





An approach based on a single bogie-mounted sensor for estimating track vertical irregularity from in-service railway vehicles

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ABSTRACT

The growing interest of the railway industry in utilising commercial trains as a cost-effective complement to conventional Track Recording Vehicles (TRVs) is widely recognised. Given that equipping commercial vehicles with sophisticated measurement systems comparable to those used in TRVs is impractical, measurement systems for commercial vehicles should ideally be based on a simplified set of sensors. This study introduces a methodology for estimating the longitudinal track level by employing the double integration of acceleration data collected from a single vertical accelerometer positioned centrally on the bogie frame. A strategy based on weighting functions has been developed to account for the filtering effect induced by the bogie wheelbase. For the assessment of track conditions, the standard deviation and the peak value of the longitudinal level, calculated within 100-metre segments, are employed as indicators. Linear regression models are established to correlate the bogie vertical displacement and track longitudinal level. The application of the methodology has been tested using experimental data, obtaining satisfactory results that are summarised in the paper.

1. Introduction

Maintenance activities are fundamental to the safe and reliable functioning of the railway transportation system. A key aspect of this effort is the ability to monitor the condition of railway assets through continual observation, which provides essential information for timely interventions and supports safety and system resilience.

In recent years, the innovative advancements in data-driven monitoring methodologies, combined with low-cost sensor nodes and data acquisition systems, are opening up new possibilities for efficiently monitoring railway assets [1–6]. Within this framework, particular attention is directed towards the state of the railway track [7–11], as its condition plays a decisive role in ensuring correct operation and sustaining overall performance.

There is growing interest within the railway community in exploiting commercial trains as a cost-effective complement to conventional Track Recording Vehicles (TRVs). This reflects a broader shift towards more scalable and resilient monitoring strategies that can better support safety and long-term asset management. European initiatives such as the Harmotrack project [12,13] exemplify this trend, promoting the development of monitoring solutions based on in-service vehicles.

TRVs remain the primary platforms for acquiring high-quality diagnostic data, including accelerations, rail profiles, track geometry parameters, overhead contact line measurements, and signalling-system diagnostics. However, their operation is costly and subject to significant logistical constraints, which limit inspection frequency. As a result, data collected by commercial trains can play a crucial role in filling the temporal gaps between periodic TRV runs, providing more continuous insight into track condition [14].

However, installing sophisticated measurement systems, like those used in TRVs, on commercial vehicles is not feasible because of the high equipment costs, intensive maintenance requirements, and the substantial volume of data generated. Consequently, measuring systems designed for commercial vehicles should preferably rely on a reduced set of sensors [15].

Various applications for monitoring track irregularities with inertial sensors have been proposed in the last years [7–11,16–19]. To minimise the filtering effects introduced by vehicle suspension, sensors are ideally mounted as close as possible to the wheel-rail interface. Therefore, axle-box accelerometers have been widely adopted for detecting track-related issues [20–23]. Sun et al [20] developed an on-board method for identifying longitudinal irregularities in high-speed lines

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using axle-box acceleration from in-service vehicles. Wang et al [24] proposed a similar axle-box acceleration-based approach for vertical irregularities, combining Savitzky-Golay smoothing, double integration with Hodrick-Prescott decomposition, and order-tracking analysis to extract fault features under variable-speed conditions. Although axle-box acceleration provides highly accurate information, these sensors face challenges due to the harsh operating environment.

On the other hand, car-body-mounted sensors are easier to install, particularly given space and accessibility constraints. This configuration has been extensively studied, especially for track condition monitoring in high-speed applications using in-service vehicles [6,7]. Tsunashima [25] examined the use of time-frequency analysis on car-body acceleration to identify vibration patterns associated with track irregularities. This work was later extended by Tsunashima and Hirose [26], who refined the method and showed that car-body vibration can indicate certain defects, though with the limitations expected from sensors positioned far from the track. Hao et al [27] introduced a deep-learning approach for high-speed rail, modelling the nonlinear relationship between car-body acceleration and underlying track geometry. Tsunashima and Yagura [28] then proposed a data-driven method for regional railways, suggesting that car-body vibration can provide an indirect means of estimating irregularities. More recently, Ghiasi et al [13] presented an unsupervised anomaly-detection framework using machine learning, focusing on identifying geometrical defects from on-board measurements without requiring labelled data.

A practical compromise between the challenges of axle-box-mounted accelerometers and the limitations of car-body-mounted sensors due to geometrical filtering relies on sensors installed on the bogie [29–31]. Research in [29,30] investigated the measurement of track geometry using in-service trains equipped with minimal sensor configurations. O'Brien et al [32,33] used bogie-mounted acceleration and angular velocity from an in-service train to estimate the longitudinal track profile through a cross-entropy optimisation method. In [34] the researchers used a bogie-mounted IMU on in-service trains to measure vertical acceleration and pitch-rate for detecting vertical track-profile irregularities. Their method applied nonlinear state-estimation filters to identify major defects while omitting suspension effects. In [35], RMS indicators are computed from bogie vertical acceleration measured in a three-bogie freight wagon to assess vehicle dynamics and detect track defects, marking an early step toward condition-based monitoring using freight vehicles. A single-sensor bogie-mounted methodology was later proposed in [36,37] for high-speed passenger applications. Overall, bogie-mounted systems have demonstrated strong potential for estimating a wide range of track defects.

This work considers bogie-mounted sensors configuration, and builds upon the findings we presented in [38] and [39]. In [38], vertical accelerations measured at the centre of the bogie frame were successfully utilised to estimate the longitudinal level on a high-speed rail line operating at constant speed. Subsequently, the introduction of double integration in [39] extended the methodology to scenarios where speed is not constant. It is worth recalling that, according to scheduled maintenance procedures, operations are triggered when the parameter quantifying the magnitude of the defect exceeds a predefined threshold. Consequently, the maximum value of the parameter within a given section has been selected as the key diagnostic indicator. The monitoring system estimates the maximum defect value over a predefined 100-metre section of track, a length determined based on prior applications of [38,39].

However, a well-known limitation of mounting accelerometers at the centre of the bogie is the bogie filtering effect caused by the bogie wheelbase [40,41]. In this work, a method for compensating the bogie filtering action is therefore 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 longitudinal level from data coming from an experimental campaign.

The paper is organised as follows. In Section 2, the track condition monitoring system is described, introducing the main data-processing steps involved. Attention is paid to filtering action associated to the bogie wheelbase, adopting a simplified rail vehicle model. Later, the regression models to estimate the standard deviation and the peak value of the track longitudinal level are presented. In Section 3, the proposed methodology is applied to specific sections of the railway line, to estimate and monitor the evolution over time of the proposed indicators. Finally, in Section 4 the conclusions of the work are drawn.

2. Track condition monitoring system

This section introduces the methodology developed to estimate the track longitudinal level within the D1 range (wavelengths in the range from 3 m to 25 m [42]), based on signals obtained from an accelerometer mounted on the bogie frame. The analysis is centred on conventional railway lines, where the velocity profile of trains is inherently non-uniform. This variability in speed is influenced by the distinct characteristics of the railway infrastructure, including track geometry, gradients, and operational constraints. Additionally, the requirement for trains to make frequent stops at stations further contributes to the variability, making speed fluctuations a key factor in the analysis.

As evidenced in [39], the dependence on speed of the bogie-centre response to track vertical geometry is lower when considering the vertical displacement rather than directly the vertical acceleration and, for this reason, double integration of the acceleration signal was introduced for the estimation of the track longitudinal level. The present study proposes an updated methodology designed to mitigate the filtering effect of the bogie wheelbase, which limits the detection of specific wavelengths.

The methodology to estimate the maximum defect amplitude over a predefined 100-metre section of the track, can be summarised in the block scheme presented in Fig. 1. The measuring setup installed on the vehicle relies on a single accelerometer mounted on the bogie centre ($a_z(t)$, sampling frequency 1000 Hz) and a dedicated geolocation algorithm to determine the 100m segments [43]. To reduce the computational effort, data processing is carried out in the frequency domain relying on the Fast Fourier Transform (FFT), adopting the single-sided spectrum. The FFT is computed considering all samples acquired while the vehicle traverses each 100 m track segment, without averaging, segmentation, overlap, or windowing, so as to preserve the amplitude of the spectral components. Therefore, the frequency resolution (inverse of time duration of each 100 m section) varies depending on vehicle speed. The methodology was verified to be robust to the variation in frequency resolution, as later evidenced by the analysis involving runs at different vehicle speeds (see, for example, the defect shown in Figure 7). After the application of the FFT, starting from the spectral components $A_z(f)$ evaluated on a 100 m section, double integration is performed and then the vertical displacement ($Z(f)$) is filtered into the D1 range [42].

At this stage, a first estimate of the vertical displacement could be made available, referred to as $Z_{D1}(f)$ in Fig. 1. In this respect, the methodology presented in [39] directly relies on $Z_{D1}(f)$ to monitor the track longitudinal level. However, the results proved to be negatively affected by the dynamic response of the vehicle, which is not sensitive to specific wavelengths of the track irregularity, depending on the choice of the sensor position. For this reason, a compensation filter is introduced in the updated methodology (highlighted as a red box in Fig. 1), leading to a more accurate estimation of the vertical displacement $Z_{D1,corr}(f)$. A detailed description of the proposed strategy will be later provided in Section 2.1.

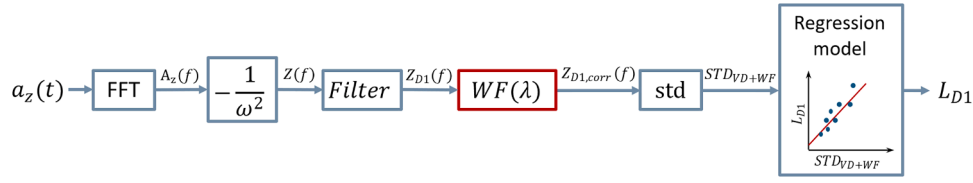


Fig. 1. Block scheme describing the data processing steps implemented in the condition monitoring system.

With reference to Fig. 1, the standard deviation STD_{VD+WF} of the weighted bogie vertical displacement is evaluated directly in frequency domain and used as input to suitable regression models that allow estimating the track conditions. Specifically, the standard deviation STD_L and the peak value MAX_L of the track longitudinal level on 100 m sections are estimated through the linear regressions of Eq. (1):

$$STD_L = m_1 \cdot STD_{VD+WF} + q_1 \quad (1)$$

$$MAX_L = m_2 \cdot STD_{VD+WF} + q_2$$

where m_1, q_1 and m_2, q_2 are the coefficients of the two regression models, estimated from experimental data collected during a long-term experimental campaign, along the reference railway line.

Once the working principle of the designed condition monitoring system has been presented, in the next section a detailed description of the compensation filter will be provided.

2.1. Compensation of bogie filtering

One of the major drawbacks of the proposed measurement system comes from the adoption of a single-sensor setup. In fact, measurements will be affected by the filter introduced by bogie wheelbase. 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 Fig. 2a), where the magnitude of 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 Fig. 2c) [39]. It is apparent that the contribution corresponding to 6 m wavelength (twice the bogie wheelbase) is completely filtered out, with the response of the vehicle that goes to zero regardless of the vehicle speed. Also, the wavelengths around this value are affected by a filtering action.

The compensation block highlighted in Fig. 1 aims at accounting for the effect of the bogie filtering action, thus improving the capability of the system to estimate longitudinal level when defects with these wavelengths are present. To achieve this objective, the methodology applies the inverse of the FRF magnitude, which describes the relationship between the track longitudinal level and the bogie vertical displacement. By using this inverse FRF magnitude as a weighting function, it becomes possible to modify the amplitude of the frequency components.

As illustrated in Fig. 2a), the vehicle response exhibits some variability depending on the speed of the vehicle. To address this dependency, the average response function, denoted as $\bar{Z}(\lambda)$, was determined (black line in Fig. 2a)) adopting Eq. (2), and considering speeds in the range from 50 km/h to 300 km/h.

$$\bar{Z}(\lambda) = \sum_{V_{train}} Z_{V_{train}}(\lambda) \quad (2)$$

The weighting function presented in Fig. 2b) is computed as the inverse of the average response, according to Eq. (3):

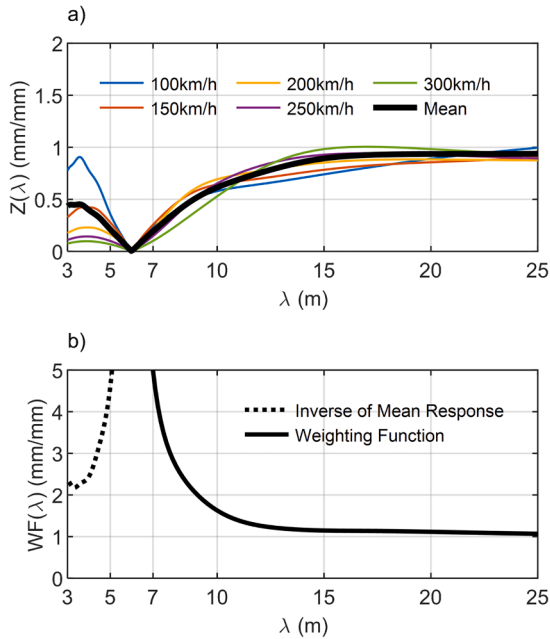


Fig. 2. Simplified vehicle model adopted to evaluate the response of the system. a) magnitude of the Frequency Response Function (FRF) between the input irregularity and the bogie motion, for different vehicle speed; b) weighting function computed as the inverse of the average bogie response; c) simplified vehicle model in the vertical plane.

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

and it is reported as a solid line. It is worth noting that only wavelengths longer than 7 m are considered in $WF(\lambda)$, to exclude the asymptotic behaviour observed at $\lambda = 6$ m, that directly comes from the wheelbase geometric filter (see Fig. 2a)). In the practical implementation of the weighting function, this leads to adopting a unitary value for wavelengths shorter than 7 m. This choice was made based on the specific characteristics of track longitudinal level signals, which demonstrate that few defects of such wavelength populate the considered railway line. This was observed considering the PSD of the defects later presented in Section 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 Eq. (4):

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

The weights listed above are used to correct the amplitude of each frequency component according to Eq. (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 Eq. (6):

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

Finally, the linear regression models to estimate the track longitudinal level (both in terms of STD_L and MAX_L) can be computed as presented in Eq. (1), using the predictor STD_{VD+WF} as input of the models.

2.2. Linear regression models

This research utilises data collected during an extensive experimental campaign spanning 24 months along the railway line under investigation [38]. Over the course of this campaign, 25 runs were performed, during which the TRV recorded bogie acceleration signals as

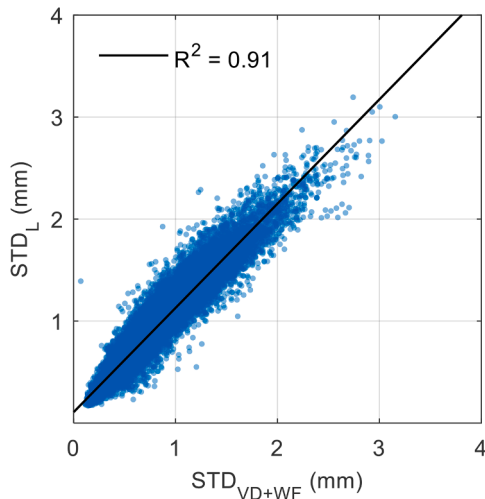


Fig. 3. Linear regression model for the estimation of the standard deviation of the track longitudinal level in D1 range.

well as track geometry information to support the training of the regression model. Fig. 3 illustrates the correlation between two standard deviations: the track longitudinal level measured directly by the TRV ($STD_{L,D1}$) and the value estimated using the proposed methodology (STD_{VD+WF}), considering 100 m sections. The regression model obtained is characterised by a coefficient of determination $R^2 = 0.91$. This high value indicates a significant and dependable alignment between the directly measured data and the values estimated by the methodology.

To assess the performance of the proposed methodology, the cumulative percentage error between the measured and estimated STD_L values was calculated. Fig. 4 illustrates a comparative analysis of the results obtained using the two approaches - one incorporating the proposed weighting function (cf. Section 2.1) and one without. Fig. 4 clearly demonstrates that the inclusion of the weighting function leads to a consistent reduction in error across the entire range under consideration. For instance, a minimum error of about 6% is registered for defects with STD_L in the order of 2.4 mm, while the maximum error is registered for defects of very small amplitude (13.5% at 0.5 mm). Although a higher error, it should be noted that such small defects are of no concerns with respect to maintenance procedures (since the corresponding peak value is small compared to maintenance attention levels), so that the result is still considered as satisfactory. Concerning defects with larger STD_L (i.e. higher than 3 mm), it is worth remarking that a reduced number of occurrences is registered (Fig. 3). In the end, 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.

Considering maintenance procedures [44], tamping operations are typically scheduled when the amplitude of track defects reaches predetermined thresholds. Therefore, in the following the attention is focused on the estimation of the peak value of the longitudinal level (MAX_L). To this end, another linear regression model between STD_{VD+WF} and MAX_L was derived, following the same procedure previously described, and it is summarised in Fig. 5.

Specifically, Fig. 5a) shows the regression model, that is characterised by a coefficient of determination $R^2 = 0.73$. As expected, the achieved accuracy is lower than the one for the estimation of STD_L ($R^2 = 0.91$), but it can still be considered as promising to the aims of this work. In fact, similar results were reported in a previous work [38], where the linear regression model was fitted using acceleration data measured at constant speed.

In addition, Fig. 5b) shows the percent error between the measured and estimated MAX_L . As expected, higher errors are observed when estimating the peak value of the longitudinal level. However, the introduction of an additional data-processing step ($VD+WF$) leads to a reduction of the error, in all the measurement range. The best and worst cases are registered for defects with amplitude of 3 mm and 9 mm respectively, with the error assuming 15% and 21%.

In the next Section, the designed regression model will be adopted to estimate the evolution over time of the longitudinal level, in specific portions of the considered railway line.

3. Results

This section presents the application of the developed linear regression models for identifying track defects through the analysis of weighted bogie vertical displacement data. To demonstrate the impact of the compensation approach, one single 100 m section of the railway line was analysed. This segment was chosen due to the presence of a defect with wavelengths affected by the filtering of the bogie. Fig. 6 displays the Power Spectral Density (PSD) of the analysed section, plotted against wavelength. The analysis highlights that, defects within the 6–10 m wavelength range (marked by red lines), dominate this portion of the track, with the largest contribution corresponding to a wavelength of 7 m.

The methodology can be then applied to a series of measurements

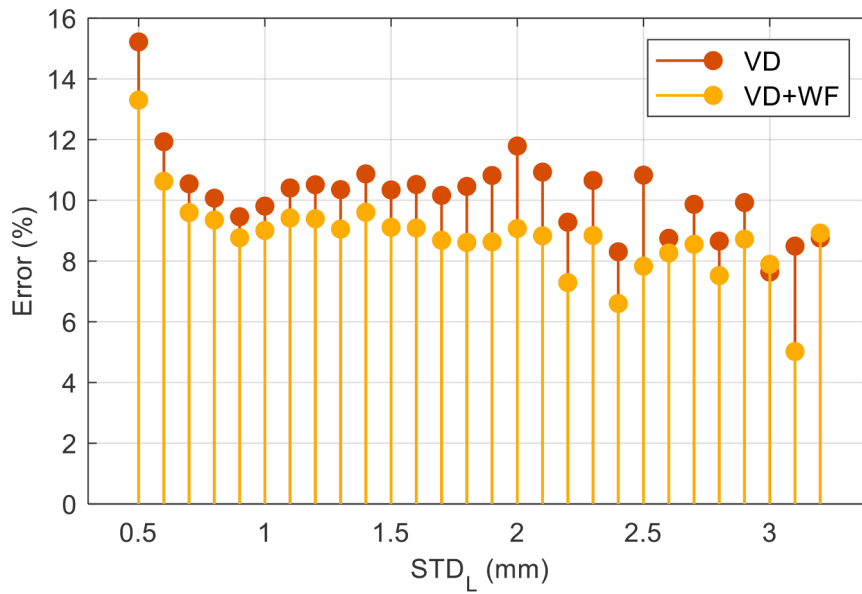


Fig. 4. Comparison of the aggregated error between measured and estimated STD_L , considering the previous (VD) and updated (VD+WF) methodology.

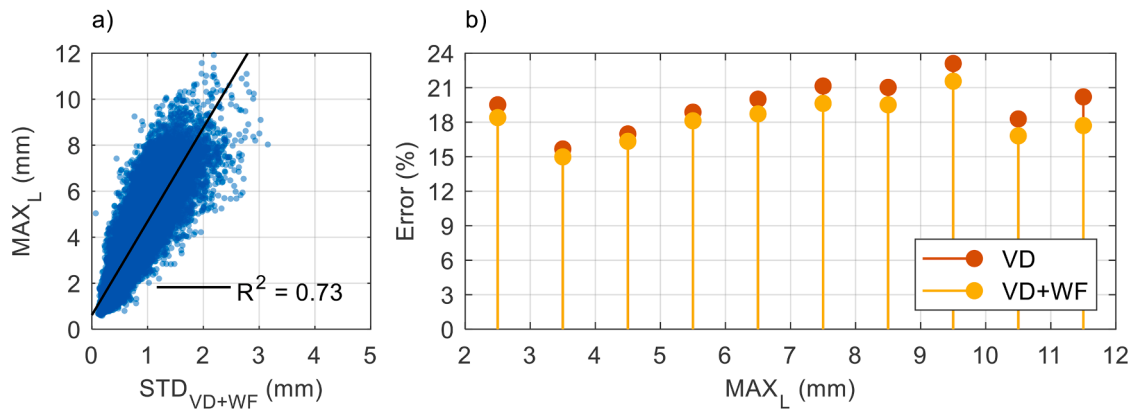


Fig. 5. Estimation of the peak value of the track longitudinal level in D1 range. a) linear regression model; b) comparison of the aggregated error between measured and estimated MAX_L , considering the previous (VD) and updated (VD+WF) methodology.

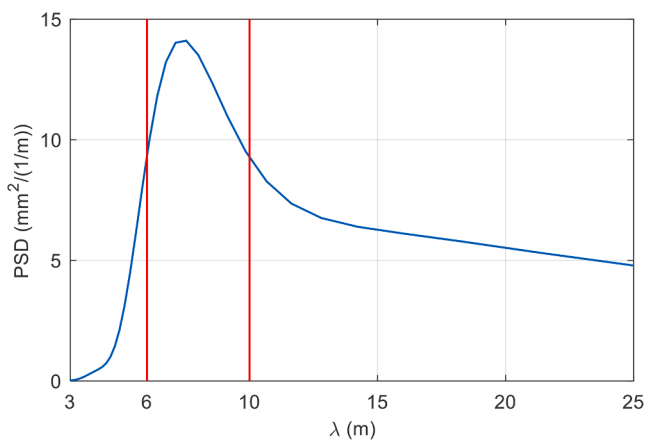


Fig. 6. PSD of the track longitudinal level in D1 range, for a reference 100 m section of the line (defect 1).

over time, for the considered track section. This approach enables the tracking of changes in the indicators throughout the 24-month

monitoring period. Both standard deviation (STD_L) and peak value (MAX_L) of track longitudinal level are considered, comparing the measurements taken by the TRV and the estimations achieved with the designed models. Specifically, in Fig. 7a) the STD_L values are reported; in Fig. 7b) the MAX_L indicators are proposed, and the average speed of the vehicle in the considered 100 m section is also reported in Fig. 7c). In all the diagrams, blue dots represent the data measured by the TRV, while the estimates achieved with the updated methodology (including the weighting function) are reported in yellow. To assess the benefits of the model update, the estimations from the simple vertical displacement of the bogie (i.e. without applying the weighting function) are also shown in red.

It can be observed that during the whole monitoring period, no significant evolution of the considered defect occurred, given that the direct measurements (blue dot) show almost constant indicators along time. This behaviour is observed for both STD_L and MAX_L indicators.

A clear indication of the effectiveness of the updated methodology can be seen in Fig. 7a) and Fig. 7b), where the yellow markers closely align with the blue ones. This alignment highlights a significant improvement compared to the less accurate estimates represented by the red markers. The results confirm that the inclusion of the compensation method enhances precision, particularly for short-wavelength defects

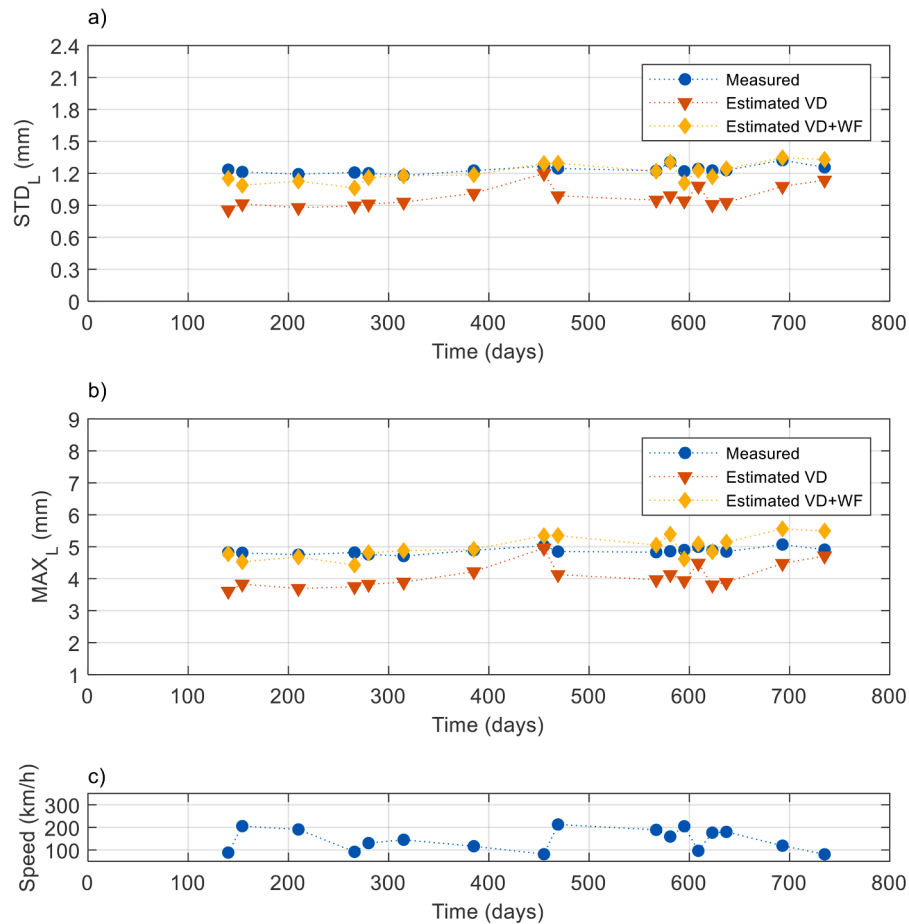


Fig. 7. Defect estimation: temporal evolution of the indicators to estimate the track longitudinal level of defect 1, with wavelengths in the range 6–10 m. a) comparison of STD_L of the defect estimated with and without the methodology update; b) corresponding MAX_L of the defect; c) average speed of the vehicle in the 100 m section.

within the 6–10 m range. Furthermore, the methodology remains reliable regardless of vehicle speed variations. Fig. 7c) reveals that speed differences exceeding 100 km/h were present during measurement runs, yet the methodology consistently delivered accurate results. This demonstrates the robustness of the double integration process, confirming no impact of different frequency resolutions in the calculation of the signal spectrum, as anticipated in Section 2. In the end, the methodology effectively accounts for speed variation, and validates the reliability of the approach.

To further validate the advantages offered by the inclusion of the weighting function, an additional defect in a distinct 100 m track segment was examined. The analysis of this defect is presented in Fig. 8, using the same data representation format as the previous track section.

As a first comment, the evolution of the defect over time is evident. In fact, considering the TRV data (blue dots), both the STD_L and MAX_L indicators show a significant increase. As for the STD_L , the indicator passes from 1.3 mm up to 2 mm in 385 days. During the same period, the MAX_L indicator shows an increase up to 9 mm, thus requiring a tamping operation to restore the track conditions. After maintenance, the amplitude of the indicators is restored, with the STD_L that returns to a value of 0.7 mm and the MAX_L that reaches about 3 mm. These values are then maintained during the remaining monitoring period, showing no evolution in time.

Attention can now be paid to the estimation of the defect of Fig. 8. If the estimations are compared to the measurements, a significant degree of agreement can be observed, independently on the specific model used (i.e., both in case of yellow and red dots). This behaviour is consistent along the entire monitoring period, both in case of STD_L and MAX_L .

Estimated values are indeed well superimposed to the measured values (blue dots), confirming the accuracy of the methodology. For instance, Fig. 8a) shows that the increasing trend of the STD_L 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. Similar comments can be made considering the MAX_L index of Fig. 8b).

To justify the comparable performances shown by the two regression models, reference can be made to the PSD of the track longitudinal level of the available records. It turns out that the major contribution is associated to wavelengths longer than 10 m (Fig. 9). Therefore, considering the FRF reported in Fig. 2b), the vehicle response to the defect under analysis is less affected by the bogie filtering effect, and the estimations obtained with both methodologies (without and with compensation) provide similar performance.

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_L but also of the MAX_L . The benefits of the update are higher when the defect under analysis is characterised by wavelength in the order of 6–10 m, that would otherwise be strongly attenuated 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

This paper outlines a methodology for estimating the track

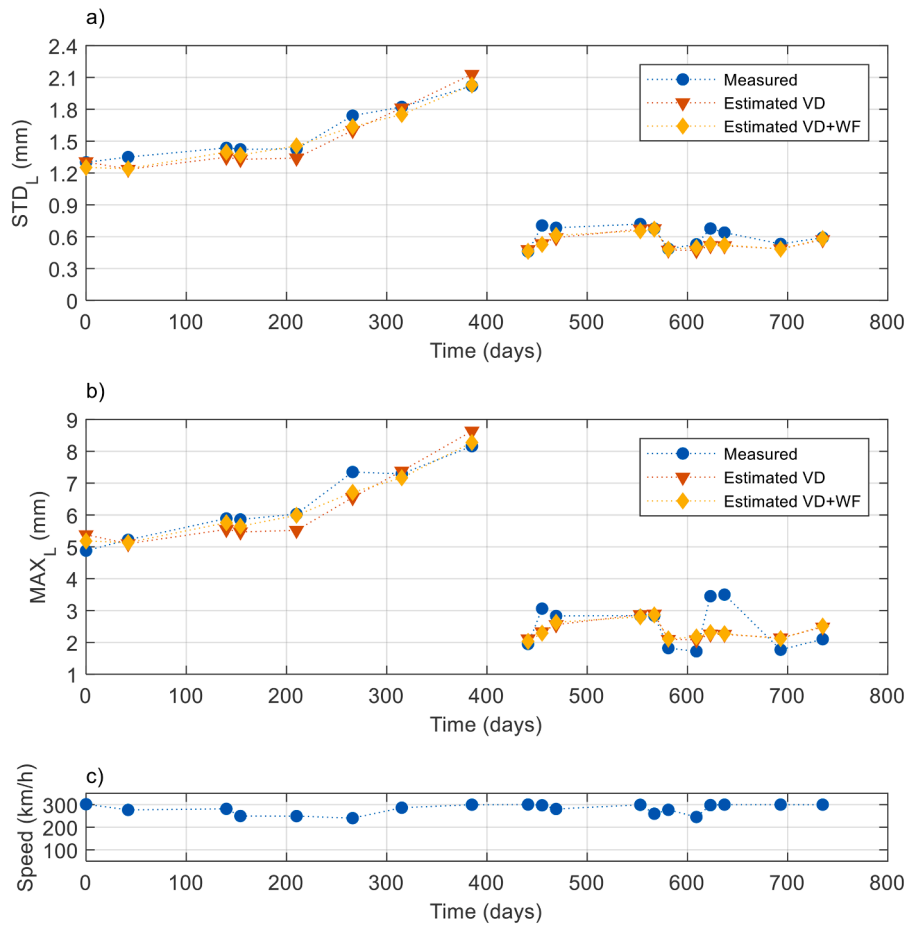


Fig. 8. Defect estimation: temporal evolution of the indicators to estimate the track longitudinal level of defect 2, with wavelengths longer than 10 m. a) comparison of STD_L of the defect estimated with and without the methodology update; b) corresponding MAX_L of the defect; c) average speed of the vehicle in the 100 m section.

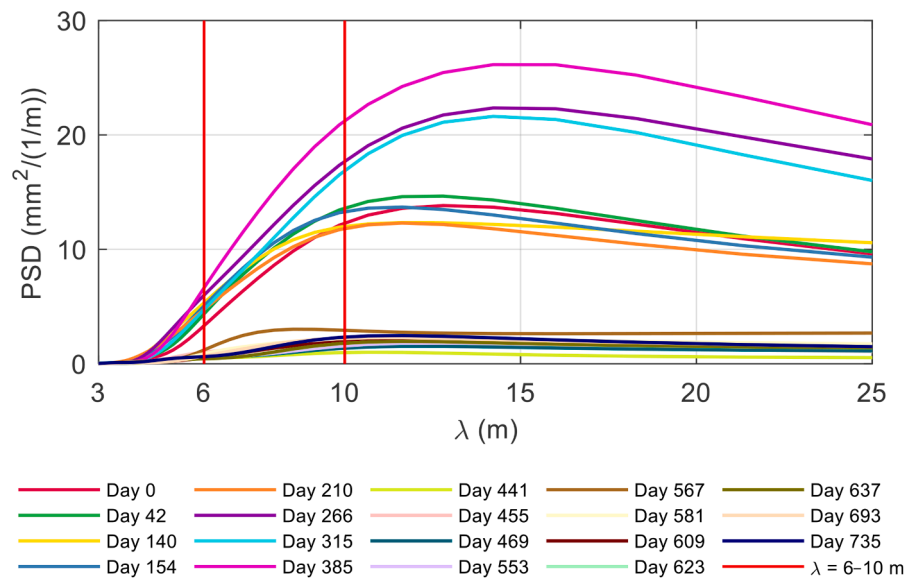


Fig. 9. PSD of the track longitudinal level in D1 range, for the 100 m section of the line corresponding to defect 2.

longitudinal level within the D1 range (that includes defects with wavelengths between 3 and 25 m). The approach, founded on acceleration measurements, is designed as a component of a condition-monitoring system for railway infrastructure, to be implemented on

in-service commercial vehicles equipped with a reduced sensor setup. To ensure its applicability on main lines, where vehicles operate at varying speeds, the system employs the double integration of vertical accelerations measured at the bogie centre.

The main drawback of the simplified sensor setup is related to the filtering effect introduced by the bogie wheelbase. A simplified model of a railway vehicle was used to study the dynamic response to track irregularity and to highlight this behaviour. The proposed methodology employs a weighting function to adjust the amplitude of frequency components associated with vertical displacement. The weighting function was calculated as the inverse of the magnitude of the response function of the vehicle, which was determined using the simplified model.

The derivation of the weighting function enabled the development of linear regression models for estimating both the standard deviation STD_L and the peak value MAX_L of the track longitudinal level, considering as regressor the STD_{VD+WF} . This parameter represents the standard deviation of the vertical displacement (obtained by double integration of bogie acceleration) where the effect of bogie geometrical filtering was compensated by the adoption of a model-based strategy. The results demonstrated a strong correlation between STD_{VD+WF} and the measured STD_L , as evidenced by the regression model achieving a coefficient of determination, R^2 of 0.91. Although slightly lower, the correlation for MAX_L remained significant, with an R^2 of 0.73.

The methodology was subsequently applied to evaluate the temporal evolution of two defects affecting distinct sections of the railway line. Notably, when defects with wavelengths in the range of 6–10 m were present, the updated methodology, incorporating compensation for the bogie filtering effect, yielded more accurate results. The enhancements were evident in the improved estimations of both STD_L and MAX_L .

Furthermore, the methodology demonstrated independence from vehicle speed, as consistent and accurate results were achieved even under significant variations in vehicle speed between successive measurements. These outcomes highlight the robustness and adaptability of the proposed approach for different operational conditions, emphasising the effectiveness of the methodology and its potential for reliable track condition monitoring through a simplified sensor setup.

CRedit authorship contribution statement

Carlos Esteban Araya Reyes: Conceptualization, Investigation, Methodology, Writing – original draft. **Ivano La Paglia:** Conceptualization, Methodology, Writing – original draft. **Egidio Di Galleonardo:** Conceptualization, Supervision, Writing – review & editing. **Alan Facchinetti:** Conceptualization, Writing – review & editing. **Stefano Bruni:** Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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