Numerical study for railway track geometry estimation using Augmented State Kalman Filter

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1. INTRODUCTION:

The necessary inspections need to be performed for determining the track condition due to amplified demand on railway networks. Sensors are mounted on in-service vehicles for collecting the acceleration and other dynamic parameters which are suitable more for condition monitoring of railway track. Track irregularity have been a problem troubling railway scientists and engineers since railways inception. Tsunashima et al. (2014) described about the Japanese in-service rail-vehicle system measuring track geometry profile using accelerometers and gyros. Saravanan et al. (2016a) performed an observability analysis on the profile estimation through augmented state space model as well as two other formulations extending it. In Saravanan et al. (2016b), Augmented State Kalman Filter (ASKF) is employed for state space models, termed as conventional ASKF and two extended approaches (a) and (b) for the profile estimation using quarter car model. In this paper, numerical study using inverse analysis on railway track profile estimation using 6 DOF train model is presented.

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). Approach (a) 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. Approach (b) 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 6 DOF vehicle model depicts the linear train vehicle model with car body and two bogies in vertical direction as shown in Figure 1. In this model, z_c and θ_c are the car body displacement and pitch angle, z_{t1} and z_{t2} are front and rear bogie displacement, θ_{t1} and θ_{t2} are front and rear bogie pitch angle. The inputs $r_{1a},\ r_{1b},\ r_{2a},\ r_{2b}$ denote the track displacement. The state vector for conventional ASKF is, $x^a = [z_c\ \theta_c\ z_{t1}\ \theta_{t1}\ z_{t2}\ \theta_{t2}\ \dot{z}_c\ \ \dot{\theta}_c\ \dot{z}_{t1}\ \dot{\theta}_{t1}\ \dot{z}_{t2}\ \dot{\theta}_{t2}\ \ r_{1a}\ r_{1b} r_{2a} r_{2b}\ \dot{r}_{1a}\ \dot{r}_{1b}\dot{r}_{2a}\dot{r}_{2b}]^T$ (5)

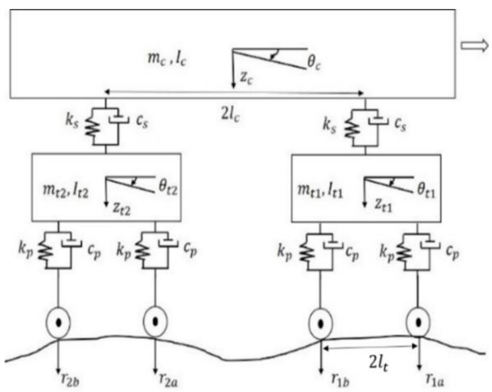

Figure 1. 6 DOF train model

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,

$$\widetilde{x^a} = [z_c\ \theta_c\ z_{t1}\ \theta_{t1}\ z_{t2}\ \theta_{t2}\ \dot{z}_c\ \ \dot{\theta}_c\ \dot{z}_{t1}\ \dot{\theta}_{t1}\ \dot{z}_{t2}\ \dot{\theta}_{t2}\ r_{1a}\ r_{1b} r_{2a} r_{2b}\ \dot{r}_{1a}\ \dot{r}_{1b}\dot{r}_{2a}\dot{r}_{2b}\ \ddot{r}_{1a}\ \ddot{r}_{1b}\ \ddot{r}_{2a}\ \ddot{r}_{2b}]^T \tag{6}$$

In approach (b), the state vector is,

$$\dot{x^a} = [\dot{z}_c\ \ \dot{\theta}_c\ \dot{z}_{t1}\ \dot{\theta}_{t1}\ \dot{\theta}_{t2}\ \ \dot{z}_{t2}\ \ddot{z}_c\ \ddot{\theta}_c\ \ddot{z}_{t1}\ \ddot{\theta}_{t1}\ \ddot{z}_{t2}\ \ \ddot{\theta}_{t2}\ \dot{r}_{1a}\ \dot{r}_{1b}\ \dot{r}_{2a}\ \dot{r}_{2b}\ \ddot{r}_{1a}\ \ddot{r}_{1b}\ \ddot{r}_{2a}\ \ddot{r}_{2b}]^T \tag{7}$$

The acceleration and angular velocity of car body and bogie mass are the minimum combination of measurements, which results in observable profile derivatives.

For the simulation purpose, the following types of measurements are considered for the 6 DOF train vehicle model as per the observability analysis results, namely,

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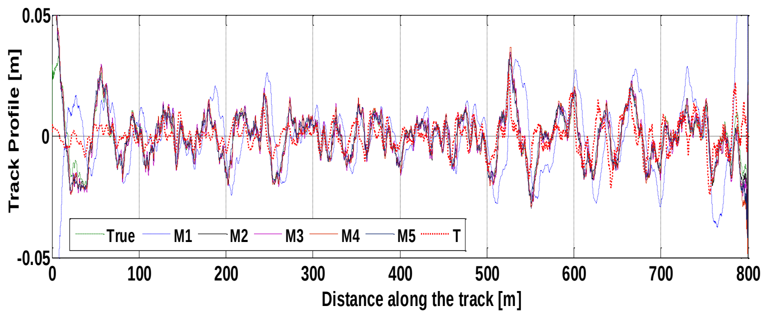
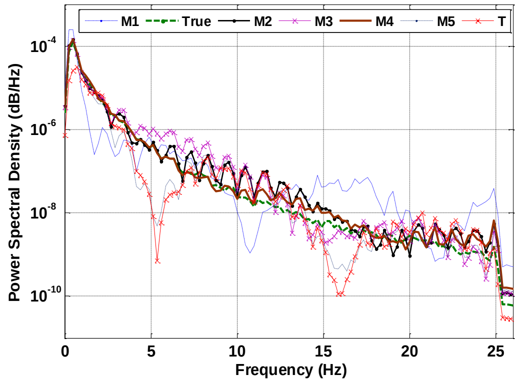
•M1: Acceleration and angular velocity measurements at front and rear bogie masses.
•M2: Acceleration and angular velocity measurements at car body, front and rear bogie masses.
•M3: Acceleration and angular velocity measurements at car body and front bogie masses.
•M4: Acceleration measurement at car body and angular velocity measurement at car body, front and rear bogie masses.
•M5: Acceleration and angular velocity measurements at car body only (do not satisfy observability condition). Still, it is considered in the numerical simulation for comparing with measurement set: acceleration and angular velocity measured at car body in simplified train model (T) as considered in Tsunashima et al. (2014).

3. ESTIMATION OF RAIL TRACK PROFILE:

For railway track profile estimation, a simplified train vehicle model has been introduced for rail track profile estimation (Tsunashima et al. 2014). In order to test the performance of the ASKF method for railway track profile estimation, 6 DOF train vehicle model (Figure 1) is considered for numerical simulation which represents the real train where pitching in bogie is included. An artificial track profile is generated using FRA (Federal Railroad administration) Class 4 standards. The reference vehicle parameters for 6 DOF train model are obtained from local railway network parameters. Furthermore, the vehicle is assumed to maintain a constant velocity of 80 km/h with simulated distance of 800 m and sampling frequency of 1000 Hz. 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. A typical case of simulated profile after using band pass filter with cut off frequency of 0.3 Hz - 25 Hz, by incorporating noise level of 5% (standard deviation of measured response and random error) and large vehicle model error is considered. Noise is added to simulated data based on the characteristics of practical sensors used to measure the respective signals. Approach (a) is performing better when comparing to conventional ASKF and Approach (b) as per the calculated statistical metrics using root mean square deviation (RMSD) and correlation coefficient (CC). Henceforth, the rail track profile estimated using proposed algorithm Approach (a), is considered for all measurement sets and a comparison plot is shown in Figure 2.



(a)



(b)

Figure 2. (a) Comparison of estimated profile obtained from Approach (a) with Class-4 track profile; (b) PSD plot

From Figure 2, 'M1' and 'T' are performing poor when compared to all other measurement sets and also shows that 'M2 to M5' is performing relatively in similar manner. Thus, depending upon the sensors availability and feasible sensor placement locations in the real field measurement, rail track geometry can be reconstructed using inverse modelling and extended ASKF algorithm with proposed Approach (a) method. Also, the estimated track profile using conventional method considered in Tsunashima et al. (2014) is performing poor when compared with all cases. In order to get the better understanding, the frequency content of estimated and simulated true track profile are compared using PSD plot. While the performances of M2 to M5 seem similar, PSD plots clearly illustrates the difference among them. 'M4' performs better when compared to the others.

4. CONCLUSION:

Different measurement sets for railway track profile estimation are numerically examined with a 6 DOF train model and it is concluded that 'M4' measurement set performs better when compared to the others. The further studies are being conducted for the effective track profile estimation using practical sensors and its installation locations on in-service train vehicle.

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