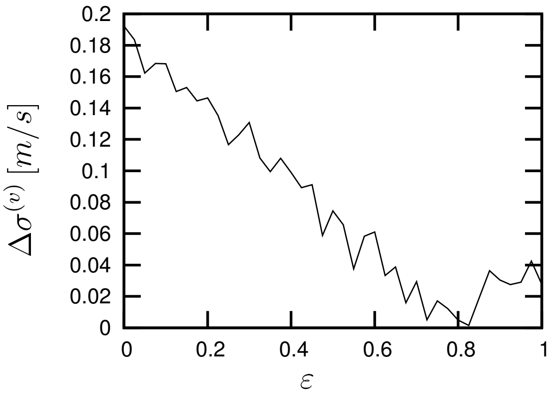
Over a lot of simulation runs the parameters in $w^{(sim)}$ was varied systematically within their valid range, and e was measured. Then the distribution of single components of e in relation to the model parameters of $w^{(sim)}$ was investigated. As expected because of equation (16), for V_{max} a significant relation to the error in mean speeds $\bar{v}$ was found (see Figure 1), which should allow a proper filtering of this parameter in this scenario. However, in congested traffic V_{max} can become effectless and thus untrackable.

FIGURE 1. Error in $\bar{v}$ as function of V_{max} in free flow regime, $V_{max}^{(real)} = 36m/s$, $\varepsilon^{(real)} = 0.85$



Because the noise factor ε limits the size of the random pertubation η, it affects the standard deviation of the measured speeds $\sigma^{(v)}$ and by this the distribution of the error in $\sigma^{(v)}$ (see Figure 2). So ε should also be filterable.

FIGURE 2. Error in the standard deviation of mean speed $\sigma^{(v)}$ as function of noise factor ε, $\varepsilon^{(real)} = 0.85$



The error distribution of the acceleration a is similar to that of ε. Therefore only one of these two parameters can properly be filtered, and a was excluded.

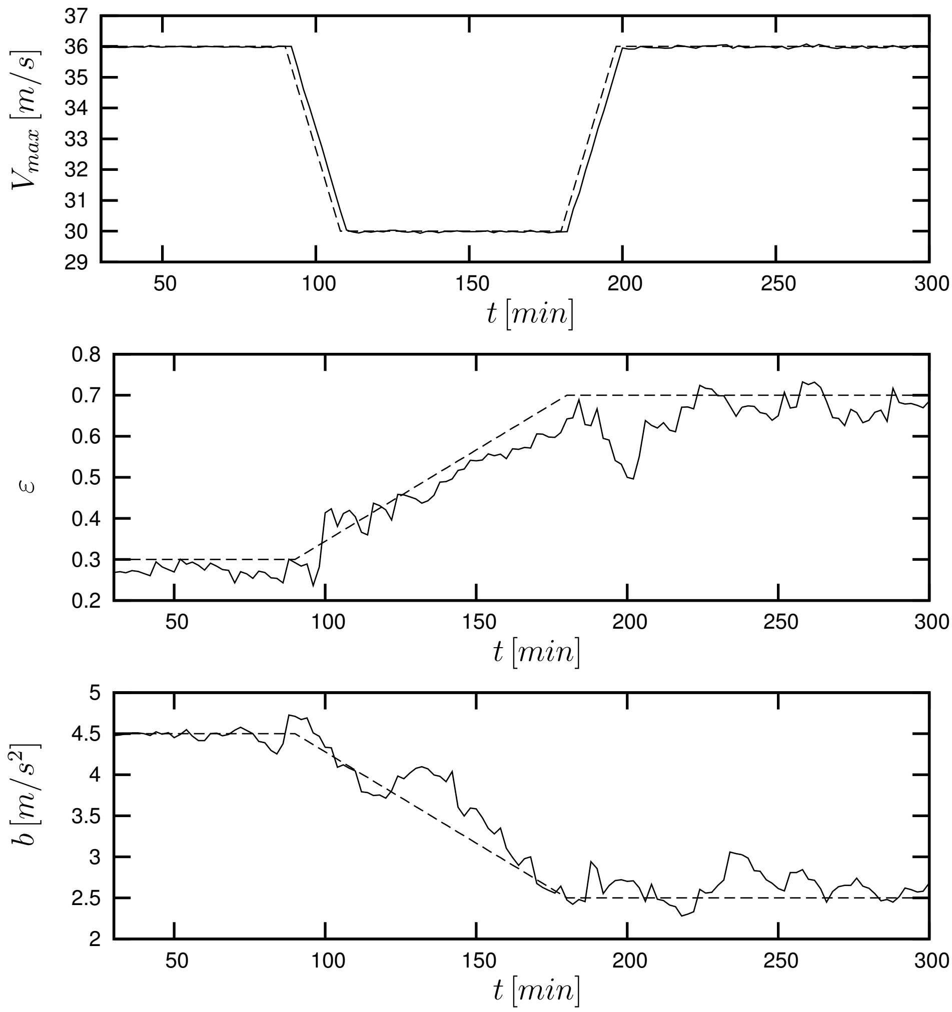
For the deceleration b no significant correlation to any of the measurands could be identified. However, it was also filtered in subsequent test.

The UKF was now used to calibrate the parameters V_{max}, ε and b of the second simulation. The filter increment was set to $\Delta t = 120s$. The diagonal values of the system noise R^r_k was set $\{0.5, 0.002, 0.7\}$ and of the measurement noise R^e_k to $\{0.001, 0.00005, 2, 1, 1\}$, because that gave the best results. Both simulations was initialized with the parameter set from Table 2. After running for 90 min the parameters of the first simulation was modified. Within 20 minutes v_{max} was decreased from 36 to 25 m/s, as it may happen e.g. in heavy rain. The deceleration b was also slowly reduced, what could be induced e.g. by a wet road. At the same time the noise factor ε was increased continuously to 0.7. A reason for that could be decreasing awareness of the drivers, e.g. because of fatigue in the night hours.

Figure 3 shows a plot of v_{max}, ε and b in both simulations.

The filter showed the best convergence and tracking performance for V_{max}, what can be explained with the significant relation between V_{max} and the error in mean speed $\bar{v}$ (see Figure 1). The filter also was able to track ε and b, but with considerable lower precision. Obviously these parameters are of less influence to the model output. Possibly for a real application the need to calibrate these parameters online would have to be examined. However, for all three parameters a continuous estimation is possible and gives usable results, at least in this simple non-real scenario.

FIGURE 3. Results of parameter estimation for V_{max} , ε and b; filtered data solid, real data dashed



CONCLUSIONS AND FUTURE WORK

The Unscented Kalman Filter can be used to continuously calibrate at least some of the dynamic parameters of a microscopic traffic flow model in an online simulation. For selecting the parameters to be calibrated the shape of their probability density functions as well as their meaning and their impact on the model results have to be considered. The number of parameters should be kept low, because for L parameters $2L + 1$ parallel simulations of the investigated road segment are needed for filtering. However, on the one hand the algorithm is predestinated for parallel computing, and on the other hand the calculation effort can be reduced by filtering the parameters just for some parts of the road net and adapt the parameters in not-filtered segments respectively.

This paper is conceptual in nature. Extensive tests of the algorithm in larger and more structured road nets, using real traffic data with a wide range of flows as well as further traffic models have to be carried out next.

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