Numerical study on the extension of Augmented State Kalman Filter for profile estimation

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1. INTRODUCTION:

In order to maintain the road/railway infrastructure efficiently, the profile along the longitudinal direction need to be monitored regularly. While the measurement of profile or vehicle's absolute displacement is not practical, but the acceleration and angular velocity measurements are feasible. Prevalent sensing devices such as smartphones are potentially utilized in vehicle body motion measurement. However, the applicability of such measurement for profile estimation is not clarified yet. Assuming the measurement of vehicle body acceleration and angular velocity, Saravanan et al. (2016) performed an observability analysis on the profile estimation through augmented state space model as well as two other formulations extending it. In the two approaches, the second derivative of the profile is included in the state vector along with other state variables. While the profile itself is not observable in any formulation, the second derivative of profile was shown to be observable. In this paper, Kalman filter technique is employed for three state space models mentioned above, termed as conventional Augmented State Kalman Filter (ASKF) and two extended approaches (a) and (b) for the profile estimation. The performances are compared numerically using quarter car (QC) 2-DOF linear vehicle model.

2. METHODOLOGY:

The state space model for the continuous time-invariant system is represented as,

$$\dot{x}(t) = Ax(t) + Bu(t);\;\; y(t) = Hx(t) \tag{1}$$

where x is the system state vector, u is the input vector, y is the measurement vector, A is the state matrix, B is the input matrix and H is the measurement matrix. In conventional ASKF, the input vector is combined with the state vector and identified as a part of state vector. The state matrix is redefined by adding the input matrix to the original state matrix and increasing the size of the state matrix.

$$\tilde{x} = \begin{bmatrix} x \\ u \end{bmatrix} \tag{2}$$

The measurement matrix is appended by a null matrix because inputs are assumed unmeasured.

$$\widetilde{H} = [H \quad 0] \tag{3}$$

The two approaches for the estimation of profile as a part of the state vector were proposed by Saravanan et al (2016). One is to include the second derivative of the profile in the state vector along with other state variables. The profile is estimated directly from the state vector, however, it has a large low frequency estimation error. A high-pass filter is need to be applied for accurate results. The other is to alter state space model by adopting the first derivative of the state vector as new state vector. Thus, only the dynamic components are considered while the static components (i.e., displacement) are excluded from the state vector. The profile is estimated as the single integration of a state vector component (i.e., the first derivative of the profile). The altered state space model is,

$$\ddot{\tilde{x}}(t) = A\dot{\tilde{x}}(t);\;\; \dot{y}(t) = \widetilde{H}\dot{\tilde{x}}(t) \tag{4}$$

where $\dot{\tilde{x}}$ is the new state vector and only the measurement matrix H, is modified while the transition matrix A, is unaltered. A QC model (Figure 1) is a well-known model for simulating one-dimensional vehicle suspension performance. The dynamic equation of motion is,

$$\begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix}\begin{Bmatrix} \ddot{z}_1 \\ \ddot{z}_2 \end{Bmatrix} + \begin{bmatrix} c_1 & -c_1 \\ -c_1 & c_1 + c_2 \end{bmatrix}\begin{Bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{Bmatrix} + \begin{bmatrix} k_1 & -k_1 \\ -k_1 & k_1 + k_2 \end{bmatrix}\begin{Bmatrix} z_1 \\ z_2 \end{Bmatrix} = \begin{Bmatrix} 0 \\ k_2 u + c_2 \dot{u} \end{Bmatrix} \tag{5}$$

where m, k, c and z are the mass, elastic coefficient, damping coefficient and position of vehicle body respectively and u is the road profile.

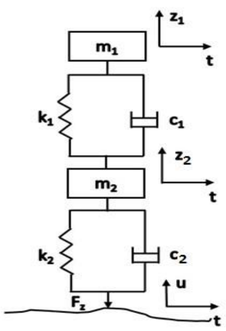

Figure 1. Quarter Car model

The state vector for conventional ASKF is defined as:

$$\tilde{x} = (z_1\ \dot{z}_1\ z_2\ \dot{z}_2\ u\ \dot{u})^T \tag{6}$$

The observability analysis shows that none of the state variables are observable. The proposed two approaches are implemented with the following state vectors.

In approach (a), the state vector is,

$$\tilde{x} = (z_1\ \dot{z}_1\ z_2\ \dot{z}_2\ u\ \dot{u}\ \ddot{u})^T \tag{7}$$

In approach (b), the state vector is,

$$\dot{\tilde{x}} = (\ \dot{z}_1\ \ddot{z}_1\ \dot{z}_2\ \ddot{z}_2\ \dot{u}\ \ddot{u})^T \tag{8}$$

Thus by measuring acceleration ($\ddot{z}_1$) only at the car body, the second derivative component of the profile is observable even though the system is unobservable.

Keywords: augmented state Kalman filter, vehicle dynamics, road profile
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3. VALIDATION OF PROFILE ESTIMATION:

Based on three formulations, profile estimation is numerically studied employing Kalman filter technique. The vehicle parameters (Table 1) for QC model are obtained from Doumiati et al. (2011). Additionally the vehicle is assumed to maintain a constant velocity of 40 km/h and simulated distance is 2.4 km. Numerical simulation is incorporated with vehicle model errors and various measurement noise levels generated as a random walk driven by Gaussian white noise and also initial condition error in the Kalman filter iteration in order to approximately obtain the exact profile. Figure 2 shows the typical case of simulated profile after using high pass filter with cut off frequency of 0.5 Hz, by incorporating noise level of 5% and large vehicle model errors as given in Table 1. The proposed approaches give better results than the conventional ASKF. The statistical metrics of root mean square deviation (RMSD) and correlation coefficient (CC) are calculated as shown in Figure 3, which indicate that the performance of the proposed approaches (a) and (b) are better than the conventional ASKF.

Table 1. Vehicle parameters

Parameter	Value (reference)	Value (varied)	Variation %
m_1	345 kg	345 kg	0
m_2	40 kg	32 kg	-20
k_1	20818 N/rad	31227 N/rad	+50
k_2	100000 N/rad	200000 N/rad	+100
c_1	300 N.s/m	120 N.s/m	-60
c_2	500 N.s/m	250 N.s/m	-50

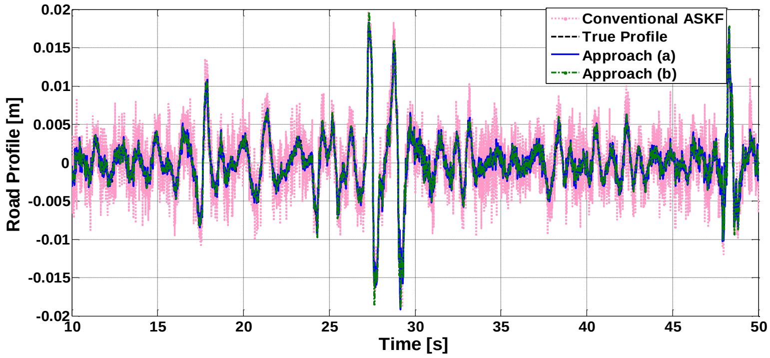
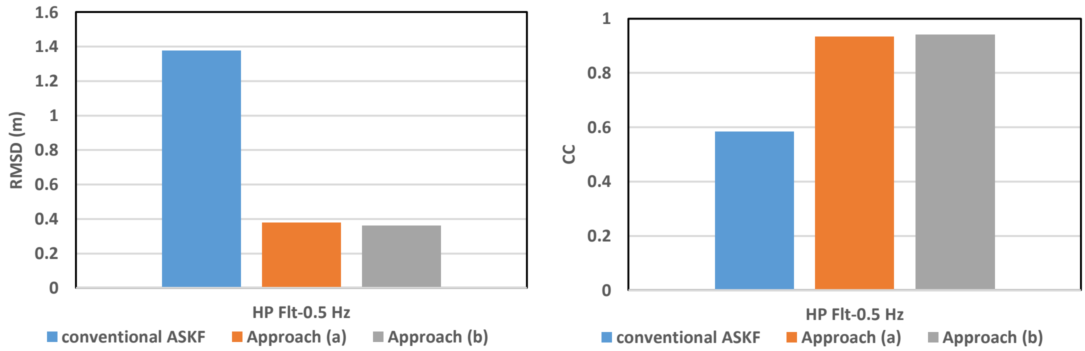


Figure 2. Comparison of profiles



(a) RMSD (b) CC

Figure 3. Quantification through statistical metrics

Figure 3 (a) shows that, the RMSD decreased from 1.38 m to 0.38 m and 0.36 m for approach (a) and approach (b), respectively. The correlation increased from 0.58 to 0.93 and 0.94 respectively as shown in Figure 3 (b). Comparatively, approach (a) performs better than approach (b) under various conditions though the differences are mostly negligibly small. Irrespective of the noise level and vehicle model error, two proposed approaches performs better than conventional ASKF method.

5. CONCLUSION:

Two approaches which are extension for ASKF for profile estimation are numerically examined with a QC model for its better performance comparing with the conventional ASKF. The further studies on different vehicle models are being conducted for the effective profile estimation using practical sensors and its installation locations.

REFERENCES

Jothi Saravanan, T., Zhao, B.Y., Su Di., and Nagayama, T.: An observability analysis for profile estimation through vehicle response measurement, International Conference on Smart Infrastructure and Construction (ICSIC) 2016, Cambridge, UK.
Doumiati, M. & Victorino, A. & Charara, A. & Lechner, D.: Estimation of road profile for vehicle dynamics motion: experimental validation, American Control Conference, San Francisco, CA, USA, 2011, pp. 5237-5242.