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Compendium of Papers

Unscented Kalman filter for urban network travel time estimation

Ré-Mi Hage^{a*}, David Betaille^a, François Peyret^a, Dominique Meizel^b

^aIFSTTAR, route de Bouaye CS, Bouguenais Cedex 44344, France

^bXLIM, Limoges University /CNRS UMR #7252, 16 rue Atlantis, Limoges 87000, France

*Corresponding author: re-mi.hage@ifsttar.fr

Abstract

To estimate urban network travel time, the classical analytical procedure uses cumulative counts at upstream and downstream locations of links. This procedure is vulnerable in urban networks mainly due to significant flow to and from mid-link sinks and sources. Moreover, most urban network links are only equipped with detectors at their end. Therefore without information on the percentage of turning movement at crossroads, the classical analytical procedure is not applicable. The algorithm proposed and validated in this research estimates urban links travel times based on an unscented Kalman filter (UKF). This algorithm integrates stochastically the vehicle count data from underground loop detectors at the end of every link and the travel times from probe vehicles. The proposed methodology can be used for estimating travel time in real-time. Moreover, with this methodology the number of upstream vehicles as well as the number of mid-link sink/source vehicles is estimated for each link.

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Keywords: Unscented Kalman filter; urban travel time estimation; cumulative plots; multi-source fusion; probe vehicles; loop detectors; map-matching.

1. Introduction

Travel time information has a significant impact on the efficiency and the capacity of the road network. It has the potential to reduce congestion at both temporal and spatial scales. An essential step towards a reliable traffic monitoring and management is accurate travel time estimation. Different techniques are used to estimate travel time on roads. These techniques depend on the type of system (i.e. fixed or mobile sensors) used to collect traffic data. Fixed sensors, such as inductive loop detectors, are the oldest and most widely used sensors for generating traffic data. They provide temporal traffic state information, though only point based data. Under certain assumptions, researchers have proposed methodologies for travel time estimation that can be characterized by deterministic [1-3] or stochastic approaches [4-5]. Mobile sensors, such as probe vehicles, are vehicles equipped with vehicle-tracking equipment (e.g. Global Positioning System). They provide trajectory data, i.e. time stamp and position coordinates, and hence probe vehicle travel time. Since probe vehicle are random sample from the

* Corresponding author. Tel.: +33-2-408-45647.

E-mail address: re-mi.hage@ifsttar.fr.

population of the vehicles in the network, the accuracy of travel time estimation with probe vehicles is related to the number of the latter. Research focused on determining the minimum number of probe vehicles required for providing statistically significant travel time estimation [6].

The properties of these two data sources are complementary. Hence, they can be harnessed by developing a solution that merges multi-sensor data for the considered problem, in particular in urban areas [7]. Most of existing fusion techniques [8-9] has not been dealing with traffic signals, which affects link travel time of probe vehicles, nor has processed the flow to and from mid-link sink and source. The CUPRITE methodology [10] addressed these problems by deterministically rectifying the cumulative number of vehicles at the upstream of each link using data from the traversing probe vehicles. CUPRITE corrects the upstream cumulative count at the minute-ceiled instant of occurrence of the probe vehicle, as well as prior and after this instant. It is a smoothing technique that does not match real-time constraint. Moreover, this methodology is sensitive to the noise on travel time probe vehicles. Finally, CUPRITE requires “a minimum” number of probe vehicles to work properly in networks, especially when the percentages of turning movements are unknown.

The majorities of above researches are limited to freeways and cannot be applied in urban networks, where the travel time estimation is more challenging. The present study bridges this gap by using a statistical filtering approach based on an unscented Kalman filter (UKF).

2. Unscented Kalman filter

The most common strategy used for applying a Kalman filter (KF) to a nonlinear system is to make use of the extended Kalman filter (EKF). In the EKF, the probability distribution function is propagated through a linear approximation of the system around the operating point at each time. Consequently, the EKF requires computing the Jacobian matrices that can be sometimes difficult and complicated to obtain. Furthermore, the linear approximation of the system at a given time may introduce errors in the state, which may lead the state to diverge over time. In order to overcome the drawbacks of the EKF, other nonlinear state estimators such as the UKF have been developed. The UKF uses a deterministic sampling technique, known as the unscented transform, to pick a minimal set of sample points (called sigma points) around the mean. These sigma points are then propagated through the non-linear functions, from which the mean and covariance of the estimate are recovered. More details can be found in [11].

3. Travel time state space modeling

By definition, the link travel time for a vehicle is the time needed to travel from the upstream point to the downstream point in the link. This research focuses on estimating the average travel time for all the vehicles that depart downstream for each link in the network. Fig. 1 illustrates the studied urban network for estimating travel time using mid-link sinks and sources. The mid-link infrastructures, such as side streets, parking lots, private properties etc., are acting as sink or source or both and are simply represented by additional mid-links. The state vector, its evolution in time, the nature of the observations and the algorithm of the proposed UKF filter are detailed below.

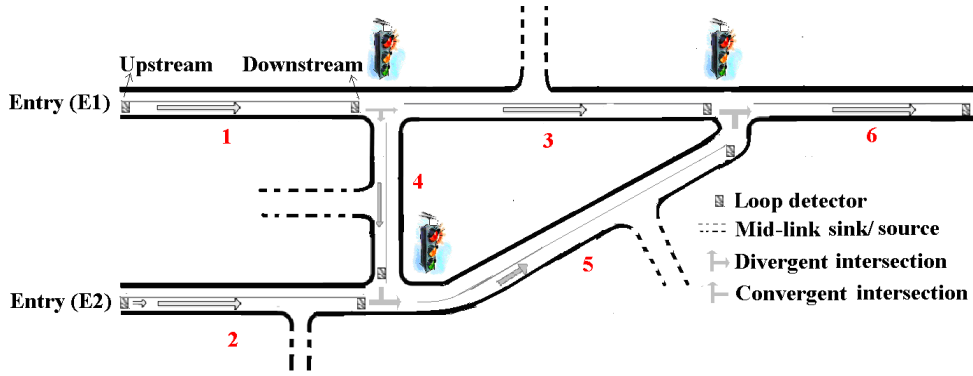


Fig. 1. Studied network.

3.1. State vector

Suppose that a given studied network (Fig. 1) is equipped with loop detector at the end of each link and at its two entries (E1 and E2). For each link k ($k=1, \dots, 6$), one needs to estimate the travel time, the number of vehicles that enter/exit from/to the mid-link source/sink and the number of vehicles at upstream with sampling time T_S of 1 minute, which corresponds to the period of loop detectors aggregation (cf. section 3.3). The state vector for each link k can be described as follows:

$$x_k(t) = \begin{bmatrix} TT_k(t) \\ N_{dk}(t) \\ N_{uk}(t) \\ q_{uk}(t) \\ p_k(t) \\ N_{uk}(t - T_S) \\ \dots \\ N_{uk}(t - h_k \times T_S) \end{bmatrix} \quad k=1, \dots, 6$$

with

- TT_k : the travel time;
- N_{dk} : the downstream cumulative count of vehicles;
- q_{uk} : the upstream flow;
- N_{uk} : the upstream cumulative count of vehicles of link k ;
- p_k : the cumulative number of vehicles that enter/exit the link from/to the mid-link source/sink; and
- Previous N_{uk} : history of the cumulative upstream count of vehicles. This history tabulates a fixed number h_k of past counts, this number being a parameter of the model and specific to each link.

3.2. Dynamic model

We suppose that the state at time t derives from the state at time $t-T_S$ as follows:

- The classical analytical procedure states that the cumulative number of vehicles at link entrance shall be equal to the cumulative number of vehicles at link exit after an average travel time TT at time t . Thus TT at time t is equal to difference between time t and the corresponding time t_1 defined such that $N_{uk}(t_1)=N_{dk}(t)$;
- The classical analytical procedure states that the cumulative number of vehicles at link entrance shall be equal to the cumulative number of vehicles at link exit after an average travel time TT at time t . Thus TT at time t is equal to difference between time t and the corresponding time t_1 defined such that $N_{uk}(t_1)=N_{dk}(t)$;
- The cumulative number at the upstream at time t is the cumulative number at the upstream at time $t-TS$, incremented by the flow at the upstream multiplied by TS ; and
- The flow at the upstream at time t is stable, as well as the cumulative mid-link vehicles number.

Therefore the evolution model is as follows:

$$\begin{aligned}
 TT_k(t) &= t - N_{uk}^{-1}(N_{dk}(t)) \\
 N_{dk}(t) &= N_{uk}(t - TT) + p_k(t) \\
 N_{uk}(t) &= N_{uk}(t - TS) + q_{uk}(t) \times TS \\
 q_{uk}(t) &= q_{uk}(t - TS) \\
 p_k(t) &= p_k(t - TS)
 \end{aligned} \tag{1}$$

The key point in this evolution model is that it depends on the state vector itself (second equation in (1)) therefore it is impossible to explicit the Jacobian matrix needed in the EKF, which justifies the use of the unscented version of Kalman filtering.

3.3. Observation model

The considered observations are the travel time from the probe vehicles and the number of vehicles counted by the loop detectors. The data from the probe vehicles contain the vehicle ID, the GPS position coordinates, the time, and eventually the speed, moving direction, etc. To estimate individual travel times, a map-matching is required. This is an important step in the process since its accuracy will directly affect the final results. Map - matching algorithms may adopt either a geometric or a topologic or a combination of both approaches [12]. Observations are threefold:

Case 1: a travel time issued from a probe vehicle gives an observation of TT associated to a noise v_{1t} that is assumed to be zero mean Gaussian white noise with covariance R_{1t} .

Case 2: the reading from the counter associated to a loop detector at the downstream of a link gives an observation of N_d with a noise v_{2t} assumed to be zero mean Gaussian white noise with covariance R_{2t} .

Case 3: the reading from the counter associated to a loop detector at the upstream of a link gives an observation of N_u with a noise v_{2t} assumed to be zero mean Gaussian white noise with covariance R_{2t} . Such upstream detector is redundant with downstream and therefore is not always set up in networks. In the one studied, only its two entries are equipped with loop detector, i.e. at the upstream of links 1 and 2.

In addition to the above observations, the law of vehicles conservation at the intersections of the network introduces constraints that can be considered as observations. This law states that (eq. 2), at an intersection and at every time t , the total number of vehicles at the exit links (with indexes $k=i$) is equal to the total number of vehicles at the entrance links (with indexes $k=j$). If we consider that the percentages of turning movements at the intersections are known “a priori”, then the N_u of the entering links is defined by the corresponding proportion of the total N_d of the exit links. In this case, the problem in the network can be considered as a decoupled problem between its different links, and every link can be processed by its own UKF. Consequently the constraint in eq. 2 becomes un-relevant.

$$\sum_i N_{di} - \sum_j N_{ij} = 0 \quad (2)$$

The covariance matrices will vary whether the counters or probe vehicles travel times are considered. Counters standard error will be fixed to 5 vehicles. In the case of probe vehicles, the covariance should characterize the possible errors occurring in the process of map-matching the GPS positions. GPS errors and the consecutive map-matching errors are fixed depending on the location of the link. In a dense city center, the order of magnitude of these errors is several tens of meters, whereas in an open area, it is only a few meters. In a very first approximation, the travel time observation errors are fixed to a maximum of 10 seconds down to a few seconds. When the intersection constraint is considered as an observation, its associated error covariance is approximately set to $\epsilon \ll 1$, because of the high confidence level assumed for the vehicles conservation law.

3.4. Algorithm

Data from detectors are aggregated each minute whereas data from probe vehicles are available between two consecutive minutes t and $t+1$. In order to use the information at its exact time, an intermediate step is performed between t and $t+1$. Fig. 2 summarizes the UKF algorithm.

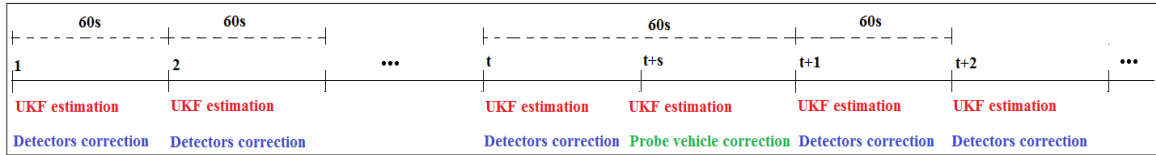


Fig. 2. UKF algorithm.

4. UKF testing

The algorithm is implemented and tested with simulated data. The simulation is made with AIMSUN in the urban network described in Fig. 1. For each link, the free flow speed is set to 36 km/h and the flow is limited to 1008 veh/h. For an hour of simulation, the demand flow, i.e. the flow at the two entries (E1 and E2), is the following. For the first period of 20 min, the average flow is 400 veh/h, for the second 20 min period, it is increased to 900 veh/h and it is further decreased to 400 veh/h during the final 20 min. The percentage of vehicles that are lost into the sink and gained from the source (perturbation) varies from one link to another. The proportion of turning movement at the divergent intersection varies in time. Moreover, probe vehicles are a random sample from the population and 1%, 5%, and 10% of the vehicles were considered as probe vehicles. For each probe vehicle, we simply use its corresponding travel time.

4.1. Model performance testing

The following statistics are used to qualify the proposed methodology:

$$error_i = actual_i - estimated_i \quad (3)$$

$$MAPE = \sum_{i=1}^n (|error_i / actual_i|) / n \quad (4)$$

$$accuracy(\%) = (1 - MAPE) \times 100 \quad (5)$$

Where,

- $actual_i$, $estimated_i$, and $error_i$ are respectively the actual average travel time, the estimated travel time, and the relative error for the i^{th} estimation interval;
- $MAPE$ stand for the mean absolute percentage error;
- $Accuracy$ indicates the mean exactitude in %; and
- n is the total number of estimation interval.

4.2. Results and analysis with known percentages of turning movements at intersections

The percentages of turning movements being known, the network travel time estimation can be decoupled link per link. This section presents the results of the classical analytical procedure, the CUPRITE model and our UKF-based model for link 3. With CUPRITE, the upstream cumulative plot is redefined deterministically using a vertical scaling and a shifting technique in order to match the information of probe vehicles travel times, whilst the downstream cumulative plot is kept unchanged. The upstream cumulative plot redefinition is made at the minute-ceiled instant of occurrence of each probe vehicle, as well as prior and after this instant. Finally CUPRITE applies the classical analytical procedure between redefined upstream and downstream cumulative plots to estimate the average travel time. In a real-time context, prior correction would not have been useful. In fact, any correction on travel times before the occurrence of a probe vehicle is questionable with regard to the “a posteriori” use of this information. In the context of this research, we have adapted CUPRITE in order to match real-time constrain, i.e. the upstream plot redefinition is made at the time and after the probe vehicle occurrence. The results of both CUPRITE and CUPRITE real-time are always presented in the sequel.

4.2.1. Sensitivity of CUPRITE

The classical analytical procedure gives an unbiased estimation of the travel time when the vehicles are conserved. In such case, the CUPRITE (as well as CUPRITE real-time) correction should remain zero. But in the eventuality of a significant deviation between the actual TT and the one from the considered probe vehicle, this correction will induce a bias in the travel time estimation Fig. 3 illustrates the sensitivity of CUPRITE to a biased probe vehicle travel time. With the UKF, this deviation has mainly an effect at the probe vehicle instant of correction. After this correction, the UKF will overcome this bias, thanks to the dynamic model and detectors corrections, whereas CUPRITE remains biased as long as no new probe vehicle passes.

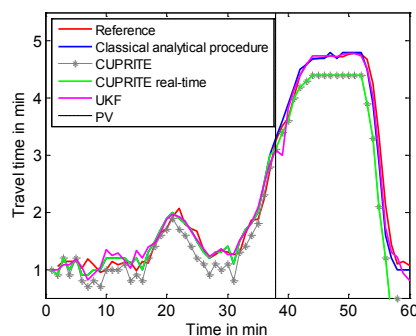


Fig. 3. Demonstration of the sensitivity of CUPRITE with 1 probe vehicle.

4.2.2. Results and analysis

Fig. 4 (a) represents the classical analytical procedure error in minute. The cumulative effect of the perturbation, especially on the last 10 minutes, can be noticed. Fig. 4 (c) and (d) represent respectively the CUPRITE and CUPRITE real-time error in minutes. They show that in some simulations, the error reaches up to ± 2 min. Here, we observe again the sensitivity of CUPRITE correction to probe vehicles TT. Fig. 4 (b) represents the UKF error. In UKF and CUPRITE, the standard deviation of the estimated travel time decreases as the percentage of probe vehicles increases. Finally, UKF estimation is observed to be less noisy than CUPRITE. Table 1 summarizes the average accuracy in percentage with 5% mid-link sinks/sources, for 20 simulations, for the classical analytical procedure, CUPRITE and UKF with 1%, 5%, and 10% of probe vehicles. It is observed that both UKF and CUPRITE correct the bias in the classical analytical procedure. As expected, their accuracies increase with probe vehicle percentage.

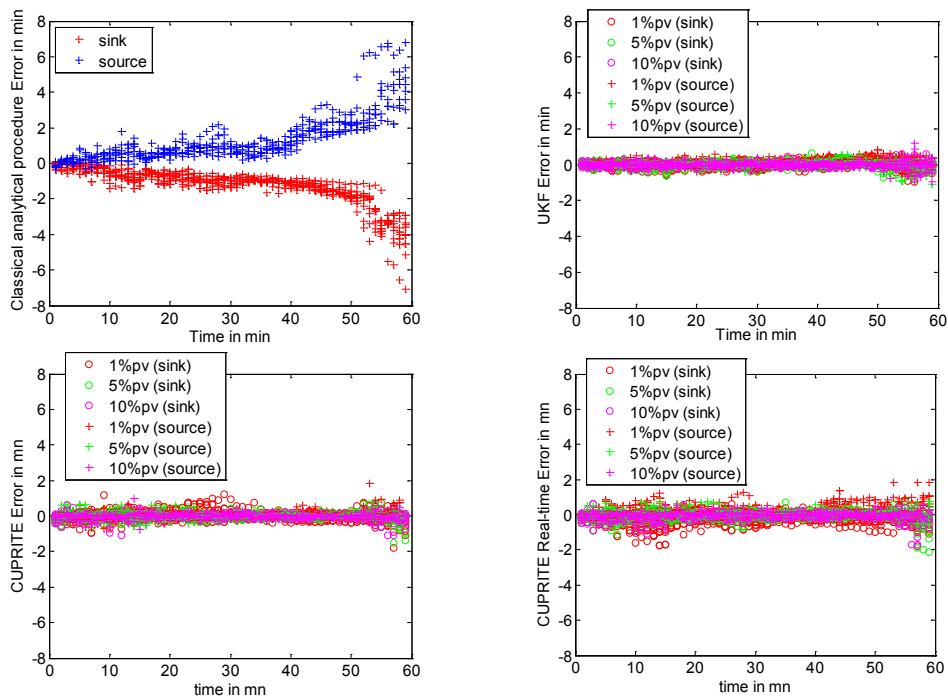


Fig. 4. (a) Classical analytical procedure error; (b) UKF error; (c) CUPRITE error, (d) CUPRITE Real-time error.

Table 1. Average accuracy (100-MAPE%) in % of CAP, UKF, CUPRITE, and CUPRITE real-time with mid-link sink/source.

% of probe vehicles	CAP	UKF	CUPRITE	CUPRITE real-time
	47			
1		82	82	81
5		91	90	89
10		94	92	91

4.2.3. Outliers detection and exclusion

Fig. 5 (a) illustrates the effect of a probe vehicle outlier (3 min vs. 2 min) on the TT estimation, whereas Fig. 5 (b) illustrates the effect of the occurrence of a detector outlier, where the counted downstream value has been fixed for 2 consecutive minutes. By means of a chi-square test on the squared normalized innovation (also called the Mahalanobis or Nyquist distance), the UKF was able to reject the outlier, whereas CUPRITE (as well as CUPRITE real-time) was not, leading to an aberrant TT estimation.

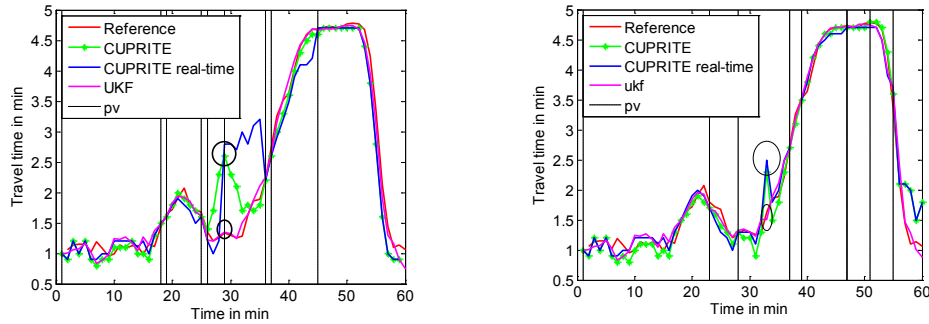


Fig. 5. TT estimation by the classical analytical procedure (CAP), CUPRITE, CUPRITE real-time, and UKF with (a) 1 probe vehicle outlier; (b) detector outlier

4.3. Results and analysis with unknown percentages of turning movements at intersections

This section presents the results of the CUPRITE model and our UKF-based model for the network described in Fig. 2 where the percentages of turning movements are unknown. In this case, the classical analytical procedure is not applicable.

4.3.1. Upstream and mid-link sink/source cumulative counts

To estimate link 3 travel time, for example, CUPRITE uses the downstream cumulative count of link 1 as the upstream cumulative number of link 3, despite part of the flow that goes to link 4. Fig. 6 illustrates the redefined upstream cumulative plot (obviously much higher than the reality) with both CUPRITE and CUPRITE real-time with 10% of probe vehicles. We notice that CUPRITE may redefine the upstream plot under the downstream plot. In fact, only when the percentage of probe vehicles reaches at least 20% CUPRITE is capable to properly correct the upstream cumulative plot. As concerns CUPRITE real-time, the link 3 upstream cumulative plot is always pulled toward the link 1 downstream cumulative plot. To conclude, with an unknown percentage of turning movement between links 1, 3 and 4, the deviation between the CUPRITE real-time and the reference travel times is significantly biased by the excessive considered flow from upstream. As per UKF, the upstream cumulative count for all the links in the studied networks is properly estimated, even with 1% probe vehicles, despite mid-link perturbations. The cumulative number of mid-link sink/source without direct measurement of this perturbation is also estimated. Fig. 7 illustrates the estimation of the latter with 1%, 5%, and 10% of probe vehicles.

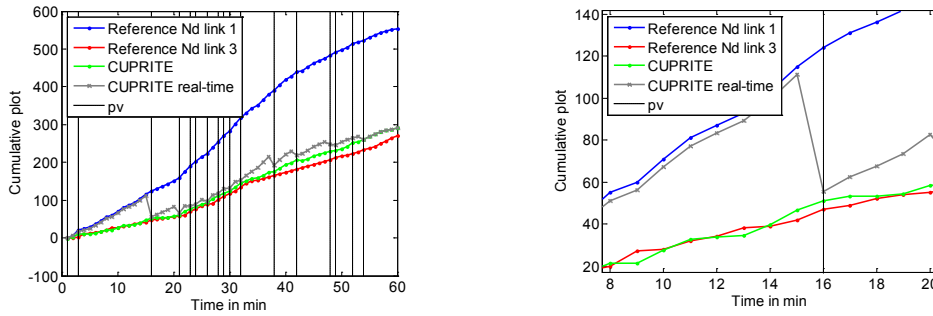


Fig. 6. The redefined upstream cumulative plot with CUPRITE and CUPRITE real-time.

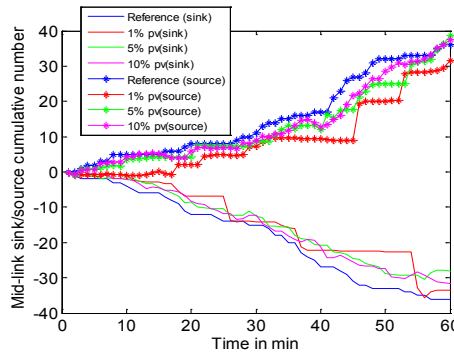


Fig. 7. The redefined upstream cumulative plot with CUPRITE and CUPRITE real-time.

4.3.2. Results and analysis

Table 2 summarizes the average accuracy in percentage of the UKF for each link with 1% to 3% mid-link sinks/sources, for 10 simulations, with respectively 1%, 5%, and 10% of probe vehicles. The performance is consistent for all links, either they are perturbed or not, and the accuracy increases with the percentage of probe vehicles as expected. Fig. 8 shows the error in minute for each link. Even without information on the turning proportion, the UKF is capable of estimating properly their TT with a maximum error of 1 minute.

Table 2. Average accuracy (100-MAPE%) in %

Probe vehicle percentage	Link number					
	1	2	3	4	5	6
1	90	90	87	87	91	94
5	91	91	90	90	92	96
10	92	92	91	91	94	97

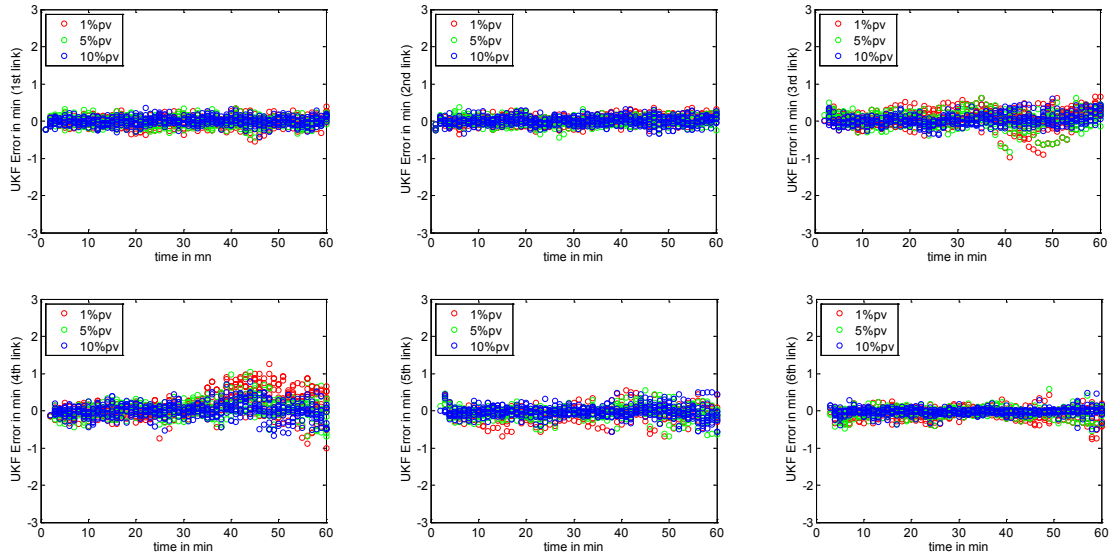


Fig. 8. UKF error (a) for the first; (b) for the second; (c) for the third; (d) for the forth; (e) for the fifth; (f) for the sixth link.

5. Conclusion

The UKF filter developed here provides encouraging results for travel time estimation in urban network with mid-link sinks and sources and unknown percentages of turning movements. The evolution model of this algorithm is based on the classical analytical procedure. The observations are the vehicle counts from the loop detectors, which are located at the end of every link, and the travel times from probe vehicles after they have been map-matched with the appropriate link.

The main contribution of this article is that the UKF stochastic approach, even with a few number of probe vehicles (1%), estimates the number of vehicles at the upstream of each link and consequently the proper travel time of the network. In addition, it estimates the number of mid-link sink/source vehicles. Moreover, the UKF offers the possibility to introduce an error model for map-matching and resulting travel times, as well as for loop detectors. Thus, the estimation is robustified by statistic tests, made possible by the UKF formalism. Indeed, this formalism enables the detection and exclusion of outliers, like mismatched GPS positions or loop deficiency. Furthermore, UKF can be applied in real-time.

In this article many simulations were run with variable flow, variable percentage of vehicles that were randomly selected and considered as probe vehicles, variable percentage of turning movements and finally variable percentage of mid-link perturbations. The determination of the travel time observation error model from GPS data is under development. In the future, work for applying this model to real data will be conducted.

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