

Freeway Traffic State Estimation with Mixed Connected Automated Vehicles and Human-driven Vehicles

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INTRODUCTION

It can be expected that connected and automated vehicles (CAVs) and human-driven vehicles (HVs) will co-exist on the transportation network in a long period. Hence, to support many traffic operation tasks, it is critical to develop a reliable traffic state estimation model under the CAV-HV-mixed environment. One of the most challenging issues in modeling traffic is to capture the traffic flow characteristics of a mixed traffic environment. To address this issue, this study introduces an extended macroscopic traffic flow model which models CAVs and HVs in dedicated groups.

METHODS

$$d_i(k+1) = d_i(k) + \frac{\Delta T}{L_i} [q_{i-1}(k) - q_i(k) + r_i(k) - s_i(k)] \quad (1)$$

$$u_i(k+1) = u_i(k) + \frac{\Delta T}{\tau_i} [V_i(d_i(k)) - u_i(k)] + \frac{\Delta T}{L_i} u_i(k) [u_{i-1}(k) - u_i(k)] - \frac{\gamma \Delta T}{\tau_i} \frac{[d_i(k) - d_i(k)]}{d_i(k)} \quad (2)$$

$$V[d_i(k)] = u_i \exp \left[-\frac{1}{a} \left(\frac{d_i(k)}{d_{cr,i}} \right)^a \right] \quad (3)$$

$$q_i(k) = d_i(k) u_i(k) \lambda_i \quad (4)$$

where the following notations are used:
 i : the index of subsections of a freeway segment;
 k : the index of the time intervals;
 $q_i(k)$: transition flow rate entering segment $i+1$ from segment i during interval k ;
 $r_i(k)$: on-ramp flow rate entering segment i during interval k ;
 $s_i(k)$: off-ramp flow rate leaving segment i during interval k ;
 $d_i(k)$: mean traffic density per lane in the segment i during interval k ;
 $u_i(k)$: mean speed in the segment i during interval k ;
 γ, τ, κ, a : traffic state model parameters;
 ΔL : Length of each freeway segment;
 λ_i : Number of lanes in subsection i .

Base model by Papageorgiou

The proposed CAV-HV hybrid model

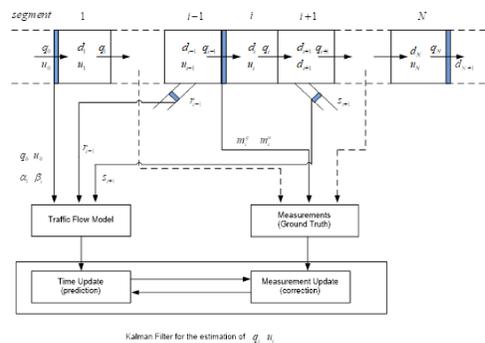


Figure 1 Traffic state estimation with extended Kalman filter

The availability of the observed traffic flow and speed of HVs is limited by the stationary detector, which is highlighted in blue in Figure 1. To obtain a reliable traffic flow estimation, this study further adopts the extended Kalman filter (EKF) for improving the estimation accuracy. EKF is an optimal state estimator applied to dynamic systems that involve random noise (e.g. sensor errors). It takes a limited amount of noised real-time measurements for correcting the prior estimates.

RESULTS/DISCUSSION

Scenario configuration

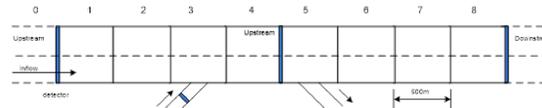


Figure 2 The network representation of the studied case

Figure 2 shows the stretch has two lanes and is divided into 8 segments of 500-meter length. The average speed of the total upstream traffic is 120 km/h. An on-ramp locates on segment 3 and an off-ramp locates on segment 5. Each of them contains a roadside detector for measuring the flow and mean speed of total vehicles. The blue bars indicate the layout of the four detectors: (a) two detectors are located on the upstream and downstream ends of the mainline freeway, respectively, which is used to collect the inflow and outflow of the entire freeway segment; (b) a detector is deployed at the on-ramp, which is used to measure the on-ramp volume. Figure 3 shows the arrival traffic flow collected by the incoming flow and the on-ramp flow.

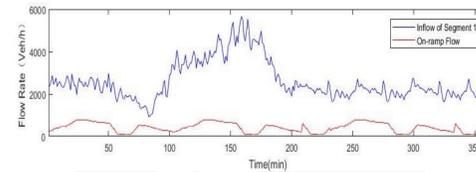


Figure 3 Arrival flows of the freeway segment

The detectors on the boundary of Segment 4 and Segment 5 collect the flow and mean speed of both CAVs and HVs vehicles. These data are transmitted to CAVs for optimizing the guided speed. In the base case, the penetration rate of CAVs is set to 20%.

Testing results

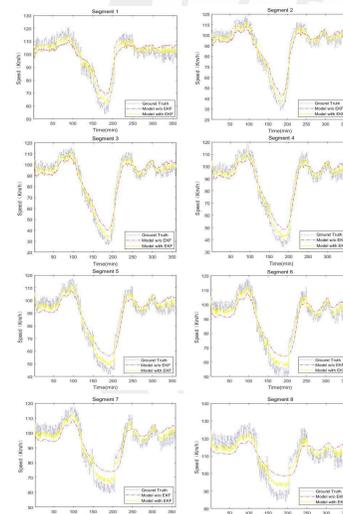


Figure 4 Speed comparison between the ground-truth, EKF, and non-EKF

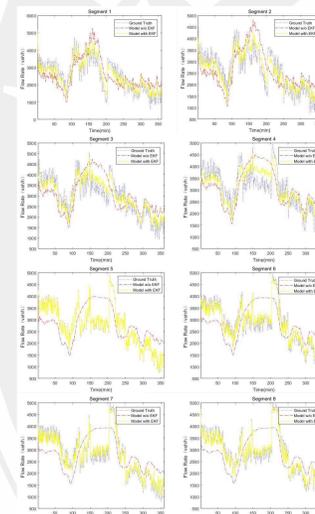


Figure 5 Flow comparison between ground-truth, EKF, and non-EKF

Table 1 Flow errors of the proposed model with EKF

| Segment # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-----------|--------|--------|--------|--------|-------|--------|--------|--------|
| 5% CAV | | | | | | | | |
| RMSE | 280.66 | 305.44 | 302.58 | 399.72 | 29.09 | 87.83 | 80.8 | 72.78 |
| MAPE (%) | 11.91 | 12.32 | 10.18 | 13.76 | 1.16 | 3.37 | 3.17 | 2.91 |
| MSPE (%) | 2.33 | 2.36 | 1.49 | 2.92 | 0.02 | 0.18 | 0.16 | 0.13 |
| RMSPE (%) | 15.25 | 15.37 | 12.19 | 17.08 | 1.48 | 4.19 | 3.95 | 3.67 |
| 15% CAV | | | | | | | | |
| RMSE | 280.9 | 306.31 | 302.85 | 396.6 | 6.99 | 119.32 | 110.21 | 92.24 |
| MAPE (%) | 11.79 | 12.34 | 10.26 | 13.71 | 0.27 | 4.47 | 4.23 | 3.6 |
| MSPE (%) | 2.3 | 2.36 | 1.51 | 2.9 | 0 | 0.31 | 0.28 | 0.02 |
| RMSPE (%) | 15.17 | 15.35 | 12.3 | 17.03 | 0.34 | 5.54 | 5.24 | 4.51 |
| 30% CAV | | | | | | | | |
| RMSE | 281.28 | 307.63 | 305.66 | 391.95 | 41.68 | 151.09 | 139.3 | 108.26 |
| MAPE (%) | 11.75 | 12.42 | 10.38 | 13.64 | 1.59 | 5.56 | 5.24 | 4.13 |
| MSPE (%) | 2.26 | 2.38 | 1.56 | 2.88 | 0.04 | 0.47 | 0.42 | 0.26 |
| RMSPE (%) | 15.05 | 15.43 | 12.5 | 16.98 | 2 | 6.86 | 6.48 | 5.13 |
| 50% CAV | | | | | | | | |
| RMSE | 281.8 | 309.38 | 307.9 | 385.77 | 59.03 | 171.31 | 155.65 | 107.81 |
| MAPE (%) | 11.73 | 12.57 | 10.55 | 13.54 | 2.23 | 6.26 | 5.82 | 4.08 |
| MSPE (%) | 2.24 | 2.44 | 1.63 | 2.85 | 0.07 | 0.6 | 0.52 | 0.03 |
| RMSPE (%) | 14.95 | 15.62 | 12.76 | 16.89 | 2.81 | 7.73 | 7.21 | 5.05 |
| 70% CAV | | | | | | | | |
| RMSE | 282.32 | 311.15 | 310.02 | 379.63 | 46.68 | 170.48 | 149.39 | 81.95 |
| MAPE (%) | 11.75 | 12.72 | 10.69 | 13.41 | 1.8 | 6.33 | 5.68 | 3.15 |
| MSPE (%) | 2.25 | 2.5 | 1.69 | 2.81 | 0.05 | 0.62 | 0.05 | 0.02 |
| RMSPE (%) | 14.99 | 15.82 | 12.99 | 16.76 | 2.27 | 7.85 | 7.09 | 3.91 |

Table 2 Speed errors of model prediction with EKF

| Segment # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-----------|-------|-------|------|------|------|------|------|------|
| 5% CAV | | | | | | | | |
| RMSE | 3.86 | 3.73 | 3.61 | 3.87 | 3.47 | 3.53 | 3.54 | 3.11 |
| MAPE (%) | 4.02 | 4.91 | 5.11 | 5.02 | 4.26 | 4.1 | 4.05 | 3.43 |
| MSPE (%) | 0.3 | 0.49 | 0.55 | 0.47 | 0.32 | 0.29 | 0.28 | 0.19 |
| RMSPE (%) | 5.45 | 7.01 | 7.39 | 6.88 | 5.69 | 5.4 | 5.25 | 4.32 |
| 15% CAV | | | | | | | | |
| RMSE | 3.85 | 3.72 | 3.58 | 3.81 | 3.43 | 3.5 | 3.51 | 3.06 |
| MAPE (%) | 4.17 | 5.33 | 5.4 | 5.16 | 4.35 | 4.18 | 4.09 | 3.42 |
| MSPE (%) | 0.32 | 0.63 | 0.64 | 0.51 | 0.34 | 0.3 | 0.28 | 0.18 |
| RMSPE (%) | 5.7 | 7.94 | 8.01 | 7.14 | 5.83 | 5.49 | 5.29 | 4.29 |
| 30% CAV | | | | | | | | |
| RMSE | 3.85 | 3.71 | 3.53 | 3.74 | 3.37 | 3.46 | 3.46 | 2.99 |
| MAPE (%) | 4.51 | 6.18 | 5.8 | 5.34 | 4.45 | 4.26 | 4.13 | 3.38 |
| MSPE (%) | 0.4 | 1.02 | 0.79 | 0.55 | 0.35 | 0.31 | 0.28 | 0.18 |
| RMSPE (%) | 6.36 | 10.11 | 8.86 | 7.43 | 5.95 | 5.58 | 5.32 | 4.23 |
| 50% CAV | | | | | | | | |
| RMSE | 3.84 | 3.69 | 3.48 | 3.64 | 3.31 | 3.42 | 3.41 | 2.9 |
| MAPE (%) | 5.25 | 7.54 | 6.16 | 5.43 | 4.5 | 4.31 | 4.15 | 3.32 |
| MSPE (%) | 0.66 | 1.93 | 0.92 | 0.57 | 0.36 | 0.32 | 0.28 | 0.17 |
| RMSPE (%) | 8.13 | 13.88 | 9.57 | 7.57 | 5.99 | 5.63 | 5.32 | 4.14 |
| 70% CAV | | | | | | | | |
| RMSE | 3.84 | 3.67 | 3.42 | 3.56 | 3.27 | 3.4 | 3.38 | 2.8 |
| MAPE (%) | 6.31 | 8.72 | 6.31 | 5.38 | 4.47 | 4.31 | 4.14 | 3.24 |
| MSPE (%) | 1.31 | 3.05 | 0.56 | 0.55 | 0.35 | 0.31 | 0.28 | 0.16 |
| RMSPE (%) | 11.42 | 17.46 | 9.79 | 7.44 | 5.9 | 5.61 | 5.29 | 4.04 |

The numerical study shows

- the speeds under the CAVs speed control can significantly improve the speed especially during the time period with heavy traffic condition (e.g. 1000th sec – 2500th sec). Even in light traffic condition, the optimized control can slightly improve the performance of the speed of vehicles.
- The estimation with EKF would have a better performance on traffic state estimation than the one without EKF.
- The sensitivity analysis shows EKF with the proposed model has RMSPE lower than 17% regarding the predicted flow and speed. The proposed method shows stable in predicting the traffic state.

CONCLUSIONS

This study introduces an extended macroscopic traffic flow model which models CAVs and HVs in dedicated groups. Assuming CAVs are operated with optimal speed guidance, the proposed model captures the interaction between CAV and HV. A new set of key factors are introduced to represent the acceleration and deceleration behavior of HVs due to following CAVs in the mixed traffic stream. To contend with the uncertainty in drivers' behaviors, this study further adopts the Extended Kalman Filter (EKF) to enhance the estimation on each segment. Numerical cases on a freeway segment involving CAV speed control are tested to evaluate the proposed model. The results show that

- the proposed model can capture the CAV impacts and estimate the mixed traffic states accurately, and
- EKF can greatly improve the estimation accuracy contending simulated noised sensors. The sensitivity analysis shows the proposed model is more robust than the conventional method on various CAV penetration rates ranged from 5% to 70%.