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A Methodology for Track Geometry Estimation using Inertial Measurements: Compensation of Bogie Filtering

**C. E. Araya Reyes, I. La Paglia, E. Di Gialleonardo,
A. Facchinetti and S. Bruni**

**Department of Mechanical Engineering, Politecnico di Milano
Italy**

Abstract

In this paper, a methodology for the estimation of track longitudinal level based on the double integration of acceleration measurements is presented. The method is meant to be implemented on vehicles in-service along main line, where trains run at various speed depending on the line characteristics. The system relies on the information coming from a single sensor, mounted at the centre of the bogie frame. A suitable strategy to account for the filtering action introduced by the bogie, that makes the system blind to specific wavelengths, is proposed. To monitor the track conditions, the standard deviation and the peak value of the longitudinal level computed over a 100 m windows are adopted as synthetic indicators. Linear regression models relating the indicators sampled from the direct measurements taken by a diagnostic vehicle and those computed by double integration of the acceleration signals are realized. Both regression models, fed with the data gathered during a long-term monitoring, are finally adopted to estimate the track longitudinal level from the instrumented commercial vehicle, showing satisfactory results.

Keywords: rolling stock-based diagnostic system, railway track monitoring, railway infrastructure, track condition, condition-based maintenance, predictive maintenance.

1 Introduction

Maintenance operations are essential for the correct operation of railway lines and rolling stock regarding safety and reliability. In general, these maintenance activities

are scheduled in such a way that regular intervals are left between subsequent interventions, but this may not be the optimal solution in terms of time and resources.

If the condition of rolling stock and infrastructure is well known, maintenance operations can be organised based on the actual requirements of the railway assets. It is then possible to move from a scheduled maintenance strategy to the so-called Condition Based Maintenance (CBM), thus allowing railway managers and operators to optimise the use of the available resources. The possibility to continuously monitor the condition of railway assets can lead to improvements in terms not only of costs and availability, but also in what regards efficiency and sustainability. With the focus on the infrastructure, railway track condition is commonly inspected but not monitored. Since the idea behind inspection is to detect some possible critical situation, the interval between consecutive inspections is sufficiently short to detect a defect, but usually it is not short enough to allow monitoring its evolution with time. To this aim, information about track condition is gathered using specifically designed diagnostic vehicles or Track Recording Vehicle (TRV). To pass from track inspection to track monitoring, the interval between passages of the TRV should be reduced, which means that the diagnostic train should run with a higher frequency on each line. Most of the time, this is not feasible in terms of costs and availability.

Using in-service trains equipped with a reduced set of sensors that can provide information about the state of the line in between inspection runs, will allow the passage from inspecting to monitoring. In [1-4], it has been shown that reduced set of sensors based on accelerometer and gyroscope measurements allow to observe track geometry. In [5,6], it has been shown that synthetic indexes based on standard deviation from acceleration measurements can be used for monitoring the state of a high-speed railway line. Techniques for track geometry estimation using commercial vehicles have been studied in [6-8]. In [9], it was proven that indexes based on vertical displacement are better indicators when relevant speed variations are registered along the line, that is the typical case of commercial trains running along main lines.

In this work, the methodology illustrated in [9] that allows the estimation of track longitudinal level using a single-sensor setup is extended. Specifically, a method for compensating the bogie filtering action is introduced. It takes advantage of the integration in frequency domain to correct the filtering effect of the bogie by means of a weighting function obtained from the inverse response function of the vehicle. Acceleration signal measured from an accelerometer mounted in the bogie centre is double integrated and corrected using the weighting function. After that, the standard deviation of the vertical displacement is calculated and considered as input for a linear regression model that correlates vertical displacement to track longitudinal level. Finally, the effectiveness of the methodology is demonstrated by estimating the track level from data coming from an experimental campaign.

2 Methods

In this section, the methodology designed to estimate track longitudinal level in D1 range [10] from the signal measured by an accelerometer mounted on the bogie frame is presented. Reference is made to conventional lines, where vehicles run at different

speed depending on the characteristics of the railway line, and many stops are required to serve the stations. In this framework of research, we demonstrated in [9] that the standard deviation of track longitudinal level better correlates with the standard deviation of the vertical displacement, rather than with the standard deviation directly computed from the acceleration signal. For the sake of clarity, the method presented in [9] is hereafter briefly recalled, before introducing the updates to the methodology. In fact, this work aims at compensating the bogie filter (that prevents observing specific wavelengths), extending the possibility of adoption and accuracy of the developed condition monitoring system.

In [9], the vertical displacement is computed by double integration of the bogie accelerations recorded by the instrumented vehicle. A single-sensor setup is used with the accelerometer mounted on the bogie centre. To reduce the computational effort, integration is performed in the frequency domain adopting the Fast Fourier Transform (FFT). Then, the vertical displacement is filtered into the D1 range (wavelengths in the range from 3 m to 25 m [10]). Once the required vertical displacement signal is obtained, synthetic indicators useful to monitor the track conditions are sampled along predefined sections of the line (100 m long) [11]. In particular, the standard deviation STD_{VD} of the filtered bogie vertical displacement is evaluated directly in frequency domain. The proposed methodology relies on linear regression models that allow predicting the track conditions using as input the data collected by the instrumented vehicle. Specifically, the standard deviation of the track longitudinal level STD_{LL} is estimated through the linear regression of Equation (1):

$$STD_{LL} = m \cdot STD_{VD} + q \quad (1)$$

where m and q are the coefficients estimated based on the experimental data collected during a long-term experimental campaign, along the reference railway line.

One of the major drawbacks of this single-sensor setup is related to the effect that the filter introduced by bogie may have on measurements. In fact, when the sensor is mounted at the bogie centre, the wheelbase of the bogie acts as a geometrical filter, thus preventing the sensor to measure track defects with specific wavelengths. In particular, the system becomes blind to defects with wavelengths $\lambda = 2L/n$, where L is the bogie wheelbase, and n is a positive odd integer. This filtering effect can be observed in Figure 1b), where the Frequency Response Function (FRF) relating the measured bogie displacement (achieved by double integration) and the input irregularity is shown. The FRF is obtained using the simplified model of Figure 1a) [9]. It is evident that the wavelength of 6 m (that is twice the bogie wheelbase) is completely filtered out, with the response of the vehicle that goes to zero. It can be observed that this behaviour is not dependent on the vehicle speed. Also the wavelengths around this value are affected by a filtering action.

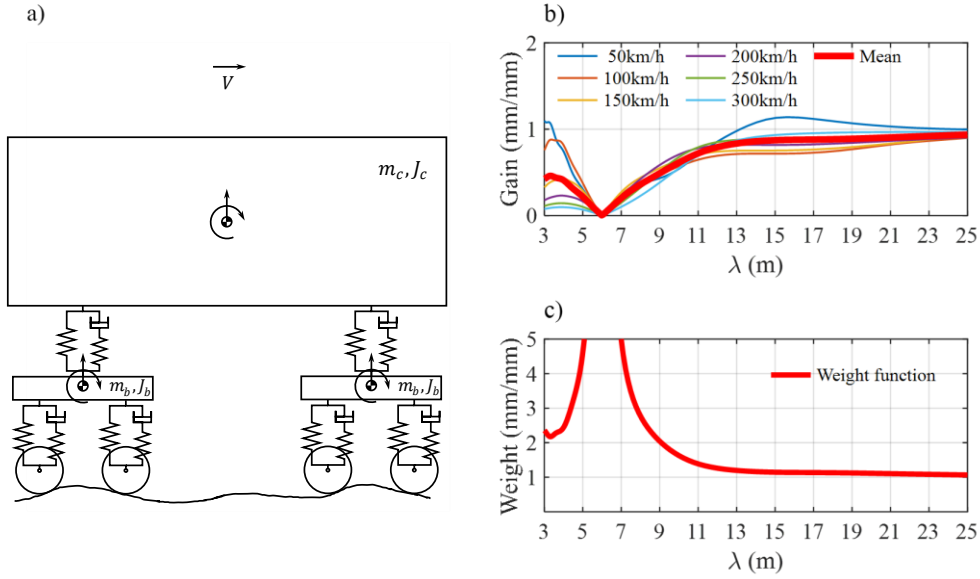


Figure 1: Simplified vehicle model adopted to evaluate the response of the system.
a) Vehicle model in the vertical plane; b) Frequency Response Function (FRF) between the bogie motion and the input irregularity, for different vehicle speed;
c) weighting function computed as the inverse of the mean bogie response.

The methodology update proposed in this work aims at compensating the effect of this bogie filtering action, thus improving the capability of the system to estimate longitudinal level when defects with these wavelengths are present. To this aim, the inverse of the FRF between track longitudinal level and bogie vertical displacement is adopted as a weighting function to correct the amplitude of the frequency components, before computing the standard deviation of the vertical displacement.

More in detail, it can be observed in Figure 1b) that the vehicle response depends on the vehicle speed. To cope with this aspect, the mean response function $\bar{X}(\lambda)$ was obtained (red line in Figure 1b)) adopting Equation (2) and considering speeds in the range from 50 km/h to 300 km/h.

$$\bar{X}(\lambda) = \sum_{v_{train}} X_v(\lambda) \quad (2)$$

The weighting function presented in Figure 1c) is computed as the inverse of the mean response, according to Equation (3):

$$WF(\lambda) = \frac{1}{\bar{X}(\lambda)} \quad (3)$$

The weights w_k , corresponding to each frequency component of the vertical displacement $Z_{k,D1}$, are obtained from the weighting function evaluated at the corresponding wavelength λ_k . It is worth mentioning that the reasonable assumption of small speed variation within each 100 m section is made, so that the conversion between wavelength and frequency domain is performed considering the average speed \bar{v} of the train, according to Equation (4):

$$w_k = WF(\lambda_k); \quad \lambda_k = \frac{\bar{v}}{f_k} \quad (4)$$

The weights listed above are used to correct the amplitude of each frequency component according to Equation (5):

$$|Z_{k,corr}| = w_k |Z_{k,D1}| \quad (5)$$

Then, the standard deviation of the compensated vertical displacement STD_{VD+WF} is calculated from Equation (6):

$$STD_{VD+WF} = \sqrt{\sum_k \frac{1}{2} |Z_{k,corr}|^2} \quad (6)$$

Finally, Equation (7) gives the estimated standard deviation of the track longitudinal level STD_{LL} obtained from STD_{VD+WF}

$$STD_{LL} = m \cdot STD_{VD+WF} + q \quad (7)$$

where m and q are the estimated coefficients of the linear regression model fitted using track geometry records from the TRV.

In the case under study, data collected during a long-term experimental campaign along the railway line under analysis was considered to train the regression model. In particular, 25 runs in a 24-month period were considered. During each run, the TRV measured both bogie accelerations and track geometry. The correlation between the standard deviation of the track longitudinal level directly measured by the TRV (STD_{LL-D1}) and the one estimated through the proposed strategy (STD_{VD+WF}) is shown in Figure 2. The regression model obtained is characterised by a coefficient of determination $R^2 = 0.91$, which can be regarded as significantly high thus confirming the correlation between the regressor and the prediction.

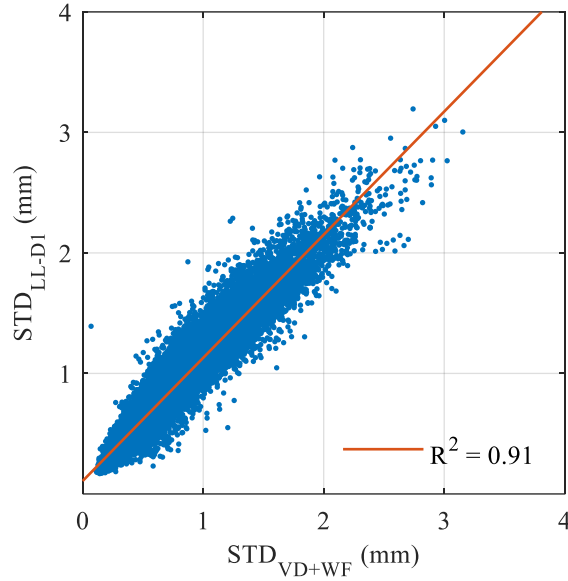


Figure 2: Linear regression model for the prediction of the standard deviation of the track longitudinal level in D1 range.

To evaluate the effectiveness of the methodology, the aggregated percentual error between the measured and estimated STD_{LL} was computed. A comparison among both methodologies (with and without the weighting function) is presented in Figure 3. It can be noticed that the error is reduced in the whole range of interest. The reduction in the error shows that the compensation is effectively introducing the contribution of track defects that are otherwise filtered by the bogie dynamics.

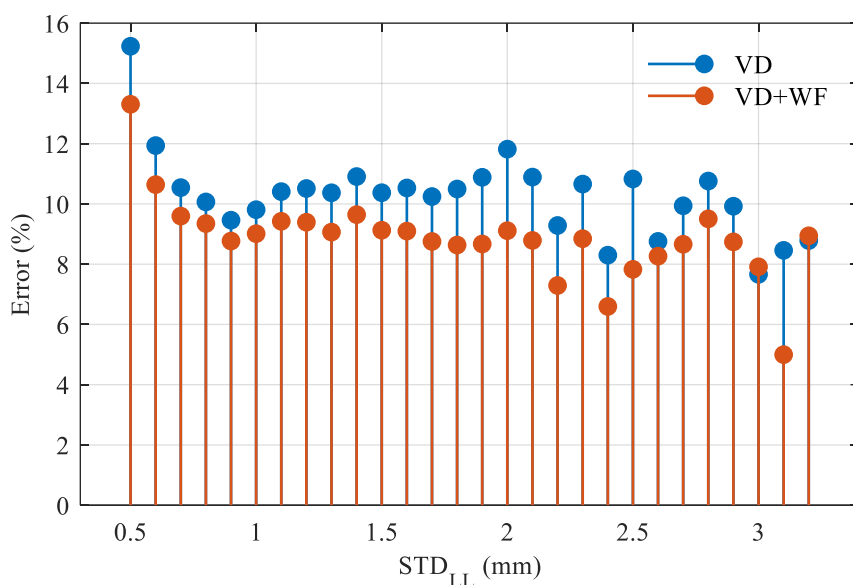


Figure 3: Comparison of the aggregated error between measured and estimated STD_{LL} , considering the previous (VD) and updated (VD+WF) methodology.

3 Results

In this section, the results obtained applying the new linear regression model to estimate the track defects adopting the weighted bogie vertical displacement are presented. The model was used to estimate track geometry of a specific 100 m section of the line, in order to highlight the effect of the compensation method. To this end, a track section characterized by a defect with a wavelength in the range affected by the bogie filtering has been first selected. The Power Spectral Density (PSD) of the section under analysis is shown in Figure 4, as a function of the wavelength. It can be observed that defects characterized by wavelengths in the range of 7-11 m are predominant in the considered track section.

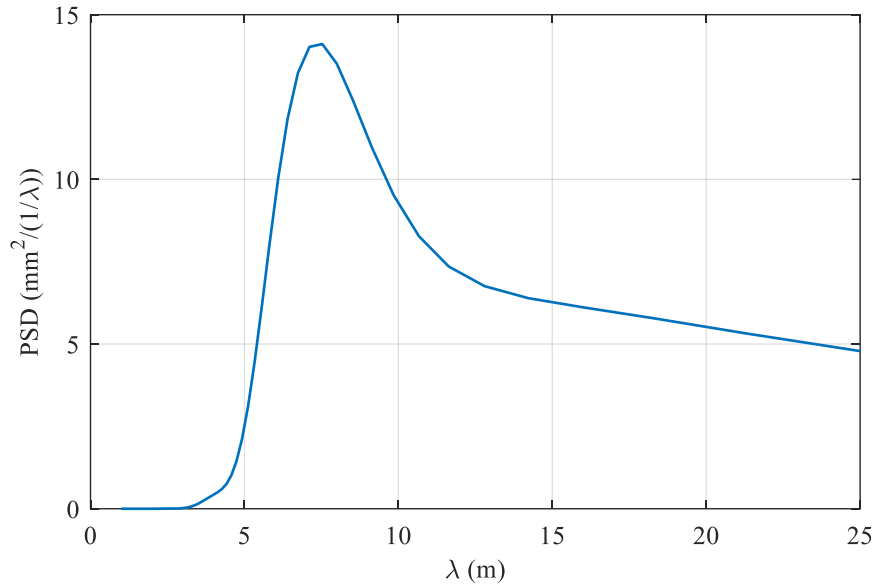


Figure 4: PSD of the track longitudinal level in D1 range, for a reference 100 m section of the line.

Let us then apply the methodology to the considered track section for a series of measurements over time, to observe the evolution of the standard deviation of track longitudinal level (STD_{LL}) over the monitoring period of 24 months. Measured and estimated values of STD_{LL} are reported in Figure 5a), and the average speed of the vehicle in the considered 100 m section is also reported in Figure 5b). Blue dots represent the data measured by the TRV; the STD_{LL} estimates from the vertical displacement of the bogie are shown in red, and the predictions achieved with the updated methodology (including the weighting function) are reported in yellow. It can be observed that during the whole monitoring period, no evolution of the considered defect occurred, given that the direct measurements (blue dot) show an almost constant STD_{LL} along time.

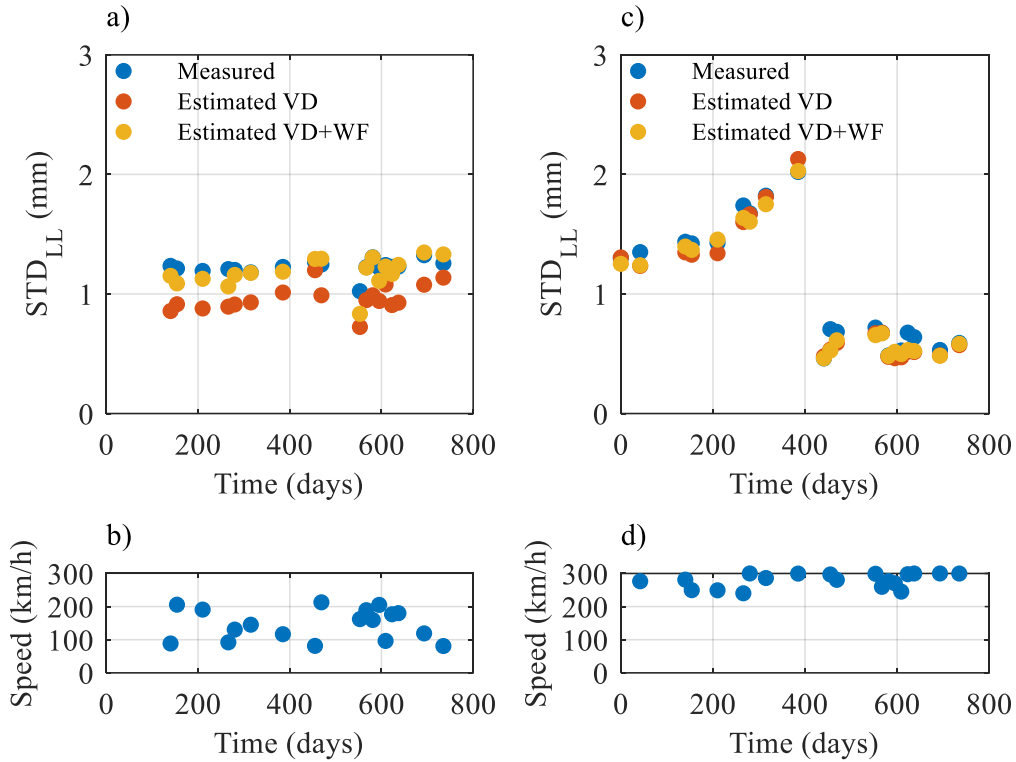


Figure 5: Defect estimation: evolution with time of the standard deviation of track longitudinal level of two different defects. a) STD_{LL} of a defect with wavelengths in the range 7-11 m; b) corresponding average speed of the vehicle in the 100 m section; c) STD_{LL} of a defect evolving with time and d) average speed.

The effectiveness of the methodology update can be noticed from the good agreement between the results. In fact, yellow dots in Figure 5a) are well superimposed to the blue ones, showing a significant improvement compared to the estimates reported with red markers. This result exemplifies that, for short wavelength defects (in the order of 7-11 m), better accuracy is achieved when the compensation method is introduced. It is also interesting to note that the methodology provides accurate results regardless of the vehicle speed. In fact, Figure 5b) shows that a considerable speed difference (of more than 100 km/h) affected the measurement runs. This result is a further confirmation of the effectiveness of double integration, that allows accounting for the speed variation.

To confirm the benefits provided by the introduction of the weighting function, another defect (characterizing a different track section of 100 m) was analysed and reported in Figure 5c), according to the same data representation. As a first comment, it is evident the evolution of the defect over time. In fact, the STD_{LL} indicator increases from 1.3 mm up to 2 mm in 385 days, thus requiring a tamping operation to restore the track conditions. After maintenance, the amplitude of the defect returns to a value of 0.7 mm, which is then maintained during the remaining monitoring period.

The attention is now focused on the estimation of the defect reported in Figure 5c). Considering one of the available measured data, it is worth noting that the PSD shows

that the major contribution is associated to wavelengths longer than 10 m. Therefore, considering the FRF reported in Figure 1b), the considered defect is expected to be less affected by the bogie filtering effect. This can be confirmed by the results shown in Figure 5c), given that the estimations obtained with both methodologies (without and with compensation, respectively reported with red and yellow dots) provide similar performance. If the predictions are compared to the measurements, a significant degree of agreement can be observed. Measured and estimated values are indeed well superimposed, confirming the accuracy of the methodology. For instance, it can be observed that the increasing trend of the STD_{LL} in the first half of the experimental campaign is well followed, as well as the index reduction due to maintenance operation carried out around day 400.

Considering maintenance procedures [12], tamping operations are typically scheduled when the peak value of track defects reaches predetermined thresholds. Therefore, in the following the attention is focused on the prediction of the maximum value of the longitudinal level (MAX_{LL}). To this end, another linear regression model between STD_{VD+WF} and MAX_{LL} was derived, following the same procedure described in Section 2. The regression model is characterised by a coefficient of determination $R^2 = 0.73$. As expected, the achieved accuracy is lower than the one for the prediction of STD_{LL} ($R^2 = 0.91$), but it can still be considered as promising to the aims of this work. In fact, similar results were reported in a previous work [6], where the linear regression model was fitted using acceleration data measured at constant speed.

In Figure 6, the same two defects are re-analysed considering the MAX_{LL} indicator instead of STD_{LL} . In the figure, the MAX_{LL} values measured by the TRV are reported as blue dots, while the ones predicted using the proposed methodology without and with compensation are shown as red and yellow dots respectively. At first, it can be noted that the MAX_{LL} indicators show the same trends observed for the STD_{LL} , with the defect of Figure 6a) showing almost no evolution and the one in Figure 6c) that overcomes the MAX_{LL} value of 8 mm, thus triggering a maintenance operation.

Focussing the attention on the defect of Figure 6a), characterised by wavelengths in the range of interest, the results show the benefits provided by the weighting function: the peak value is well estimated, with the predictions reported as yellow dots that are well superimposed to the measurements. When the second defect reported in Figure 6c) is considered, minor differences can be observed if the two predictions are compared, as already discussed during the analysis of Figure 5c).

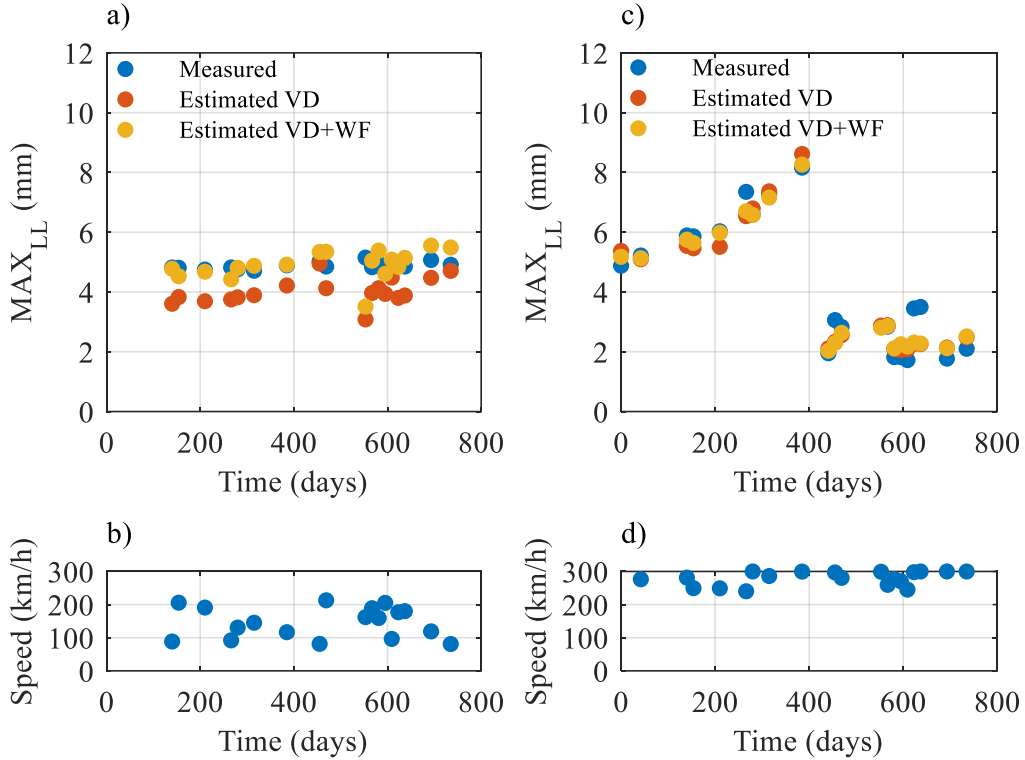


Figure 6: Defect estimation: evolution with time of the peak value of track longitudinal level of two different defects. a) MAX_{LL} of a defect with wavelengths in the range 7-11 m; b) corresponding average speed of the vehicle in the 100 m section; c) MAX_{LL} of a defect evolving with time and d) average speed.

In the end, the methodology proposed in this work allows to compensate the effect of the filter introduced by the bogie, thus improving the estimates not only of the STD_{LL} but also of the MAX_{LL} . The benefits of the update are higher when the defect under analysis is characterized by wavelength in the order of 7-11 m, that would otherwise be missed by the bogie measurements. Moreover, the methodology is not affected by the vehicle speed, as it is based on the double integration of the bogie vertical acceleration. This would allow to estimate the track longitudinal level along main lines, where vehicles run at different speeds depending on the track characteristics.

4 Conclusions and Contributions

In this paper, a methodology to estimate the track longitudinal level in D1 range (3-25 m wavelength) is presented. The method is based on inertial measurements taken by a commercial instrumented vehicle, and it is intended to be part of a condition-monitoring system for the railway infrastructure. In particular, to be suitable for main lines where the vehicle runs at different speeds, the proposed system relies on the double integration of bogie vertical accelerations.

Major attention was devoted to the bogie filtering action. A simplified model of a railway vehicle was used to study the dynamic response to track irregularity and to

highlight this behaviour. The methodology proposed in this work relies on the introduction of a weighting function that corrects the amplitude of the frequency components of the vertical displacement, before computing synthetic indicators representative of the track conditions (STD_{VD+WF}). Specifically, the weighting function was computed as the inverse of the response function of the vehicle, computed with the simplified vehicle model.

Once the weighting function was derived, attention was paid to the definition of linear regression models to predict both the standard deviation STD_{LL} and the peak value MAX_{LL} of the track longitudinal level, considering as regressor the STD_{VD+WF} . Excellent correlation was observed between the STD_{VD+WF} and the measured STD_{LL} , with the regression model that is characterised by an $R^2 = 0.91$, while $R^2 = 0.73$ is reached in case of MAX_{LL} .

The methodology was then adopted to estimate the evolution over time of two defects affecting different sections of the railway line. When defects with wavelengths in the range of 7-11 m are present, the new methodology that includes the compensation of the bogie filter provides more accurate results. The benefits of the proposed update were observed both for the prediction of STD_{LL} and MAX_{LL} .

Finally, the methodology was proven to be independent of the vehicle speed, since consistent and accurate results were observed also in case of considerable vehicle speed changes between subsequent measurements.

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References

- [1] 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
- [2] J. Real, L. Montalbán, M. Bueno, "Determination of rail vertical profile through inertial methods", Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 225, 1, 14-23, 2011. DOI:10.1243/09544097JRRT353
- [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] 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
- [5] 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
- [6] 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.ymsp.2022.109869
- [7] H. Tsunashima, Y. Naganuma, T. Kobayashi, "Track geometry estimation from car-body vibration", Vehicle System Dynamics, 52, 207-219, 2014, DOI:10.1080/00423114.2014.889836
- [8] 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
- [9] 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.
- [10] EN 13848-5:2017. Railway applications - Track - Track geometry quality. Part 5: Geometric quality levels - Plain line, switches and crossings; 2017.
- [11] M. Carnevale, I. La Paglia, P. Pennacchi, "An algorithm for precise localization of measurements in rolling stock-based diagnostic systems", Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 235, 7, 827-839, 2021, DOI:10.1177/0954409720965798
- [12] RFI TCAR ST AR 01 001 D, "Standard di qualità geometrica del binario e parametri di dinamica di marcia per velocità fino a 300 km/h". Rete Ferroviaria Italiana S.p.A, 2013.