Title:

Model based observer synthesis for the longitudinal dynamics estimation of a wheelset

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Introduction

The trade-off between safety, comfort and wear is an essential aspect of nearly every research activity that deals with railway technology. Regarding the longitudinal railway dynamics the wheel-rail interaction strongly influences all of the three criteria. Current traction and braking systems like wheel slide and skid protection already ease the trade-off to a certain extent [1]. To further improve the smoothness of the longitudinal motion and reduce the wear of wheels and rails, advanced measures for the traction and brake control are necessary.
Most of the advanced control algorithms require the knowledge of the full system states to continuously minimize the impact of the time- and path-dependent friction conditions in the wheel-rail interface. However, a direct measurement of all states is usually not feasible due to technical and economic reasons. Thus, the current longitudinal dynamics of the railway vehicle have to be estimated by an observer which provides information on each system state.
Therefore, this work presents a model based observer synthesis for the longitudinal dynamics estimation of a wheelset. First of all, the implementation of a nonlinear analytical observer model is illustrated in the methods section. In addition, this section describes the parameter estimator method and the disturbance observer approach. These two methods are chosen to specifically consider the influence of the friction conditions in the wheel-rail interface and also the varying friction coefficient between the brake pads and the brake discs. In the results section, the two different observers are optimized and applied to measurement data. At the end, the results are discussed, a conclusion is drawn, and the contribution of the presented work is highlighted.

Methods

In the following, the wheelset on the test rig is considered as a nonlinear system in the form

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}) + \boldsymbol{w}\,, \qquad \mathbf{y} = \boldsymbol{c}(\boldsymbol{x}) + \boldsymbol{z}\,, \tag{1}$$

with the states $\boldsymbol{x}$, the inputs $\boldsymbol{u}$ and the outputs $\mathbf{y}$. The system dynamics $\boldsymbol{f}(\cdot)$ are influenced by the system noise $\boldsymbol{w}$ and the measured outputs are affected by the sensor noise $\boldsymbol{z}$. The observer for this system is described by

$$\dot{\hat{\boldsymbol{x}}} = \boldsymbol{f}(\hat{\boldsymbol{x}}, \boldsymbol{u}) + \boldsymbol{L} \cdot (\boldsymbol{y} - \hat{\boldsymbol{y}})\,, \qquad \hat{\boldsymbol{y}} = \boldsymbol{c}(\hat{\boldsymbol{x}})\,, \tag{2}$$

with the observer feedback $\boldsymbol{L}$ that ensures convergence between $\boldsymbol{x}$ and $\hat{\boldsymbol{x}}$, if it is properly defined. Thus, the observer design process covers three steps: implementation of the observer dynamics $\boldsymbol{f}(\hat{\boldsymbol{x}}, \boldsymbol{u})$, definition of the measurement signals via $\boldsymbol{c}(\hat{\boldsymbol{x}})$, and specification of the observer correction $\boldsymbol{L}$.
As this work focuses the longitudinal dynamics, the observer model only comprises the two states wheelset velocity ω_{W} and roller velocity ω_{R}, which corresponds to the translational speed v. The dynamics $\boldsymbol{f}(\hat{\boldsymbol{x}}, \boldsymbol{u})$ are established using Lagrange's equations [2] and $\boldsymbol{f}(\hat{\boldsymbol{x}}, \boldsymbol{u})$ considers a nonlinear wheel-rail interface due to the implementation of the Polach contact [3], [4]. The inputs $\boldsymbol{u}$ are the roller torque τ_{R} and the brake pressure of the axle brake units c_{p}. The system (2) is observable for $\hat{y} = \omega_{\mathrm{W}}$ as well as for $\hat{y} = \omega_{\mathrm{R}}$. Nevertheless, both states are assumed to be outputs, since ω_{W} and ω_{R} (or v respectively) are continuously measured in modern trains.
As mentioned above, a parameter estimator and a disturbance observer are implemented. The parameter estimator

$$\dot{\hat{\boldsymbol{x}}} = \boldsymbol{f}(\hat{\boldsymbol{x}}, [\boldsymbol{u}, \boldsymbol{u}_{\mathrm{S}}]^T), \qquad \hat{\boldsymbol{y}} = \boldsymbol{c}(\hat{\boldsymbol{x}}) \tag{3}$$

generates additional inputs $\boldsymbol{u}_{\mathrm{S}} = [\Delta\mu_{\mathrm{WRI}}, \Delta\mu_{\mathrm{BU}}]^T = \boldsymbol{L}_{\mathrm{PE}} \cdot (\boldsymbol{y} - \hat{\boldsymbol{y}})$ representing the variation of the friction conditions in the wheel-rail interface and the brake units. The disturbance observer

$$\begin{bmatrix} \dot{\hat{\boldsymbol{x}}} \\ \dot{\hat{\boldsymbol{x}}}_{\mathrm{S}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{f}([\hat{\boldsymbol{x}}, \hat{\boldsymbol{x}}_{\mathrm{S}}]^T, \boldsymbol{u}) \\ \boldsymbol{g}_{\mathrm{S}}([\hat{\boldsymbol{x}}, \hat{\boldsymbol{x}}_{\mathrm{S}}]^T) \end{bmatrix} + \boldsymbol{L}_{\mathrm{DO}} \cdot (\boldsymbol{y} - \hat{\boldsymbol{y}}), \quad \hat{\boldsymbol{y}} = \boldsymbol{c}([\hat{\boldsymbol{x}}, \hat{\boldsymbol{x}}_{\mathrm{S}}]^T) \tag{4}$$

extends the state vector by the disturbance states $\hat{\boldsymbol{x}}_{\mathrm{S}} = [\Delta\mu_{\mathrm{WRI}}, \Delta\mu_{\mathrm{BU}}]^T$ and the system dynamics are extended by the disturbance dynamics $\boldsymbol{g}_{\mathrm{S}}([\hat{\boldsymbol{x}}, \hat{\boldsymbol{x}}_{\mathrm{S}}]^T)$.

Results

This section illustrates the optimization of the observer parameters as well as some results of the test rig experiments. The observer feedback $\boldsymbol{L}_{\mathrm{PE}} \in \mathbb{R}^{2\times4}$ is a time invariant matrix comprising the two parts $(\boldsymbol{y} - \hat{\boldsymbol{y}})$ and $\int(\boldsymbol{y} - \hat{\boldsymbol{y}})dt$. The extension by the integral part results in an improved performance. The disturbance observer is realized as a Kalman filter [5] with the diagonal covariance matrices $\boldsymbol{Q} \in \mathbb{R}^{4\times4}$ and $\boldsymbol{R} \in \mathbb{R}^{2\times2}$ representing the process noise and the observation noise, respectively. The disturbance dynamics are defined as an exponential regression over time. Thus, there are eight parameters of $\boldsymbol{L}_{\mathrm{PE}}$, four parameters of $\boldsymbol{Q}$, and two of $\boldsymbol{g}_{\mathrm{S}}(\cdot)$ that are optimized via a multi case optimization [6].
Table 1 shows a comparison between the optimized observers and a model without feedback correction but with optimized friction parameters. The two columns on the left denote the deviations Δd of the observed and the measured brake distances. The two columns on the right show the deviations of the longitudinal wheel-rail forces ΔF_{x} integrated over time and divided by the scenario specific mean value of $\bar{F}_{\mathrm{x}}$ and the experiment duration t_{end}. For both quantities the average values of the test scenarios as well as the maximum values are illustrated.

	Δd [m]		$\frac{1}{t_{\mathrm{end}} \cdot \bar{F}_{\mathrm{x}}} \cdot \int \Delta F_{\mathrm{x}}\, dt$ [−]	
	average	max	average	max
optimized model	178	429	0.50	0.97
parameter estimator	17.2 (-90.4 %)	21.5 (-95.0 %)	0.36 (-27.7 %)	0.90 (-6.4 %)
disturbance observer	0.08 (-99.9 %)	0.16 (-99.9 %)	0.39 (-21.0 %)	0.61 (-36.3 %)

Table 1: Results of the observer synthesis for the optimization scenarios

Both observers show a significantly improved accuracy of the brake distance estimation, since ω_{R} is available to the observers. The observed wheel-rail forces indicate clearly the advantages of the observer methods, as the average values show an improvement of more than 20 % in relation to the optimized model. The enhancement of the maximum force deviation for the parameter estimator is comparatively slight due to the high frequency of the wheel slide protection.

Conclusions and Contributions

The previous sections give an overview on the entire observer synthesis from the setup of an observer model to the optimization of the observer parameters. The presented results show that the observers estimate the system states with a high accuracy and provide information regarding the longitudinal dynamics like the longitudinal wheel-rail force. Exploiting this information in an advanced control setup facilitates a row of promising applications to improve safety, comfort and wear all at once. First of all, the variation of brake distances might be minimized even on varying friction conditions, what essentially enhances the safety. Furthermore, the functionalities of the traction and braking systems can be upgraded, so that the gap between two trains can be shortened and the utilized capacity of the existing rail infrastructure increases.

There are some aspects that are not yet investigated but are expected to lead to an even higher accuracy of the observer results. One of these features is a temperature and velocity dependent modelling of the disturbance dynamics $g_S(T, \omega_W)$. Another approach is the combination of state and parameter estimation that allows for a specific consideration of the quickly time-varying states and the slowly time-varying friction disturbances, cf. [7]. Further tasks to be tackled in the future are to adapt the observers to an entire train system and to validate them with data from track tests.

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