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Off-line Calibration of Dynamic Traffic Assignment System Based on FlowSIM

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Abstract: Advanced dynamic traffic assignment (DTA) system can be utilized to mitigate traffic congestion. Therefore, the calibration of DTA parameters is becoming increasingly significant in traffic research area. Based on extended Kalman Filter (EKF) and unscented Kalman Filter (UKF) algorithms, a case study for the off-line calibration of DTA was proposed using the microscopic traffic simulation system of FlowSIM. *Experiments with a synthetic network validate the effectiveness of the two solutions, and the UKF shows better accuracy than the EKF algorithm. Furthermore, the performance of FlowSIM is promising to conduct the calibration of traffic system in future studies.*

Keywords: dynamic traffic assignment; extended Kalman Filter; unscented Kalman Filter; FlowSIM simulation

基于 FlowSIM 的动态交通分配系统离线参数标定研究

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摘要：交通拥堵已经成为最严重的城市问题之一，而先进的动态交通分配系统能够用来缓解日益严重的交通拥堵。因此，动态交通分配系统的参数标定问题一直以来都是研究领域内的热点。结合微观交通仿真系统 FlowSIM，利用扩展卡尔曼滤波和无迹卡尔曼滤波算法，对动态交通分配系统的离线参数标定问题进行了实例研究。*结果表明，两种求解算法都能够很好的实现标定功能，其中无迹卡尔曼滤波优于扩展卡尔曼滤波。研究表明，FlowSIM 能够很好的应用于交通系统的参数标定及其相关研究中。*

关键词：动态交通分配；扩展卡尔曼滤波；无迹卡尔曼滤波；FlowSIM 仿真
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Introduction

Traffic congestion is becoming a major urban problem in many countries, especially in large cities. As a solution, advanced dynamic traffic assignment (DTA) system can be utilized for the analysis and mitigation of congestion. With the development of intelligent transportation system (ITS), simulation-ased DTA study has become increasingly popular, due to its superior ability to describe the real traffic system and provide significant information for both road users and traffic authorities[1-2]. However, the

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successful implement of DTA depends largely on the accuracy of the input parameters, including both supply side and demand side. Therefore, the calibration of DTA has become a key study in traffic engineering community and has drawn many researchers' attention. Existing simulation-based DTA systems can be divided into three categories, including microscopic, macroscopic and mesoscopic level[3]. The microscopic traffic simulation system has been attractive to researchers as it can simulate vehicles in a detailed manner, which will improve the simulation accuracy[4-5]. However, the calibration study of microscopic simulation-based DTA is even more challenging for its high dimension of detailed parameters. More effective algorithms are still needed for the calibration of microscopic DTA system, under both off-line and on-line scenarios.

Based on the extended Kalman Filter (EKF) and unscented Kalman Filter (UKF) algorithms, this paper proposes a case study for the off-line calibration of DTA using the microscopic traffic simulation system of FlowSIM. The microscopic simulation system of FlowSIM is introduced in this study as the DTA model. Experiments are implemented with a synthetic network to verify both the computation and accuracy performances of the EKF and UKF, and simulation results are further discussed. The rest of the paper is organized as follows. The related literature is presented in the next section. The methodology of the EKF and UKF is described in Section 3. Section 4 presents the case study and experiment results. Finally, conclusions and future research plans are given.

1 Background

The calibration of DTA system has recently drawn much attention in both the state-of-the-art and the state-of-the-practice area. After calibration, the DTA system can be utilized to evaluate the traffic situation and thus to provide references for traffic management and control. In this regard, the development of calibration algorithm with excellent computational accuracy has been studied by many papers. A previous research proposed the framework for a DTA system to monitor and predict the actual network, and the computational results showed the advantages of DTA calibration[6]. As for the solutions for calibration models, a series of papers studied the transfer function methods and also its simulation application to calibrate the speed-density function based on real traffic data from Texas and California, USA[7-9]. These researches were implemented using the dynamic simulation model of DYNASMART, providing a systematic methodology for the calibration of simulation-based DTA system.

Another famous solution for the calibration of DTA system is the state-space model and the EKF algorithm family. In early papers, only the traffic demand parameters were calibrated for DTA systems. The approximation and deviation methods were introduced into the state-space model for the calibration of Origin-Destination (OD) matrix, and field studies were carried out to verify the performances[10]. More explicitly, the authors proposed a stochastic mapping theory for the OD assignment matrix and applied the new models in calibration cases, which showed better results compared to conventional models[11]. The automated vehicle identification (AVI) data was also considered to facilitate the OD calibration procedure with a demonstration case[12]. The calibration of supply parameters was also investigated. The speed-density relationship was formulated in state-space model, and the EKF, iterated EKF (IEKF), and unscented Kalman

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filter (UKF) solutions were selected[13].

The aforementioned calibration researches are mainly aimed for mesoscopic simulation-based DTA systems. For macroscopic ones, a general state-space approach has been conducted to predict traffic state on a freeway using EKF solution, while special attention was paid to unknown parameters[14]. Then a case study and the adaptive capabilities of the proposed stochastic macroscopic DTA model were tested in Germany, and the results were quite satisfactory[15-16].

In most cases, only the demand side is calibrated, while the supply parameters have been estimated separately[17-18]. However, the models calibrated this way cannot fit the microscopic simulation-based DTA studies. In this regard, the joint calibration of both demand and supply parameters should be emphasized to overcome the problem. More papers have focused on this area with new methods to utilize real-time data and to improve the calibration accuracy[19-20]. Among the solutions, the algorithms in Kalman filter family have received much attention, including the EKF, the UKF, and the particle filter (PF) solutions[21].

In conclusion, the calibration of DTA system still needs more research, especially for microscopic ones. Furthermore, the joint calibration of both demand and supply parameters is challenging, due to the model structure limits and solution algorithm shortcomings. Thus, this paper presents a new algorithm for the off-line calibration of FlowSIM, a microscopic simulation-based DTA system. The FlowSIM has been developed based on the fuzzy logic behavioral models[4], and has been validated by field data collected from both Europe and China, and the simulation results showed good agreement with observed data[5].

2 Methodology

2.1 Model Formulation

The state-space theory is introduced in this paper to develop the off-line calibration model. The state-space model is mainly formulated by a transition equation and a measurement equation. The transition equation describes the time-series relationship of the state vector, which represents the parameters to be calibrated. The measurement equation describes the mapping of the parameters on the DTA system, which represents the FlowSIM. The model can be written as follows

$$\begin{cases} \mathbf{x}_h = f(\mathbf{x}_{h-1}) + \mathbf{w}_h \\ \mathbf{y}_h = h(\mathbf{x}_h) + \mathbf{v}_h \end{cases} \tag{1}$$

where $\mathbf{x}_h$ means the state vector at interval h, $\mathbf{y}_h$ means the measurement vector at interval h, $f(\cdot)$ means the transition equation, $h(\cdot)$ means the measurement equation, $\mathbf{w}_h$ means the random error during transition, and $\mathbf{v}_h$ means the random error during measurement. To be noticed, the $\mathbf{w}_h$ and $\mathbf{v}_h$ should fulfill the following conditions

$$E(\mathbf{w}_h) = E(\mathbf{v}_h) = 0 \tag{2}$$

$$E(\mathbf{w}_h, \mathbf{w}_{h'}^T) = \begin{cases} \mathbf{Q}_h & h = h' \\ 0 & h \neq h' \end{cases} \tag{3}$$

$$E(\mathbf{v}_h, \mathbf{v}_{h'}^T) = \begin{cases} \mathbf{R}_h & h = h' \\ 0 & h \neq h' \end{cases} \tag{4}$$

$$E(\mathbf{w}_h, \mathbf{v}_{h'}^T) = 0 \qquad \forall h, h' \tag{5}$$

The state vector represents the parameters to be calibrated, including both demand side and supply side. For the FlowSIM DTA system, the demand parameter is the OD matrix which contains all the travel information in the network, while the supply parameters are the capacity and free-flow speed for each road section. The dimension of the state vector is decided by the network scale.

Another concern about the state vector is how to modify the model to better describe the traffic flow characteristics. A reasonable method is to introduce the idea of deviations from historical data, in which way the temporal and spatial feature of the parameters can be achieved[10-13]. The incorporation of historical data can reflect the evolution of traffic flow, thus provide accurate priori values for the transition equation. Therefore, the state-space model can be rewritten as

$$\begin{cases} \Delta\mathbf{x}_h = \mathbf{x}_h - \mathbf{x}_h^{his} = f(\mathbf{x}_{h-1} - \mathbf{x}_{h-1}^{his}) + \mathbf{w}_h \\ \Delta\mathbf{y}_h = h(\Delta\mathbf{x}_h + \mathbf{x}_h^{his}) - \mathbf{y}_h^{his} + \mathbf{v}_h \end{cases} \tag{6}$$

where $\mathbf{x}_h^{his}$ means the historical value of the state vector, and $\mathbf{y}_h^{his}$ means the historical value of the measurements.

The auto-regressive (AR) process has been assumed to be the transition equation in most previous researches and received promising results[10-13]. The degree of the AR process is decided by the evolution pattern of traffic flow in objective network.

As for the measurement equation, which represents the FlowSIM in this paper, it receives the state vector as input and then generates the measurement vector by conducting simulation module. The measurement defined in this study contains the average speed and volume count during each time interval.

2.2 Extended Kalman Filter

It is noticeable that the transition equation of AR is a linear process, whereas the measurement equation of FlowSIM is nonlinear. In result, some typical algorithms, such as the Kalmen filter (KF)[22-23], cannot be utilized to solve the aforementioned state-space model. Towards the nonlinearity of the calibration model, a series of algorithms have been developed based on the KF method. One of the famous solutions is the EKF algorithm and its modified extensions. While the original KF algorithm only applies to linear systems, the EKF utilizes the Taylor expansion to linearize the measurement equation. Although only the first order expansion is reached, the EKF method can still have good performances in the traffic engineering community[24-26].

The EKF algorithm is shown below.

Step 1. Initialization

$$\mathbf{x}_{0|0} = \mathbf{x}_0 \tag{7}$$

$$\mathbf{P}_{0|0} = \mathbf{P}_0 \tag{8}$$

Step 2. Linearization

$$\mathbf{F}_{h-1} = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\mathbf{x}_{h-1|h-1}} \tag{9}$$

$$\mathbf{H}_h = \frac{\partial h(\mathbf{x})}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\mathbf{x}_{h|h-1}} \tag{10}$$

Step 3. Prediction

$$\mathbf{x}_{h|h-1} = f_{h-1}(\mathbf{x}_{h-1|h-1}) \tag{11}$$

$$\mathbf{P}_{h|h-1} = \mathbf{F}_{h-1}\mathbf{P}_{h-1|h-1}\mathbf{F}_{h-1}^T + \mathbf{Q}_h \tag{12}$$

$$\mathbf{K}_h = \mathbf{P}_{h|h-1}\mathbf{H}_h^T(\mathbf{H}_h\mathbf{P}_{h|h-1}\mathbf{H}_h^T + \mathbf{R}_h)^{-1} \tag{13}$$

Step 4. Update

$$\mathbf{x}_{h|h} = \mathbf{x}_{h|h-1} + \mathbf{K}_h(\mathbf{y}_h - h(\mathbf{x}_{h|h-1})) \tag{14}$$

$$\mathbf{P}_{h|h} = \mathbf{P}_{h|h-1} - \mathbf{K}_h\mathbf{H}_h\mathbf{P}_{h|h-1} \tag{15}$$

where **P** means the covariance matrix of the state vector, **K** means the Kalman gain for each iteration, **F** means the linearization of transition equation, **H** means the linearization of measurement equation, the term h/h-1 is the subscript for predicted value, and the term h/h is the subscript for updated value.

Equation (9) and (10) linearize the state-space model locally to ensure the prediction and update steps. However, as discussed before, the transition equation of DTA calibration is linear. So the main focus in many papers is the linearization of the DTA system.

The Equation (10) can be solved by finite difference method, as shown below.

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$$\mathbf{H}_h = \frac{\partial h(\mathbf{x})}{\partial \mathbf{x}}\bigg|_{\mathbf{x}=\mathbf{x}_{h|h-1}} = \frac{h(\mathbf{x}+\Delta\mathbf{x})-h(\mathbf{x}-\Delta\mathbf{x})}{2\Delta\mathbf{x}}\bigg|_{\mathbf{x}=\mathbf{x}_{h|h-1}} \quad (16)$$

where $\Delta\mathbf{x}$ means the perturbation term.

The **H** matrix is computed column by column using Equation (16), showing the change of all measurements caused by each element in the state vector.

2.3 Unscented Kalman Filter

Towards the nonlinear problem for the traffic system, there has been another algorithm to efficiently adjust the filter structure, which is known as the Unscented Kalman Filter (UKF). The UKF uses a deterministic sampling approach to represent a random variable using a number of deterministically selected sample points, denoted as sigma points. The sigma points can capture the mean and covariance of the random variable and can also capture the posterior mean and covariance accurately to the second order, which theoretically will lead to higher accuracy than the EKF[27-29].

Step 1. Unscented Transformation (UT)

$$\chi_{i,h-t:h-1} = \begin{cases} \mathbf{x}_{h-t:h-1} & i=0 \\ \mathbf{x}_{h-t:h-1} + (\sqrt{(n+\lambda)\mathbf{P}_{\mathbf{x},h-1}})_i & i=1,2,...,n \\ \mathbf{x}_{h-t:h-1} - (\sqrt{(n+\lambda)\mathbf{P}_{\mathbf{x},h-1}})_i & i=n+1,2,...2n \end{cases} \quad (17)$$

$$W_i^m = \begin{cases} \dfrac{\lambda}{n+\lambda} & i=0 \\ \dfrac{1}{2(n+\lambda)} & i=1,2,...,2n \end{cases} \quad (18)$$

$$W_i^c = \begin{cases} \dfrac{\lambda}{n+\lambda} + (1-\alpha^2+\beta) & i=0 \\ \dfrac{1}{2(n+\lambda)} & i=1,2,...,2n \end{cases} \quad (19)$$

Step 2. Initialization

$$\mathbf{x}_{0|0} = \mathbf{x}_0 \quad (20)$$

$$\mathbf{P}_{0|0} = \mathbf{P}_0 \quad (21)$$

Step 3. Time Update

$$\chi_{i,h|h-1} = f(\chi_{i,h-t:h-1}) \quad (22)$$

$$\mathbf{x}_{h|h-1} = \sum_i W_i^m \chi_{i,h|h-1} \quad (23)$$

$$\mathbf{P}_{\mathbf{x},h|h-1} = \sum_i W_i^c (\chi_{i,h|h-1} - \mathbf{x}_{h|h-1})(\chi_{i,h|h-1} - \mathbf{x}_{h|h-1})^T + \mathbf{Q}_h \quad (24)$$

$$\gamma_{i,h|h-1} = h(\chi_{i,h|h-1}) \quad (25)$$

$$\mathbf{y}_{h|h-1} = \sum_i W_i^m \gamma_{i,h|h-1} \quad (26)$$

Step 4. Measurement Update

$$\mathbf{P}_{\mathbf{y},h} = \sum_i W_i^c (\gamma_{i,h|h-1} - \mathbf{y}_{h|h-1})(\gamma_{i,h|h-1} - \mathbf{y}_{h|h-1})^T + \mathbf{R}_h \quad (27)$$

$$\mathbf{P}_{\mathbf{xy},h} = \sum_i W_i^c (\chi_{i,h|h-1} - \mathbf{x}_{h|h-1})(\gamma_{i,h|h-1} - \mathbf{y}_{h|h-1})^T \quad (28)$$

$$\mathbf{K}_h = \mathbf{P}_{\mathbf{xy},h}\mathbf{P}_{\mathbf{y},h}^T \quad (29)$$

$$\mathbf{x}_{h|h} = \mathbf{x}_{h|h-1} + \mathbf{K}_h(\mathbf{y}_h - \mathbf{y}_{h|h-1}) \quad (30)$$

$$\mathbf{P}_{\mathbf{x},h} = \mathbf{P}_{\mathbf{x},h|h-1} - \mathbf{K}_h\mathbf{P}_{\mathbf{y},h}\mathbf{K}_h^T \quad (31)$$

where χ means the matrix of sigma points, γ means the measurement vector, W means the weight, and α, β, and λ are preset parameters.

The EKF and the UKF belong to the same family of Kalman Filter. However, different approaches are utilized to capture the nonlinear features of the random variable.

3 Experiment

3.1 Scenario Description

As shown in Fig.1, the synthetic network has nine intersections, with 12 OD points and 120 road sections. For demand side, the 12 OD points can generate 144 OD parameters. For supply side, the speed-capacity relationship function in FlowSIM is shown below.

$$q = uk_j[1-(\frac{u-u_0}{u_f-u_0})^{1/\alpha}] \quad (32)$$

where q denotes the flow, u denotes the speed, k_j denotes the jam density, u_f denotes the free-flow speed, u_0 denotes the minimum speed, and α is the nonlinear parameter.

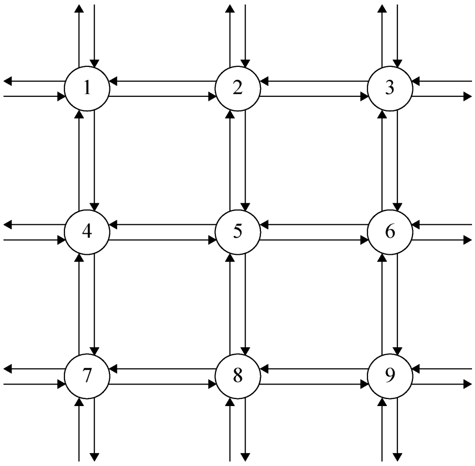

Fig. 1　Graphic of synthetic network

Including k_j, u_f, u_0, and α, the section capacity is also considered as a supply parameter in FlowSIM. In this regard, each section has five parameters to be calibrated, making the total supply parameters to be 600. As a result, the dimension of the state vector is 744 at each interval.

The calibration period is 7:00~19:00, with 48 intervals of 15-minute. A warm-up period is set 6:30~7:00 to make the simulation network more realistic. The number of total parameters to be calibrated in the entire experiment is 35 712.

For the measurement, each road section has been equipped with a traffic sensor, which can record the flow count and average speed for each interval. Thus the measurement vector has a dimension of 240.

For the transition equation, the degree of AR for demand side is set as two, while the degree for supply side is one. To generate historical data, Equation (33) is used to randomly prepare various scenarios.

$$\mathbf{x}_h^H = (0.7 + 0.3 \times \text{Rand}) \times \mathbf{x}_h^{true} \tag{33}$$

where $\mathbf{x}_h^{true}$ denotes the state vectors for the study period, $\mathbf{x}_h^H$ denotes the vectors generated for historical scenarios, and Rand means the random vector.

Then the historical measurement vectors can be obtained by simulation using historical parameters. To evaluate the calibration performance, the estimated state vector will be simulated by FlowSIM to generate the measurements. The normalized root mean square error (RMSN) is used in this paper to compare the discrepancies between simulated and real measurement vectors, as shown below.

$$\text{RMSN} = \sqrt{N\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \Big/ \sum_{i=1}^{N} y_i \tag{34}$$

3.2 Experiment Results

Compared with real data, Fig.2 shows the calibration RMSN for estimated flow by using EKF and UKF algorithms, as well as the flow RMSN for historical data. Similarly, Fig.3 presents the calibration results for speed values. The simulation experiments are all conducted at 15 min intervals.

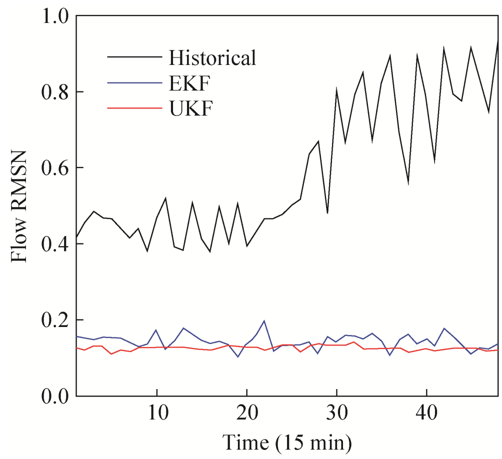

Fig. 2　Comparison between new model and typical model

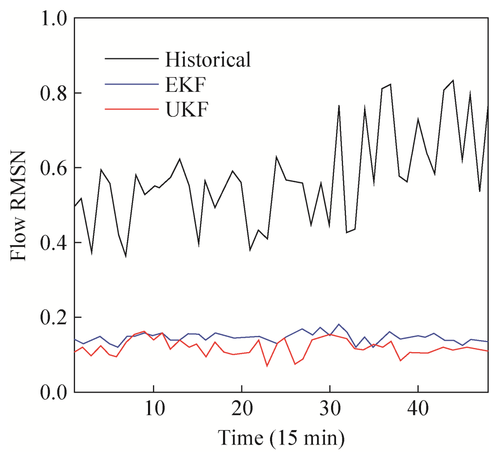

Fig.3　Comparison between steady state and non-steady state

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Tab.1 presents the overall RMSN values for all the algorithms. The second row provides the RMSN error of previous data without calibration. The next two rows provide the evaluation performances using the calibration results of EKF and UKF algorithms. The RMSN from historical data can be regarded as the worst case.

Tab. 1 Comparison of RMSN error for EKF and UKF

Data	Flow RMSN	Speed RMSN
Historical	0.596 2	0.573 3
EKF	0.148 7	0.147 5
UKF	0.129 0	0.120 0

From all the results in figures and table, it can be observed that both the EKF and UKF algorithms are effective for the calibration of DTA system. Furthermore, the UKF solution outperforms the EKF, which shows consistency with previous studies.

4 Conclusions

In this paper, a case study for the off-line calibration of DTA system is proposed, using the microscopic traffic simulation system of FlowSIM. Both the EKF and the UKF algorithms are presented as solutions for the state-space model. Experiments are presented with a synthetic network, and the results show that both solutions are effective for the off-line calibration task of FlowSIM, and the UKF shows better accuracy than the EKF algorithm. The advantage of EKF and UKF is that this kind of filter algorithms can solve the nonlinear problem of the DTA system to be calibrated. Furthermore, it can be observed that the performance of FlowSIM is promising to conduct the calibration of traffic system.

The accuracy of EKF and UKF depends on the nonlinear procedure. As a result, the computation complexity can be too expensive when the dimension of the network is high. Therefore, further research should focus on the reduction of computational time, especially for the purpose of on-line calibration. Moreover, the study based on real traffic network is expected.

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