Proceedings of the Sixth International Conference on
Railway Technology: Research, Development and Maintenance
Edited by: J. Pombo
Civil-Comp Conferences, Volume 7, Paper 19.5
Civil-Comp Press, Edinburgh, United Kingdom, 2024
ISSN: 2753-3239, doi: 10.4203/ccc.7.19.5

An Application of the Unknown Input Observer Algorithm for the Identification of Vertical Railway Track Irregularity

I. La Paglia, M. Santelia, S. Alfi, E. Di Gialleonardo and A. Facchinetti

Department of Mechanical Engineering, Politecnico di Milano Italy

Abstract

In this paper, a model-based solution for the identification of the railway track irregularity from simulation data is presented. The proposed methodology relies on the application of the Unknown Input Observer algorithm. A Simpack railway vehicle model is adopted to simulate the acceleration levels that vehicle-mounted sensors (for instance on the bogies and carbody) would measure during operation. A vehicle running at constant speed on a straight track is considered, considering different type of track irregularity (longitudinal level, cross-level) to test the algorithm capability to identify the input irregularity. In the analysed cases, satisfactory results are achieved both in terms of signal histories and corresponding frequency content, proving the methodology suitable for the identification of the track irregularity for monitoring purposes, adopting an instrumented vehicle.

Keywords: railway infrastructure, track condition, model-based solution, rail vehicle dynamic simulation, condition-based maintenance, predictive maintenance.

1 Introduction

To ensure the safety of the railway network, track geometry is periodically inspected [1]-[3] by Track Recording Vehicles (TRVs), which are special purpose vehicles typically equipped with inertial and optical sensors. Given their high operating costs, new strategies have been proposed in the latest years to support the condition monitoring of railway infrastructure, relying on instrumented in-service vehicles. On one hand, data driven methodologies can be adopted. For instance, in [4]-[7], the evolution of the longitudinal level over time was monitored adopting indicators (computed from the bogie accelerations) representative of the track condition. Other examples can be found in [8]-[10], where spectral analysis, band-pass filters, wavelet transform are used to identify different track defects.

On the other hand, model-based strategies can be followed. Given a rail vehicle model whose complexity depends on the target of the study, these methodologies typically aim at solving an inverse problem: the input track irregularity is estimated based on the data collected on the vehicle. Popular examples can be made referring to Kalman Filters [9],[11]-[12]. Although generally accurate, this method requires a wide set of sensors and a statistical evaluation of the system variance. Therefore, other model-based techniques have been proposed, that still aims at identifying the track irregularity profile, supporting maintenance strategies.

In this paper, reference is made to the Unknown Input Observer (UIO) [13] as a methodology to identify the railway track irregularity profile. The algorithm allows evaluating the unknown input disturbance estimating the state of a linear system. In this work, the Manchester Benchmark model will be used to simulate the operation of an instrumented in-service vehicle. The obtained acceleration data will be fed to the UIO algorithm willing to identify the input track irregularity.

2 Methods

In this section, at first the principles of the Unknown Input Observer (UIO) will be presented; secondly, the application to the estimation of the track irregularity will be addressed.

2.1 Unknown Input Observer (UIO)

The UIO is a model-based algorithm which can be used to reconstruct a non-deterministic input through the adoption of a linearized model of the system, when measurements are available. Consider a mechanical system described in the typical state-space form expressed in Equation (1), where x(t) represents the state of the system, u(t) the vector of the known inputs and d(t) the unknown disturbances acting on the system (with no direct influence the output dynamics):

$$\begin{cases} \dot{x}(t) = A\,x(t) + B\,u(t) + E\,d(t) \\ y(t) = C\,x(t) \end{cases} \tag{1}$$

where A, B, C, E are real constant matrices of suitable dimensions. To simplify the notation, the time dependency will be hereafter omitted.

An estimation of the disturbance $\hat{d}$ can be obtained by manipulating Equation (1), leading to:

$$\hat{d} = (CE)^{+}\,(\dot{y} - CA\,x - CB\,u) \;=\; M(\,\dot{y} - CA\,x - CB\,u) \tag{2}$$

Note that the pseudo-inverse operator $(\square)^{+}$ is adopted, being CE a rectangular matrix (generally, a smaller number of inputs is considered with respect to the available measurements).

A necessary condition for the applicability of the UIO is associated to the rank of matrix CE that must be equal to the rank of matrix E, which in turn must be equal to the number of unknow inputs n_d acting on the system (3).

$$rank(CE) = rank(E) = n_d \tag{3}$$

It is evident that Equation (2) requires the knowledge of the system state x. Therefore, the disturbance estimation is combined with a Luenberger observer, so as to generate a state estimation, as reported in Equation (4):

$$\begin{cases} \dot{\hat{x}} = A\,\hat{x} + B\,u + E\,\hat{d} + L(y - C\,\hat{x}) \\ \hat{d} = (CE)^{+}\,(\dot{y} - CA\,\hat{x} - CB\,u) \;=\; M(\dot{y} - CA\,\hat{x} - CB\,u) \end{cases} \tag{4}$$

For the sake of clarity, the algorithm can be visually represented as shown in Figure 1 (where u is set to zero in view of the application presented in Section 2.1).

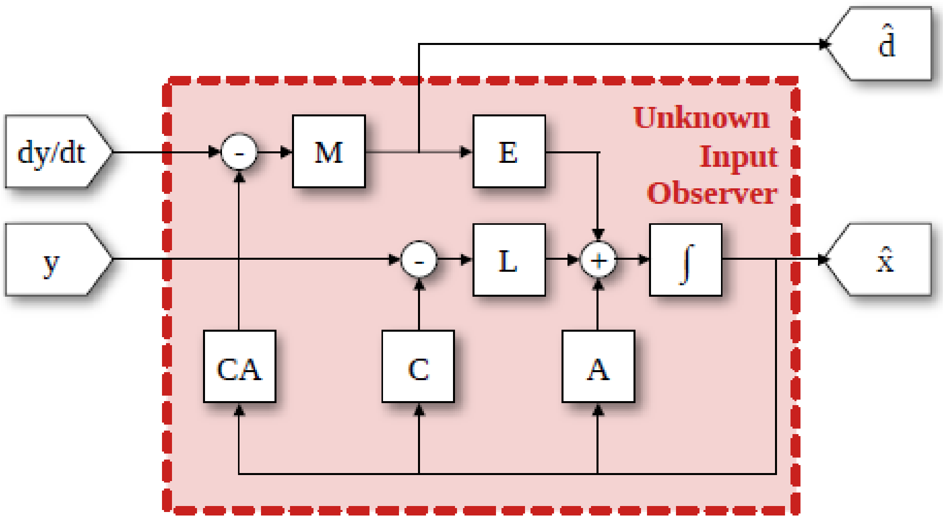

Figure 1: UIO block diagram.

Note that the observer of Equation (3) requires the knowledge of $\dot{y}$. Defining the matrix T as:

$$T = I - EMC \tag{5}$$

it turns out that the observer dynamics is governed by the following equation:

$$\dot{\hat{x}} = (TA - LC)\,\hat{x} + TB\,u + EM\,\dot{y} + L\,y \tag{6}$$

A second condition for the existence of the UIO is therefore that the couple of matrices TA and C is detectable. The gain matrix L can be defined according to different approaches, as the pole placement or an optimal one.

2.2 Application of the UIO for track irregularity estimation

In this work, an application of the UIO algorithm is proposed, aiming at the estimation of the vertical railway track irregularity. To this aim, a simplified model of a rail vehicle (making reference to the Manchester Benchmark parameters [14]) in the vertical plane is adopted. The scheme of the model is reported in Figure 2. The model includes the bounce and pitch motions of the carbody, the front and the rear bogies, which lead to 6 free degrees of freedom (dofs), highlighted with red arrows in Figure 2. Primary and secondary suspensions are modelled as linear springs and dampers in parallel, acting both along the vertical direction and the longitudinal one (not reported in Figure 2 for simplicity).

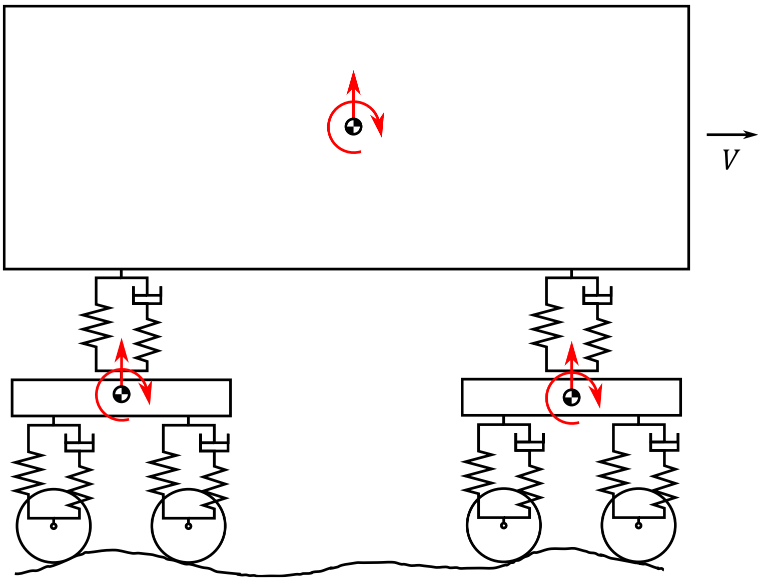

Figure 2: Railway vehicle model.

The track irregularity is introduced as imposed displacement to the 4 wheelsets. Actually, the multi-input system can be addressed given the pivot pitch, the wheelbase and the vehicle speed. This way, taking as reference the leading wheelset, the three remaining inputs can be defined by suitable delay functions.

Once the vehicle model has been presented, attention is paid to the definition of the state of the system. 20 variables define the extended state, as hereafter described:

- 12 states associated to the independent coordinates and their time derivatives;
- 4 states accounting for the disturbances, under the assumption that the inputs to the system are the displacements of the wheelsets and their time derivatives. Since in the formulation described in Section 2.1 the inputs are inserted in the equations without any time derivative, the state is augmented introducing also the inputs, thus their time derivatives will be the results of the estimation performed by UIO;
- 4 states related to the Padè approximation introduced to account for the time delay between the inputs. The approximation relies on the Taylor expansion of the time delay expressed through an exponential function. A 2nd order Padè approximation is considered in this work for each trailing wheelset in the bogies.

Considering this model, in order to satisfy the necessary condition for the observability of the disturbances expressed in Section 2.1, a minimum number of four measurements should be available. In particular, these measurements must be associated with the motion of the bogies. In order to improve the accuracy of the estimation, also measurements on the carbody are considered. As final configuration, it is assumed to measure two vertical accelerations on the carbody and on each bogie so to have a total number of six sensors.

3 Results

The Manchester Benchmark model was run in Simpack to generate the measurements required by the UIO. Different sensors positions were selected, willing to investigate the minimum set of data required to successfully estimate the track irregularity. Moreover, several operating scenarios were considered, including the effect of speed variability (100-160 km/h), track characteristics (straight-curves) track irregularity amplitude (low-high) and type of defectiveness (alignment, longitudinal level, cross-level).

For the sake brevity, in this work an exemplary result is presented, making reference to a simulation considering a straight track where the vehicle is running at 160 km/h.

Regarding the irregularities, the presented simulation takes into account vertical, horizontal, and cross-level irregularities defined by a standard power spectral density (ERRI B176).

Figure 3 shows the comparison between the track irregularity considered as a reference input and the one estimated by the UIO, respectively reported as a blue and red line.

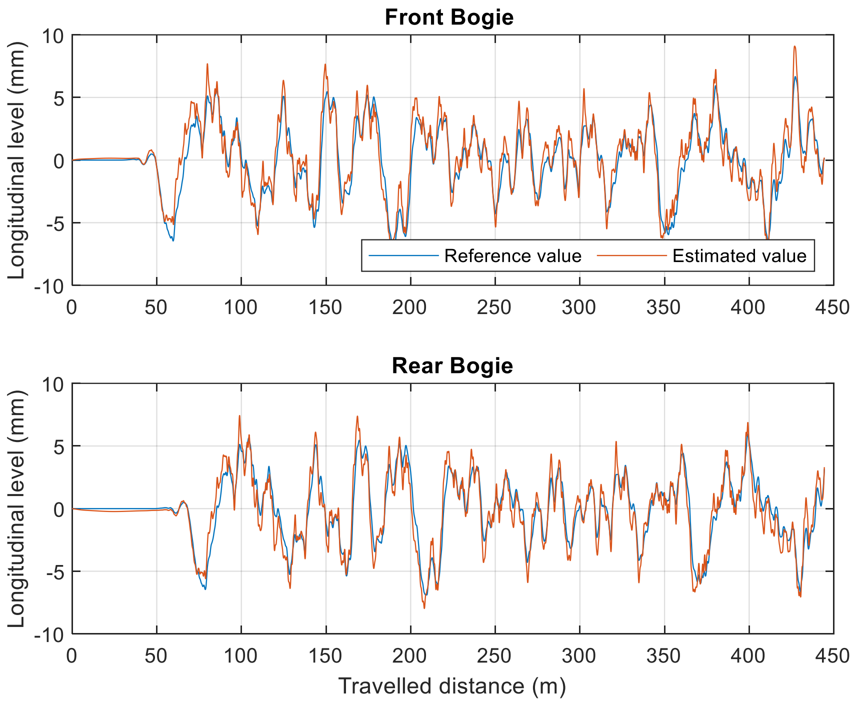

Figure 3: Comparison between the longitudinal level irregularity considered as reference (to run the vehicle dynamic simulation in Simpack) and estimated by the UIO algorithm. Signal histories for a) front bogie and b) rear bogie. Simulation along straight track at 160 km/h.

Specifically, Figure 3a) shows the results for the front bogie, while in Figure 3b) the rear bogie is proposed. The first 50 m of the straight track was designed as an ideal one to allow initialising the simulation. From 50 m on, the vehicle runs over the track irregularity. Comparing the reference and estimated track profiles, a satisfactory agreement can be recognised for both bogies, the two lines being almost superimposed. However, an overestimation can be observed in most of the irregularity peaks. To deepen the results, the Power Spectral Density Functions (PSDs) of the signal were analysed, as reported in Figure 4. It can be recognised that while the low frequency content is well identified, an overestimation characterizes the 5-8 Hz range, which justifies the signal histories of Figure 3. This fact may be related to the weights considered in the design of the UIO algorithm, but can be still considered as promising as they prove the model capability to identify the track irregularity.

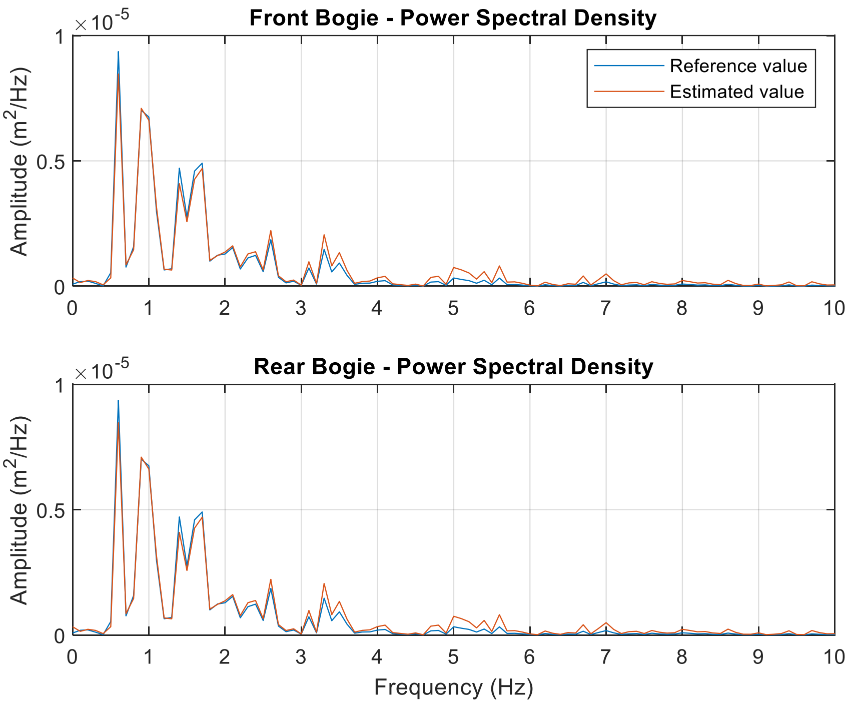

Figure 4: Comparison between the longitudinal level irregularity considered as reference (to run the vehicle dynamic simulation in Simpack) and estimated by the UIO algorithm. PSD for a) front bogie and b) rear bogie. Simulation along straight track at 160 km/h.

Finally, to further validate the results presented in Figure 3 and Figure 4, two indices, denoted respectively with α and β, are proposed to assess the overall consistency, both in time and frequency domains. For the time domain, the normalized squared error defined in Equation 7 is employed. A similar index is proposed for the frequency domain, with the error evaluation based on the differences in spectral intensity as described in Equation 8.

$$\alpha = \frac{\sum_{t=0}^{T}\left(x_{irr}(t) - x_{est}(t)\right)^2}{\sum_{t=0}^{T} x_{irr}(t)^2} \tag{7}$$

$$\beta = \frac{\sum_{f=0}^{f_{NYQ}}(|FFT_{irr}(f)| - |FFT_{est}(f)|)^2}{\sum_{f=0}^{f_{NYQ}}|FFT_{irr}(f)|^2} \tag{8}$$

Table *1* shows the results of the two indices expressed in percentage. For the considered straight track simulation the α index is equal to about 13%, showing a good agreement between the estimated irregularity and the actual one. The α index takes into account not only the magnitude of the irregularity but also its position along the line, a small delay of the reconstructed signal generating a worsening of the index. The second index β instead focuses on the capacity of the observer to reconstruct the magnitude of the different wavelengths present in the irregularity. The index β is about 1.5% showing how the observer is able to estimate, with a high degree of accuracy, the spectral content of the irregularity.

Bogie	Index α	Index β
Front	13.9%	1.5%
Rear	12.4%	1.3%

Table 1 – Identification indexes.

4 Conclusions and Contributions

In this paper, an application of the UIO algorithm to identify the railway track irregularity is proposed. To generate the data required by the algorithm, a vehicle dynamic simulation was performed in Simpack, considering the Manchester Benchmark vehicle.

A reference simulation along a straight track at 160 km/h, with vertical, lateral and cross-level irregularity was considered, and the attention was devoted to the estimation of the vertical track irregularity. To this end, carbody and bogies acceleration data were used as input signals for the UIO algorithm.

The validation of the results was performed comparing the reference and estimated track vertical track irregularity both in terms of signal histories and PSD. The comparison shows satisfactory results, although some overestimations associated to frequency component in the 5-8 Hz frequency range were observed. In addition, to further validate the results, two indices were proposed to assess the overall consistency of the algorithm.

Acknowledgements

This study was carried out within the MOST – Sustainable Mobility National Research Centre and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR – NATIONAL RECOVERY AND RESILEINCE PLAN) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4

(MISSION 4 COMPONENT 2, INVESTMENT 1.4) – D.D. 1033 17/06/2022, CN00000023). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

References

[1] EN 13848-5:2017. Railway applications – track – Track geometry quality. Part 5: geometry quality levels – plain line, switches and crossings. European Standard, 2017.

[2] P. Weston, C. Roberts, G. Yeo, E. Stewart, "Perspective on railway track geometry condition monitoring from in-service railway vehicles", Vehicle System Dynamics, 53, 7, 1063-1091, 2015, DOI:10.1080/00423114.2015.1034730

[3] G. Rosano, D. Massini, L. Bocciolini, C. Zappacosta, E. Di Gialleonardo, C. Somaschini, I. La Paglia, L. Pugi, "Diagnostics of the railway track-Possibility of development through the measurement of accelerations and contact forces | La diagnostica dell'armamento ferroviario-Possibilità di sviluppo attraverso la misura di accelerazioni e forze di contatto", Ingegneria Ferroviaria, 79 (2), 2024, DOI: 10.57597/IF.02.2024.ART.1

[4] I. La Paglia, M. Carnevale, R. Corradi, E. Di Gialleonardo, A. Facchinetti, S. Lisi, "Condition monitoring of vertical track alignment by bogie acceleration measurements on commercial high-speed vehicles", Mechanical System and Signal Processing, 186, 109869, 2023, DOI:10.1016/j.ymssp.2022.109869

[5] I. La Paglia, E. Di Gialleonardo, A. Facchinetti, M. Carnevale, R. Corradi, "Acceleration-based condition monitoring of track longitudinal level using multiple regression models", Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 238 (5), 2024, DOI:10.1177/09544097231201513

[6] I. La Paglia, E. Di Gialleonardo, A. Facchinetti, M. Carnevale, R. Corradi, "A Methodology to Estimate Railway Track Conditions from Vehicle Accelerations Based on Multiple Regression", Lecture Notes in Civil Engineering, 432 LNCE, 203 – 2102023, Experimental Vibration Analysis for Civil Engineering Structures - EVACES 2023 - Volume 2, Milan, August 2023, DOI:10.1007/978-3-031-39109-5_21

[7] I. La Paglia, C. E. Araya Reyes, E. Di Gialleonardo, A. Facchinetti, M. Carnevale, "A speed-dependent condition monitoring system for track geometry estimation using inertial measurements", 28th IAVSD Symposium on the Dynamics of Vehicles on Roads and on Tracks (IAVSD 2023). National Research Council Canada, Ottawa, Canada, 21-25 August 2023.

[8] P. F. Weston, C. S. Ling, C. Roberts, C. J. Goodman, P. Li, R. M. Goodall, "Monitoring vertical track irregularity from in-service railway vehicle", Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 221, 75-88, 2007, DOI:10.1243/0954409JRRT65

[9] H. Tsunashima, Y. Naganuma, T. Kobayashi, "Track geometry estimation from car-body vibration". Veh Syst Dyn 2014; 52(sup1): 207–219. DOI: 10.1080/00423114.2014. 889836

[10] M. Bocciolone, A. Caprioli, A. Cigada, et al., "A measurement system for quick rail inspection and effective track maintenance strategy". Mech Syst Signal Process 2007; 21(3): 1242–1254.
[11] A. De Rosa, S. Alfi, S. Bruni, "Estimation of lateral and cross alignment in a railway track based on vehicle dynamics measurements". Mech Syst Signal Process 2019; 116: 606–623, DOI: 10.1016/j.ymssp.2018.06.041
[12] A. De Rosa, R. Kulkarni, A. Qazizadeh, et al., "Monitoring of lateral and cross level track geometry irregularities through onboard vehicle dynamics measurements using machine learning classification algorithms". Proceedings of the Institution of Mechanical Engineers. Part F: Journal of Rail and Rapid Transit - ISSN:0954-4097 2021; 235(1): 107–120. DOI: 10.1177/0954409720906649
[13] S.X. Ding, "Model-Based Fault Diagnosis Techniques", Advances in Industrial Control, DOI 10.1007/978-1-4471-4799-2, Springer-Verlag London 2013
[14] S. Iwnicki, "Manchester Benchmarks for Rail Vehicle Simulation", Vehicle System Dynamics, (1998) 30:3-4, 295-313, DOI: 10.1080/00423119808969454