ADAPTIVE FREEWAY TRAFFIC STATE ESTIMATOR BASED ON MEASUREMENT FUSION METHOD

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Abstract— In this paper, real-data testing results of a real-time freeway traffic state estimator are presented. The general method used for real-time freeway traffic state estimation is based on extended Kalman filter algorithm and nonlinear macroscopic traffic flow modeling. Macroscopic traffic flow model contains three important and unknown parameters (free speed, critical density and exponent), which should be estimated with off-line or on-line methods. One innovative approach of the estimator is the real-time joint estimation of traffic flow variables (traffic flow, mean speed and traffic density) and model parameters, that leads to some significant features such as: avoidance of prior model calibration, automatic adaption to changing external conditions (e.g. weather conditions, traffic composition,…).
The purpose of the reported real-data testing is, first, to demonstrate some drawbacks in previous methods, second, to propose two methods based on dual filtering and measurement fusion to improve the previous methods.
Keywords: Traffic State Estimation, Macroscopic Traffic Flow Model, Extended Kalman Filter, Adaptive Filter, Estimation Fusion.

I. Introduction

Real-time freeway traffic state estimation is related to estimating traffic flow variables (traffic speed, traffic flow and traffic density) with an appropriate time step (5-10 s), and limited amount of information from traffic measurements ([8], [9], [11] and [12]). Real-time estimation of traffic flow variables is an important task in traffic control and surveillance and has been investigated for the past three decades [7]. The essential contribution of the freeway traffic state estimation task is that usually the number of traffic variables to be estimated are larger than the number of traffic variables that are measured directly.

Many of the researches in the traffic state estimation are based on second order macroscopic traffic flow modeling and Extended Kalman filter (EKF) algorithm, see a concise review in [8]. Also, in [4] a particle filter is used to formulate the problem of real-time estimation of traffic state for a freeway stretch and in [5] application of traffic state estimation is reported for short inter-detector distances.

One of the main aspects in recent experiments is on-line estimation of the model parameters ([8], [9], [10] and [14]). Some advantages of this approach are:

(i) Avoidance of off-line model calibration: The model parameters must be valued by available off-line measurement data ([1], [6]). However, by online estimation of these model parameter values (i.e. joint estimation of traffic flow variables and model parameters),the off-line model calibration can be avoided.

(ii) Automatic adaption to external changes in conditions: With fixed model parameter values, a traffic state estimator may lead to unacceptable performance under changing external conditions [3]. However, if the estimator can adapt its model to changes in external conditions via online model parameter estimation, this drawback may be overcome.

These features are completely illustrated in [8], [13] and [14]. In these works, joint estimation of the model parameters and traffic variables are done by one EKF (joint filtering). In this paper, it is illustrated by real-data testing that joint filtering approach may lead to unstable performance and dual filtering approach is proposed and tested for this problem. In both joint and dual filtering methods, speed and density of one specific segment from the freeway stretch have to be chosen for the model parameters estimation. It is shown that the estimator performance is very sensitive to this selection and the simulation results based on different segments are not the same. In order to improve the proposed dual filtering method, measurement fusion technique is suggested for fusion of speed and density of all segments. In order to draw more reliable conclusions, all mentioned methods were tested using real traffic measurement data collected from a 2-lane eastbound stretch of Interstate 494 in Minnesota, USA.

This paper is organized as follows: In section II, a stochastic nonlinear macroscopic traffic model and a traffic measurement model is presented. In section III, the I-494 stretch, real-data and some important parameters of the model and estimator are mentioned. Then, three approaches used in this paper to estimate the model parameters and traffic variables including: joint filtering, dual filtering and data fusion-based estimator are described and the I-494 real-data testing is reported. Finally, the main conclusions are summarized in section IV.

II. Traffic Flow Modeling

a. Macroscopic Traffic Flow Model Of Freeway

The second-order macroscopic traffic flow model was introduced by Papageorgiou et al. ([6]) for a freeway stretch. Traffic variables in this model are: traffic density, space mean speed and traffic flow. In order to use this model, a considered freeway is divided into **N** segments by length of about 500 m for each segment. Also time is discretized with the time step T.

The variables of this discrete space-time frame are as follows:

- T : time step size,
- L_i : length of segment i,
- λ_i : number of lanes in segment i,
- $\rho_i(k)$: traffic density in segment **i** (the number of vehicles in segment **i** at time **kT** divided successively by length of the segment and the lane number, measured in (veh/km/lane)),
- $v_i(k)$: mean speed in segment **i** (mean speed of all vehicles in segment **i** at time **kT** measured in (km/h)),

- $q_i(k)$: traffic flow in segment **i** (the number of vehicles passing through segment **i** during [**kT, (k+1)T**], measured in (veh/h*))*;

Macroscopic traffic flow model is described by following equations:

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{\Delta_i \lambda_i}[q_{i-1}(k) - q_i(k) + r_i(k) - s_i(k)] \tag{1}$$

$$s_i(k) = \beta_i(k) q_{i-1}(k) \tag{2}$$

$$\begin{aligned} v_i(k+1) = {} & v_i(k) + \frac{T}{\tau}[V(\rho_i(k)) - v_i(k)] + \\ & \frac{T}{\Delta_i} v_i(k)[v_{i-1}(k) - v_i(k)] - \frac{\nu T}{\tau \Delta_i} \frac{[\rho_{i+1}(k) - \rho_i(k)]}{(\rho_i(k) + \kappa)} - \\ & \frac{\delta T}{\Delta_i \lambda_i} \frac{r_i(k) v_i(k)}{(\rho_i(k) + \kappa)} + \xi_i^v(k) \end{aligned} \tag{3}$$

$$q_i(k) = \rho_i(k) v_i(k) \lambda_i + \xi_i^q \tag{4}$$

$$V(\rho) = v_f \, exp[-\frac{1}{a}(\frac{\rho}{\rho_{cr}})^a] \tag{5}$$

Where $\tau, \nu, \kappa, v_f, \rho_{cr}, a$ are model parameters which are equal for all segments; ξ_i^v and ξ_i^q are zero-mean Gaussian white noises representing unmodeled dynamics. Although (1) is an exact equation and therefore does not include unmodeled dynamics. The model parameters are usually estimated with respect to off-line data. Their effect on model is tested in [6] and three parameters v_f, ρ_{cr} *and a* (free speed, critical density and exponent) are the most sensitive parameters. This paper focuses on the estimation of these parameters. According to (4), For segment ***i*** at time ***kT*** traffic flow can be calculated by traffic density and traffic speed, so $\rho_i(k)$ and $v_i(k)$ can be considered as independent variables of segment ***i.*** The variables, q_0, v_0 *and* ρ_{N+1} are boundary variables where q_0 *and* v_0 can be measured but ρ_{N+1} can not be measured directly and must be estimated. In this paper, these boundary variables are estimated by the other traffic variables. The dynamic model used for these boundary variables is random walk:

$$\begin{cases} q_0(k+1) = q_0(k) + \xi_0^q(k) \\ v_0(k+1) = v_0(k) + \xi_0^v(k) \\ \rho_{N+1}(k+1) = \rho_{N+1}(k) + \xi_{N+1}^{\rho}(k) \end{cases} \tag{6}$$

Where $\xi_0^q, \xi_0^v, \xi_{N+1}^{\rho}$ are zero-mean white Gaussian noises.

b. Model of Traffic Measurements

Common measurement devices in traffic case are for measuring speed and flow. For segment ***i*** which is equipped with flow and speed sensors (installed at the boundary of segment ***i*** and ***i+1***) the measurement equations are:

$$\begin{cases} y_i^q(k) = q_i(k) + \eta_i^q(k) \\ y_i^v(k) = v_i(k) + \eta_i^v(k) \end{cases} \tag{7}$$

Where $q_i(k)$ *and* $v_i(k)$ are flow and speed of the segment at time ***kT***, $y_i^q(k)$ *and* $y_i^v(k)$ are flow and speed measurements respectively and $\eta_i^q(k)$ *and* $\eta_i^v(k)$ are flow and speed measurement noises.

c. State Space Representation

For a freeway network with N segments, there are 2N independent variables $\rho_1, v_1, \rho_2, v_2, ..., \rho_N, v_N$ and three boundary variables q_0, v_0 *and* ρ_{N+1}. So by considering state vector $X = [\rho_1, v_1, \rho_2, v_2, ..., \rho_N, v_N, q_0, v_0, \rho_{N+1}]$, and the measurement vector y_k which contains flow and speed measurements from (7), the macroscopic traffic model of the freeway can be expressed in a state-space form:

$$\begin{cases} X(k+1) = \mathbf{h}(X(k), \rho_{cr}, v_f, a) + \zeta(k) \\ y(k) = \mathbf{g}(X(k)) + \eta(k) \end{cases} \tag{8}$$

In this state-space model, in order to estimate the traffic states, EKF is used whereas to estimate unknown model parameters (v_f, ρ_{cr}, a), approaches described in next section are used.

III. Real Data Testing

The test of the proposed traffic state estimators is done with real traffic measurement data collected from a 2-lane eastbound stretch of the I-494 freeway in Minnesita, USA. As shown in Fig. 1. This test stretch is divided into 13 segments (each with a length of 200~550 m) and has one on-ramp and one off-ramp while 9 detector stations (black bars) are installed along the stretch.

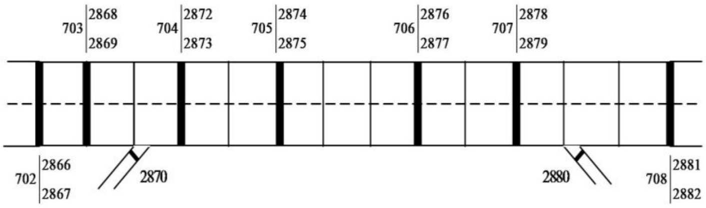

Fig. 1. Test stretch in intermediate 494, Minnesota.

Data recorded by the detectors are converted into aggregated traffic measurements of flow and space mean speed for every minute. Flow and speed measurements of September 1, 2009 and September 2, 2009 were utilized for testing. In simulations, CASE1 refers to the situation where the measurements from stations 702, 708, on-ramp and off-ramp are used to feed the estimator whereas the measurements from stations 702, 703, 707, 708, on-ramp and off-ramp are used to feed the estimator in CASE2. The model parameters $\nu, \kappa, \tau, \delta$ are, 35 km^2/h , 40 veh/km/lane, 25 s and 1.1, respectively, for the whole stretch. The following covariance values are used in simulations:

$$Cov\{\xi_i^q(k)\} = 300\,(veh/h)^2, Cov\{\xi_i^v(k)\} = 10\,(km/h)^2,\ i = 1,\ldots,13$$

$$Cov\{\xi_0^q(k)\} = 300\,(veh/h)^2, Cov\{\xi_0^v(k)\} = 10\,(km/h)^2,$$

$$Cov\{\xi_{14}^\rho(k)\} = 1\,(veh/km/lane)^2,$$

$$Cov\{\xi_3^r(k)\} = 30\,(veh/h)^2, Cov\{\xi_{12}^\beta(k)\} = 0.00001,$$

$$Cov\{\eta_i^q(k)\} = 100\,(veh/h)^2, Cov\{\eta_i^v(k)\} = 50\,(km/h)^2,$$

$$Cov\{\eta_3^r(k)\} = 3\,(veh/h)^2, Cov\{\eta_{12}^s(k)\} = 3\,(veh/h)^2$$

The performance of freeway traffic estimators are evaluated by the relative performance index defined as:

$$J = \sqrt{\frac{1}{KN}\frac{\sum_{i=1}^{N}\sum_{k=1}^{K}(x_i(k) - \hat{x}_i(k))^2}{\sum_{i=1}^{N}\sum_{k=1}^{K}(x_i(k))^2}} \tag{9}$$

Where the vector $\mathbf{x}$ denotes the real data, $\hat{\mathbf{x}}$ is the corresponding estimation, N is dimension of state vector and K is the simulation horizon.

a. Simulation for Adaptive Estimator Based on Joint Filtering

In the joint filtering approach, both the traffic variables and model parameters are considered as an augmented system and state estimation of this augmented system is performed by one EKF. Therefore in this case, state vector is $X = [\rho_1, v_1, ..., \rho_N, v_N, q_0, v_0, \rho_{N+1}, v_f, \rho_{cr}, a]$. State space representation of the model parameters is as follows:

$$\begin{cases} X(k+1) = A_k X(k) + v_k \\ y(k) = g(X(k), U(k)) + w_k \end{cases} \quad (10)$$

Where:

$X = [v_f \ \rho_{cr} \ \alpha]^T$, $A_k = I_{3\times3}$, $v_k = [\xi_{v_f} \ \xi_{\rho_{cr}} \ \xi_\alpha]$

$y(k) = V(k)$, $U(k) = \rho(k)$, $g = v_f .exp[-\frac{1}{a}(\frac{\rho}{\rho_{cr}})^a]$, $w_k = \xi_\rho^V$

$\xi_{\rho_{cr}}, \xi_{v_f}, \xi_a, \xi_\rho^V$ are zero-mean white Gaussian noises. In the measurement equation of this state space, estimated values of speed and density of one specific segment are used as V and ρ. The necessary parameters for these augmented states were chosen to be:

$v_f(0) = 180\, km/h$, $\rho_{cr}(0) = 10 veh/km/lane$, $a(0) = 1.5$,

$\mathrm{cov}(\xi_{\rho_{cr}}(k)) = 0.03\,(veh/km/lane)^2$, $\mathrm{cov}(\xi_{v_f}(k)) = 0.2\,(km/h)^2$,

$\mathrm{cov}(\xi_a(k)) = 0.0001$,

As shown in figures 2, 3 and 4, estimation of the model parameters and traffic states based on joint filtering for CASE1 did not result in a good performance (J=1.15).

Also this method was tested for CASE2, which resulted in acceptable performance with J=0.0374. These results show that when the amount of available information is low and also due to estimating two dynamic systems with different behavior and characteristics with one EKF, the joint estimator may lead to unstable performance. In order to go around this problem dual filtering approach is suggested.

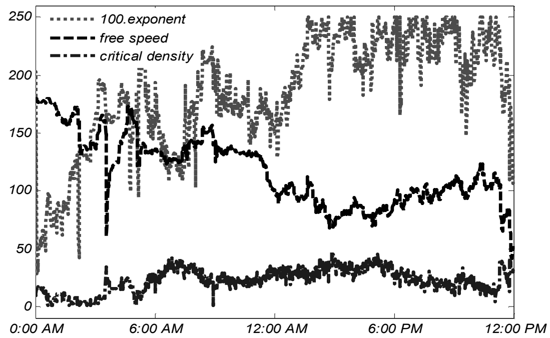

Fig. 2. On-line parameters estimation with joint filtering

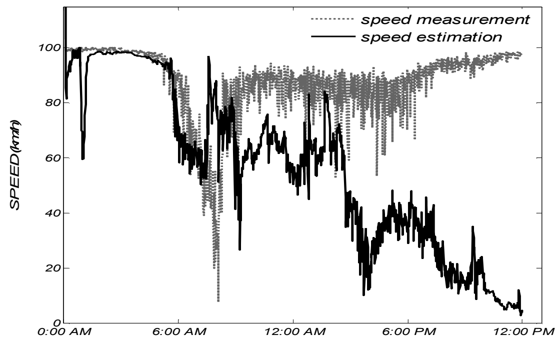

Fig. 3. Speed estimate at 705 with adaptive estimator (joint filtering)

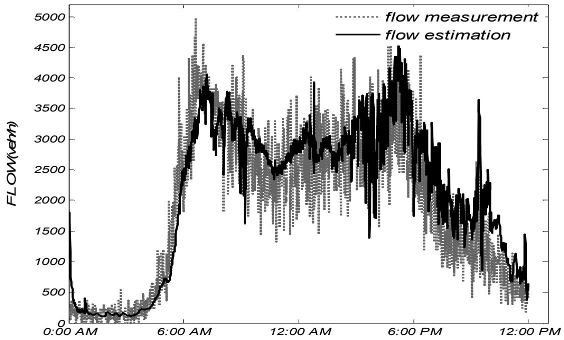

Fig.4. Flow estimate at 705 with adaptive estimator (joint filtering)

b. Simulation for Adaptive Estimator Based on Dual Filtering

In this approach two separate filters were designed, one for traffic state estimation and the other for model parameters estimation. The initial and necessary parameters are the same as joint filtering. Estimation results of the model parameters as well as speed and flow at station 705 for the CASE1, are displayed in figures 5, 6 and 7. Performance index for this case improved to 0.051 in comparison to the joint filtering.

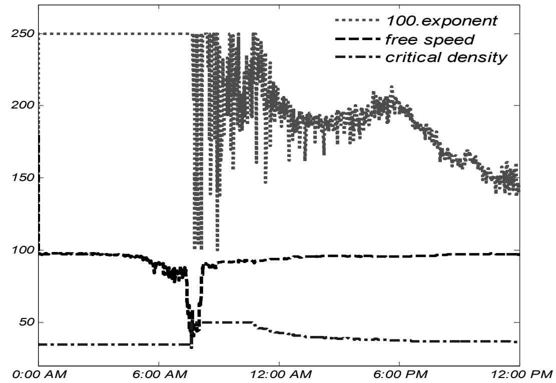

Fig.5. On-line parameters estimation with dual filtering

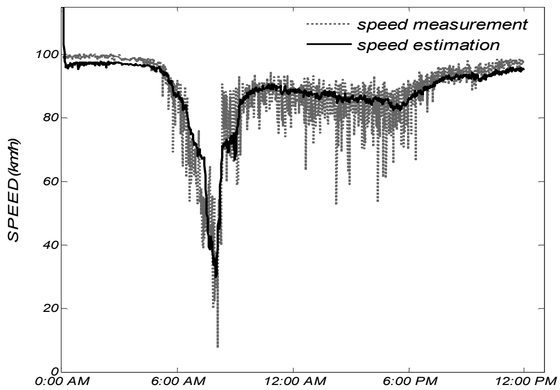

Fig.6. Speed estimate at 705 with adaptive estimator (dual filtering)

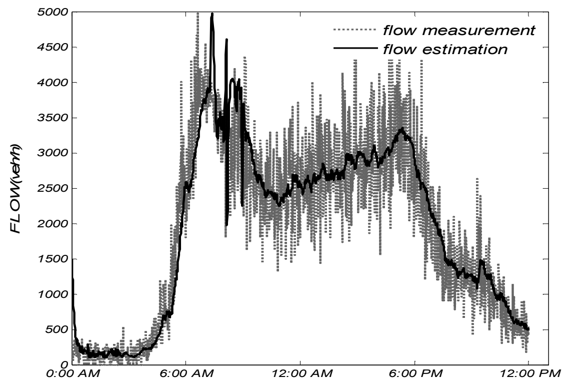

Fig.7. Flow estimate at 705 with adaptive estimator (dual filtering)

In this dual filtering, online estimation of the model parameters is done by considering density and speed estimation of the segment 3 as input and output in measurement equation of the model (10), respectively. This test is also done for two different days(1 September and 2 September, 2009), where the model parameters are estimated based on all segments individually. Results are show in tables I and II.

TABLE I

Performance index for different segments used to estimate model parameters (September 1, 2009)

Segment Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Cost	**0.77**	**2.369**	**0.05**	**0.89**	**1.047**	**1.08**	**1.098**	**1.1**	**1.09**	**1.078**	**0.49**	**1.08**	**1.203**

TABLE II

Performance index for different segments used to estimate model parameters (September 2, 2009)

Segment Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Cost	**2.48**	**0.26**	**0.39**	**0.45**	**0.84**	**1.92**	**1.84**	**0.69**	**0.69**	**1.61**	**1.37**	**1.59**	**0.06**

Based on these results, for the first day, the best performance is for segment 3 and the worst is obtained by segment 2. But in the second day, the best and the worst performances are for segments 13 and 1, respectively. Hence, it is clear that estimator performance is highly dependent on the selected segment and also for different days, performance of the segments for online model parameters estimation are not the same. In order to improve the dual filtering estimator, data fusion approach is tested.

c. Simulation for Adaptive Estimator Based on Measurement Fusion

Due to lack of knowledge in selecting adequate segment for online model parameters estimation, the optimal weighting measurement fusion (OWMF) method is proposed. In OWMF, measurements, which in this case are speed and density of segments, are combined based on a minimum-mean-square-error criteria [2]. The observation information to the Kalman filter is given by:

$$V_{owmf} = \left(\sum_{j=1}^{N} R_{v_j}^{-1}(k) \right)^{-1} \sum_{j=1}^{N} R_{v_j}^{-1}(k) V_j(k) \tag{11}$$

$$C_{owmf} = \left(\sum_{j=1}^{N} R_{v_j}^{-1}(k) \right)^{-1} \sum_{j=1}^{N} R_{v_j}^{-1}(k) C_j(k) \tag{12}$$

$$R_{owmf} = \left(\sum_{j=1}^{N} R_{v_j}^{-1}(k) \right)^{-1} \tag{13}$$

$$\rho_{owmf} = \left(\sum_{j=1}^{N} R_{\rho_j}^{-1}(k) \right)^{-1} \sum_{j=1}^{N} R_{\rho_j}^{-1}(k) \rho_j(k) \tag{14}$$

Where N in the number of segments, V_j and ρ_j are estimated speed and density of segment **j,** R_{v_j} and R_{ρ_j} are associated values of V_j and ρ_j in a posteriori estimate covariance of KF used to estimate traffic variables and $C_j(k) = [\frac{\delta g}{\delta \upsilon_f} \ \frac{\delta g}{\delta \rho_{cr}} \ \frac{\delta g}{\delta \alpha}]$, calculated for $v_f(k-1), \rho_{cr}(k-1), \alpha(k-1)\, and\ \rho_j(k)$. Fused values of speed and density (V_{owmf}, ρ_{owmf}) are used as output and input in (10).

For the CASE1, the estimation of the model parameters which are obtained by OWMF method and estimation of the speed and flow at station 705 are displayed in figures 8-12. Performance indices for 1 September, 2009 and 2 September, 2009 are 0.04 and 0.049, respectively, which are better than the best performance without fusion, and also by using OWMF method the main challenge in choosing proper segment is handled appropriately.

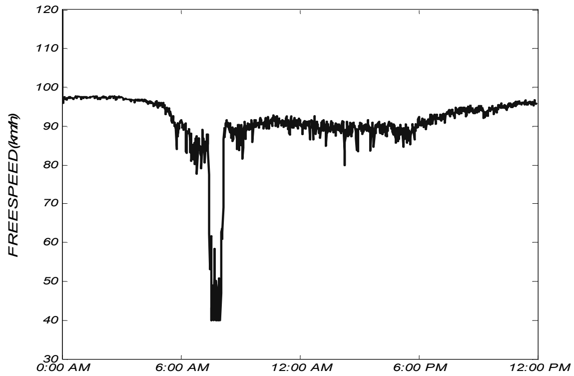

Fig.8. On-line estimation of free speed with dual filtering based on OWMF method

Fig.9. On-line estimation of critical density with dual filtering based on OWMF method

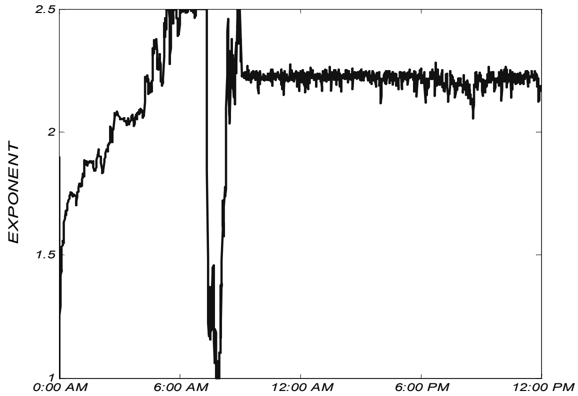

Fig.10. On-line estimation of exponent with dual filtering based on OWMF method

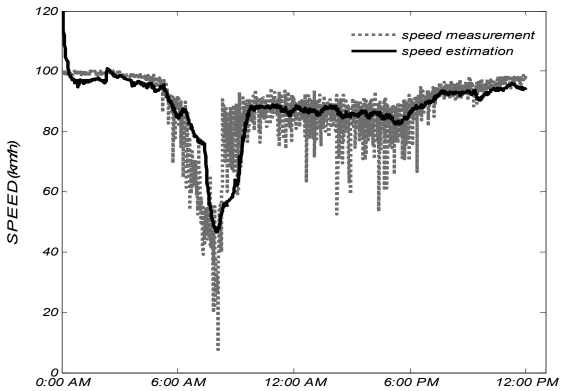

Fig.6. Speed estimate at 705 with adaptive estimator (dual filtering based on OWMF)

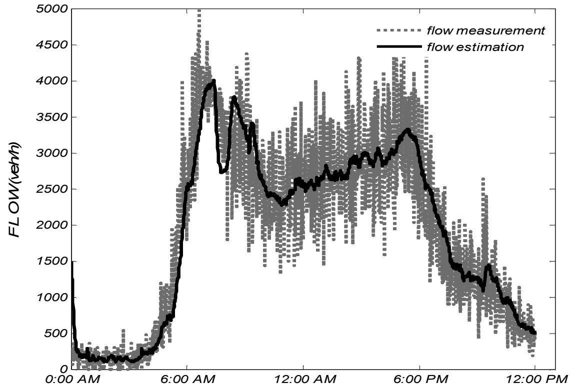

Fig.6. Flow estimate at 705 with adaptive estimator (dual filtering based on OWMF)

IV. Conclusion

Several adaptive filter configurations were tested for freeway traffic state and parameter estimation. These filters were investigated using real data collected from a stretch of the Intermediate 494 freeway in Minnesota. The main conclusions of the simulations are:

1- In joint filtering approach, due to using one filter for state estimation of two different systems, the estimator result may be unacceptable.
2- State estimates of both systems in dual filtering approach, are unbiased and acceptable, but performance of the estimators is very sensitive to selected segment for estimation of the model parameters.
3- In dual filtering based on OWMF method, fused speed and density of all segments were applied to estimate model parameters by one separate EKF from that used to estimate traffic variables.

By comparing results of joint filtering, dual filtering and dual filtering based on measurement fusion approach, it can be seen that, performance obtained by dual filtering is acceptable while the best segment for estimation of the model parameters is known, but practically it is not possible. So, using dual filtering based on measurement fusion is proposed to deal with this problem which its performance index is better than dual filtering in the best case.

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