Proceedings of the Sixth International Conference on
Railway Technology: Research, Development and Maintenance
Edited by: J. Pombo
Civil-Comp Conferences, Volume 7, Paper 8.12
Civil-Comp Press, Edinburgh, United Kingdom, 2024
ISSN: 2753-3239, doi: 10.4203/ccc.7.8.12

Machine Learning Methodology for Identification of Multiple Out-of-Round Railway Wheels using Data from Wayside Monitoring Systems

J. Magalhães[1], T. Jorge[1], A. Meixedo[2], A. Guedes[2], R. Silva[2] and D. Ribeiro[1]

[1]CONSTRUCT-LESE, School of Engineering, Polytechnic of Porto, Portugal
[2]CONSTRUCT-LESE, Faculty of Engineering, University of Porto, Portugal

Abstract

This research presents a new automated diagnosis methodology for out-of-round multi-damage wheels that addresses the damage detection and localization, using only acceleration and strain data measured on the railway track. The methodology is based on wavelet relative energy and comprises two stages: i) detect damage through the wavelet entropy derived from vertical acceleration responses and ii) localize damage by mathematically processing wavelet decomposition and using strain responses to determine the specific axle location of the detected damaged wheel. The proposed methodology is numerically validated for two different types of out-of-round damage in railway vehicles, such as polygonal wheels and wheel flats, and for a five-car freight train with different damage combinations and localizations.

Keywords: out-of-round (OOR) railway wheels, wayside monitoring system, damage detection, damage localization, damage type, multi-damage, machine learning, relative wavelet energy.

1 Introduction

In railway engineering, the safety of railway circulation through SHM involves the systematic observation and analysis of a vehicle-track system over time through regularly sampled response measurements, aiming to detect any changes. Nowadays, the condition of railway systems began to be monitored by on-board or wayside approaches, the main difference being the location of the measuring devices. Most on-board techniques are based on vibration [1], acoustic [2] and ultrasonic techniques [3] in which sensors are installed on the vehicle for management of the condition of both rolling stock and railway track. On the other hand, wayside systems are a more cost-effective solution for identifying vehicle defects, since the condition of all wheels is indirectly estimated by measuring the responses of in-service trains on the railway track [4]. Wayside techniques include strain gauges [5], fiber optic [6], accelerometers [7], ultrasonic sensors [8], acoustic emission [9], as well as lasers and high-speed cameras [10].

The most common wheel defects in railway vehicles are known as out-of-roundness (OOR), defined as a deviation in the radial profile of the wheel [11]. OOR wheels are typically categorized into two types of defects: i) wheel flat, a discrete tread defect that results from repetitive wheel/rail abrasion during braking as the wheels sliding on the rails [12], and ii) polygonal wheel, which is commonly attributed to polygonization [13] and it is characterized by periodic irregularities around the wheel circumference deviating from the mean wheel radius.

Signal-based approaches for damage diagnosis involve analyzing changes in damage-sensitive features derived directly from measured time-series data. Time-frequency techniques enable the simultaneous analysis of input data records in both time and frequency domains [14]. Within this domain, the wavelet transform stands out as a highly efficient technique in scientific community for feature extraction [14, 15]. Some recent studies in the structural engineering field have been using wavelets for damage detection and localization with good results [15, 16]. Until now, many studies have shown good results in detecting wheel defects using a wayside approach.

Although all these works present good results in identifying defective wheels, only a few are able to localize the damage, as most studies only address single damages. Furthermore, damage localization is not yet robust enough, particularly when it comes to considering different types of damage (and not just wheel flats), different types of operational scenarios, and different vehicles. Aligned with these assumptions the present work proposes a machine learning methodology based on a wayside system to detect and localize OOR multiple wheel defects in a railway vehicle.

2 Methods

The present section shows the interaction between all steps of the proposed method with a brief description of each one. The flowchart presented in Figure 1 illustrates the procedure implemented in MATLAB® [17], which is divided into two main stages. The first stage, denominated as baseline acquisition, consists of acquiring dynamic responses of vehicles with healthy wheels. This procedure should be done with different vehicles speeds and train loads to create a baseline of passages that is as robust as possible. The second stage analyses new unknow passages and englobes two steps: i) damage detection and ii) damage localization.

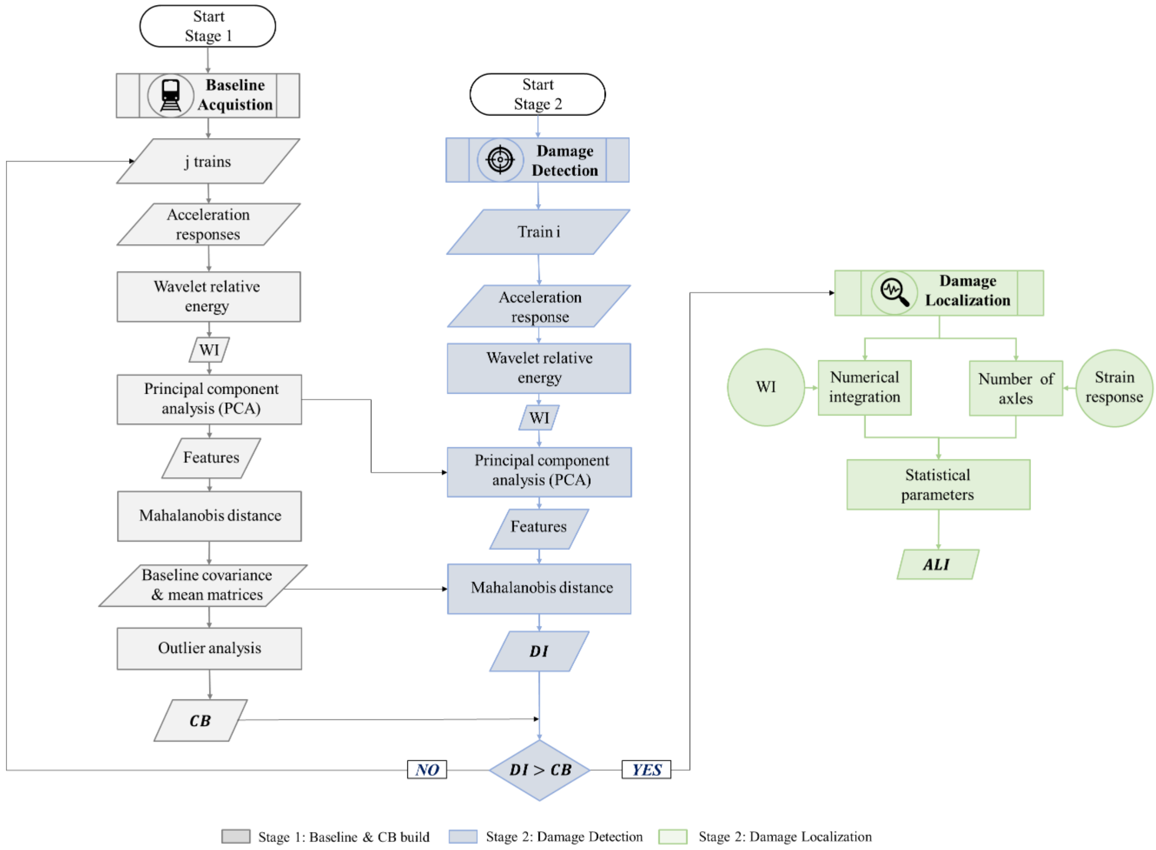


Figure 1: Flowchart of the proposed method.

The feature extraction approach combines two different techniques, a time-frequency analysis with wavelet relative energy and a Principal Components Analysis (PCA). The goal is to achieve damage-sensitive features from the acquired data.

The wavelet relative energy is calculated due wavelet decomposition of the acceleration records, where the first two decompositions of each sensor are fused (WI). The characteristics of the acceleration response can be defined by its energy, which is one of the measures that characterize the feature of a signal. Inspired by the Fourier analysis the energy at decomposition j is defined by [18]:

$$\mathrm{E}_j = \sum_{i=0}^{k} \left| C_j(k) \right|^2 \tag{1}$$

Where $C_j(k)$ represents the wavelet coefficients, obtained by Maximum Overlap Discrete Wavelet Transform (MODWT) [19]. And the energy at each sampled time k will be:

$$E(k) = \sum_{j=-N}^{-1} \left| C_j(k) \right|^2 \tag{2}$$

In consequence, the total energy can be obtained by:

$$\mathrm{E}_{tot} = |S|^2 = \sum_{i<0}^{j} \mathrm{E}_j \tag{3}$$

Then, the normalized values, which represent the relative wavelet energy, is defined according to:

$$p_j = \frac{\mathrm{E}_j}{\mathrm{E}_{tot}} \tag{4}$$

Given the relative wavelet energy for j= 1,2, these features are fused with Euclidean distance, creating a more representative decomposition, characterized as WI.

Consequently, the PCA technique is used to extract features from this data. Principal component analysis (PCA) is a popular and classic multivariable analysis technique used in damage identification, which allows for the reduction of the dimensionality of complex data, preserving as much as possible the variations present in the data [20]. This technique transforms the original variables into a new set of variables, called principal components (PCs), which are linear combinations of the original variables. After calculating the principal components, four statistical parameters are extracted from the PCA scores, namely, the root mean square (RMS), the standard deviation (SD), the skewness and the kurtosis.

Due this method, the WI acquired on each sensor is reduced to these four features, and a Mahalanobis Distance (MD) is computed between baseline scenarios and potential damage passages, to fuse the sensors and the features, resulting in a Damage Index (DI). Finally, in order to automatically detect the presence of damage on each train crossing, an unsupervised approach based on machine learning, called outlier analysis, is used. This approach automatically compares the DI values obtained in the data fusion stage with a Confidence Boundary (CB), which is calculated using the inverse cumulative Gaussian distribution function (ICDF), considering the mean value, $\bar{\mu}$, and standard deviation, σ, of the baseline feature vector, such as follow:

$$CB = invF_x(1-\alpha) \tag{5}$$

Where,

$$F(x|\bar{\mu},\sigma) = 1/\left(\sigma \cdot \sqrt{2}\pi\right) \int_{-\alpha}^{x} e^{\left(-1/2\cdot\left((x-\bar{\mu})/\sigma\right)^2\right)} dy, x \in \mathbb{R} \tag{6}$$

If the DI is below the CB, it is regarded as a baseline case and is included with the other cases to enhance the robustness of the CB. Consequently, when the DI is equal to or higher than CB, the feature is an outlier and its transfer for the next step of the procedure, damage localization.

The damage localization step is based on the numerical integration of the WI associate at each outlier, where the damage zones are emphasized, according to sudden transitions along the curve. Even so, the identification of the number of axles acquired from strain responses are also calculated. Consequently, an Axle Location Index (ALI) is calculated, based on statistical parameters. Firstly, the data acquired from the WI is subjected to a moving standard deviation, in order to highlight the areas of the domain where damage occurs. For each WI, made up of N scalar observations, the standard deviation T, is defined as:

$$T = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|WI_i - \mu|^2} \tag{7}$$

Where μ is the mean of WI, and the obtained vector T is integrated through cumulative trapezoidal numerical integration. This integration is cross with the total number of axles presented in a single passage, acquired from strain responses. The total number of axles is achieved by automatically removing outliers from the strain response using curve fit techniques, where smooth and exclude data approaches are applied to acquire new information representative of the original signal. Firstly, the smooth data algorithm, smooths the response data in column vector y using a moving average filter, resulting on a $\hat{y}$ vector. Each element of that smooth data response $\hat{y}_n$ is normalized between [-1,1] and the exclude data algorithm returns the values between [0,1]. This data processing allows to make a transformation of original strain response, where the axles of a passage could be defined as a domain range.

To achieve the ultimate goal of establishing the number of damages and their respective location, a last step is implemented. In each passage, for each axle found, the respective integral is evaluated, and the difference between the extreme values of the integral is computed. A comparation is established between all the differences from a single passage with the average of the differences in all the identified axles, which makes it possible to identify the axles that present abnormal discrepancies, thus revealing the location and quantification of damages. Due to the differences between the sensor positions, a mean is obtained per sensor pair, and the statistical parameter mode is applied to quantify the total number of damages and the position of the respective damaged axles, resulting in an Axle Location Index (ALI).

3 Results

Based on crossing records, the proposed methodology aims to detect and localize OOR damage wheels of a five-wagon Laagrss freight train. As it is not always possible to install sensors due to the costs involved, a dynamic interaction analysis between the vehicle and the track is implemented, through an in-house software called VSI - Vehicle-Structure Interaction. First, the numerical modelling of the train and the track is performed in ANSYS® [21], as well as the modelling of the track irregularities and OOR defects in MATLAB® [17]. Subsequently, the structural matrices are imported and integrated into the VSI software using a fully coupled strategy. More details can be found in references [22, 23].

The virtual wayside monitoring system employs 6 accelerometers and 6 strain gauges, installed on the rail at mid-span between two sleepers, as illustrated in Figure 2. To account for varying sensor sensitivities due to different damage capture levels, sensors from the left and right sides are combined. For instance, the first accelerometer and strain gauge on the right, paired with their counterparts on the left, constitute the first sensor pair (P1).

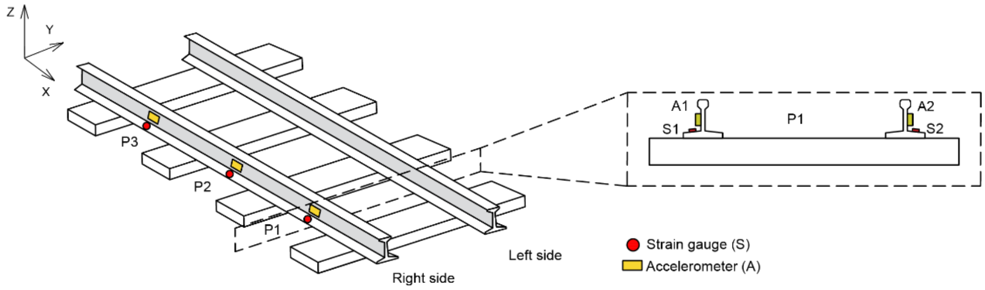
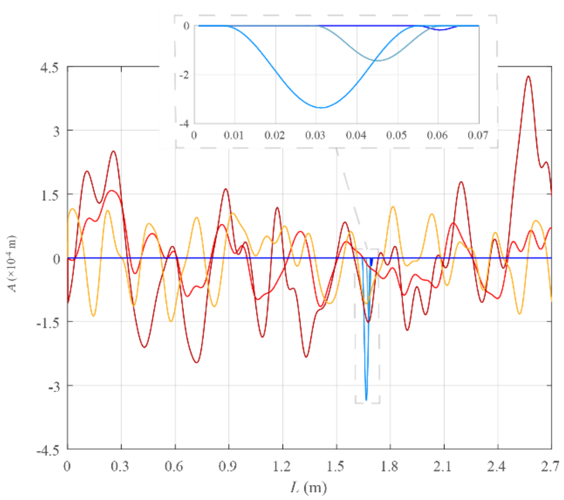


Figure 2: Wayside monitoring system.

Regarding OOR defects, the polygonal defect - P (continuous periodic wear across the wheel surface) and flat defect - F (discreet damage), are modelled by transforming the wheel defect into an equivalent and spaced rail defect, over which a perfect wheel runs, such as also implemented in previous studies [24]. Figure 3 shows the differences between these two types of damages.



OOR dimensions

Polygonal wear			
Amplitude (mm)	A1 [0.25-0.35] & A2 [0.55-0.65]		
Harmonic order	H6-8,	H12-14,	H19-20
Wheel Flat	L1	L2	L3
Depth (mm)	[0.02-0.06]	[0.09-0.16]	[0.23-0.26]
Length (mm)	[10-20]	[25-35]	[40-50]

Figure 3: Differences between the two types of OOR damage profiles.

To test the robustness and feasibility of the methodology, different records of train crossings were simulated, using different speeds, train loads, localizations and combinations of damage (single and multiple damage). All the information on the types of scenarios simulated is organized in Table 1.

Scenarios	Speed (km/h)	Train Load	OOR defects Type	OOR defects Axle	Total Passages
Baseline	[40-120]	Full, Half & Empty	-	-	120
Single Damage	{60,80,100}	Full & Empty	P	1^{st} & 10^{th}	17
			F	6^{th}	10
Multiple Damage	{60,80,100}	Full & Empty	F+P	1st + 5th	6
			F+F	1st + 3rd/2nd + 3rd/ 1st + 5th/1st + 9th	12
			P+P	1st + 3rd/2nd + 3rd/ 1st + 5th/1st + 9th	12
			P+P+P	1^{st} + 3^{rd} + 5^{th}	3

Legend

Laagrss Freight Vehicle Scheme

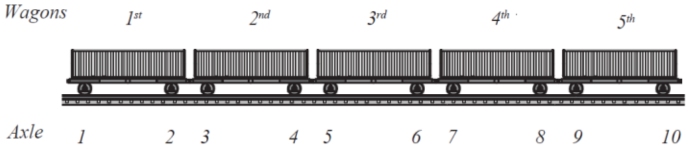
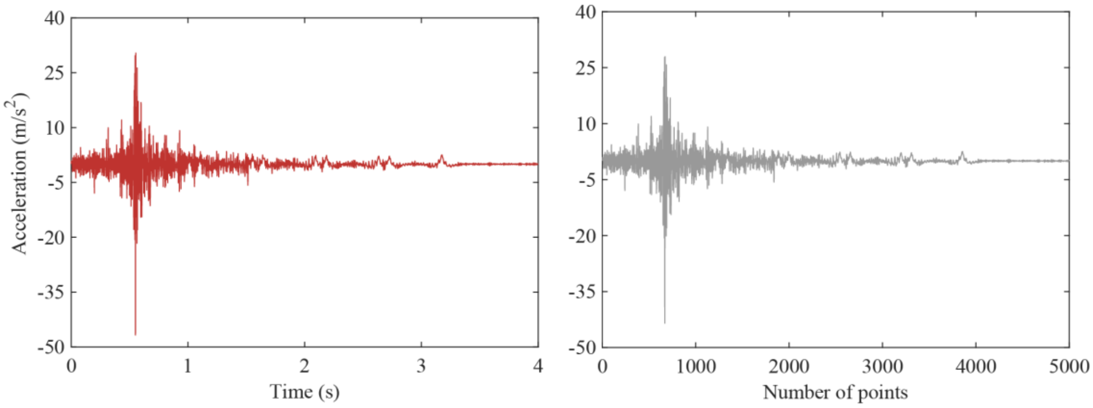


Table 1: Information about simulated scenarios.

For damage detection step, the acceleration responses from each sensor are normalized to 5000 domain points to ensure uniform wavelet decompositions. Figure 4a shows the original acceleration response for a polygonal wheel passage, and Figure 4b presents the corresponding normalized signal.



a) **b)**

Figure 4: Acceleration response in A1 from a polygonal wheel: a) original; b) normalized.

The normalized data are decomposed into 12 wavelet components using MODWT, resulting in relative energy (Figure 5). This figure displays wavelet decompositions, for a baseline case (5a) and for a wheel flat damage (5b), from accelerometer number 1, showing that the signal is gradually decomposed by frequency and amplitude. Regarding the damage case, its visible higher relative energies compared to the baseline. Furthermore, the decompositions 1 to 5 reveal detailed damage characteristics, while decompositions 6 to 12 do not visually indicate damage.

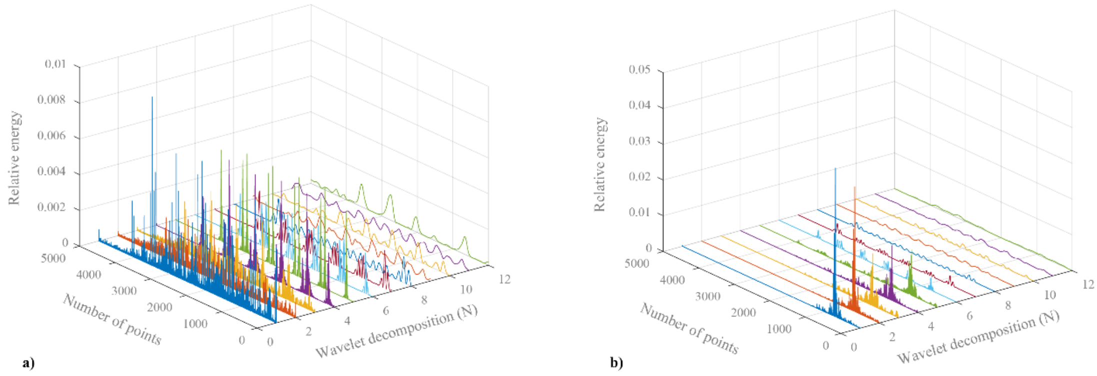


Figure 5: Wavelet decompositions from A1 for a passage of a) baseline; b) wheel flat.

This time-frequency domain technique enables the detection of various signal changes, principally in the first two relative wavelet energies. These energies are selected and fused using the Euclidean distance to highlight different types of damages, resulting in a Wavelet Index (WI). Figure 6 illustrates the WI obtained from the first pair of accelerometers (P1) for the same damage case shown in Figure 5, where the WI amplitude is significantly higher on the damaged side.

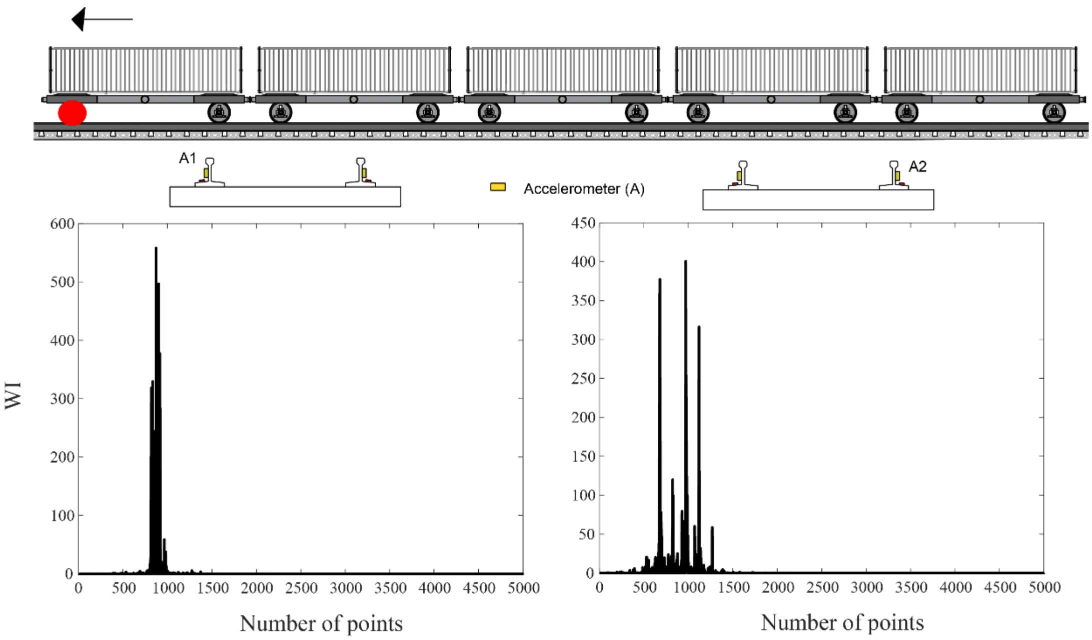


Figure 6: WI for a wheel flat damage for P1.

From WI, PCA features are extracted, and Mahalanobis distance is applied to merge the information. After that, the outlier analysis technique is applied to calculate CB. The results obtained are presented in Figure 7, showing 96.7% of accuracy, due the 3 false positives.

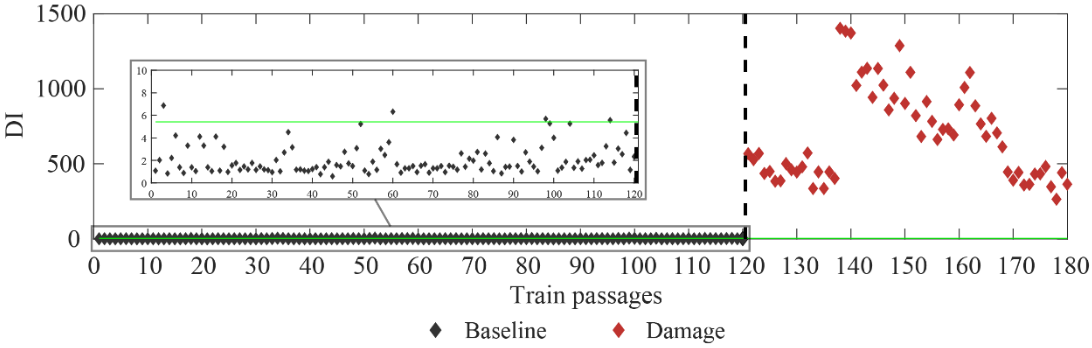


Figure 7: Automatic OOR damage detection.

After identified the damage passages, these outliers are transferred to the next stage in the methodology, the damage localization. In this step, the strain responses of each true positive outliers are used to determine the existing axles in each passage, discarding false positives. Additionally, the input used to extract PCA features, characterized by the WI, is approximated to a function enabling the determination of their accumulative differential. This operation will facilitate the calculation of axle location index (ALI), which is characterized by a number of damaged axles and their associated domain range. Figure 8 shows the results for various damage cases, obtained from the first pair of sensors (P1). The strain responses and the integral of the WI are scaled between 0 and 1 for easier visualization. In all cases, damage is clearly visible when assessed using acceleration responses. On the other hand, when evaluated in terms of strains, this difference is no longer observed. It is important to note that axles are more easily identifiable in the strain records, which are marked by red lines in Figure 8. The integration of the WI, represented by the black curve, enables automatic damage identification, where the identified axle coincides exactly with the sharp variations in the integral. When comparing the integral curve with the presence of two defects, the graphical "stairs" effect from wheel flat impact (Figure 8b) is evident, whereas the polygonal defect (Figure 8a) results in a more uniform curve. The same behaviour is visible in the multiple damage cases, as show in Figure 8c. It should be noted that this procedure is effective regardless of the number of existing damages, as the presence of damage will always be indicated by a sudden variation in the differential results.

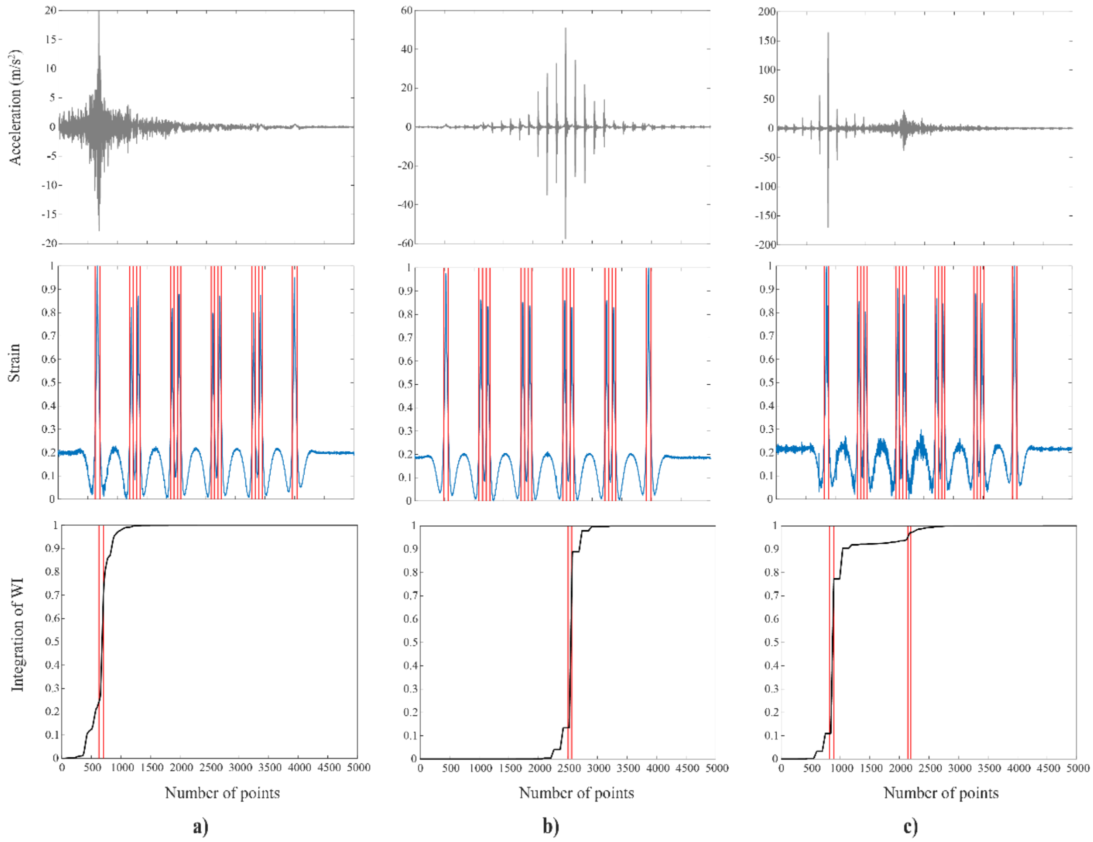


Figure 8: Damage localization: a) polygonal wheel; b) wheel flat; c) wheel flat + polygonal wheel.

Table 2 presents the confusion matrix of the proposed method for the ALI results, where axle 0 corresponds to axles not detected. In general, the results proved the accuracy of the methodology regarding localization of the damages in each axle for the scenarios tested. By analysing Table 2 when the damages are localized in the axle 1, three misclassification occurs. Furthermore, for scenarios where the damages are localized in the axles 2, 3, 5 and 9 only one misclassification are noticed. This misclassification can be interpreting as a false negative, given that the damages axle was not found. The results show that in the case of multiple closest damages simulated on 2nd and 3rd axles, the methodology is not capable of identifying all the damages. In polygonal wheels, the methodology presents 100% accuracy, as this is a type of continuous defect. Regarding the wheel flat, the position of the vibration's sensors and the position of the flat on the wheel in the moment of crossing can induce limitations one the damage localization, so only one of the three passages guaranteed the correct ALI.

True Axle \ Predicted Axle	0	1	2	3	5	6	9	10		
0										
1	2	34	1						91.9%	8.1%
2	1		5						83.3%	16.7%
3	1			11					91.7%	8.3%
5	1				16				94.1%	5.9%
6						10			100.0%	
9	1						5		83.3%	16.7%
10								6	100.0%	
		100.0%	83.3%	100.0%	100.0%	100.0%	100.0%	100.0%		
	100.0%		16.7%							

Table 2: Confusion matrix for ALI.

4 Conclusions and Contributions

This paper proposes an automatic wavelet relative energy-based methodology for multi-damage identification of OOR damage wheels from railway track acceleration response. The core of the proposed method involves a numerical cumulative integration of wavelet relative energy, where the damage region is clearly visible, and the strain response allows determining the specific damaged axle.

Regarding the damage detection phase:

- only three false positives were observed, and all damage cases were classified;
- the variability of railway vehicles can be misleading, so a greater amount of data and continuous learning of the methodology makes it possible to overcome detection flaws.

Looking on the results obtained on the damage localization phase:

- the accuracy obtained for the axle location index (ALI) was greater than 90% in most simulated scenarios, except in the scenarios where the damages were in axle 2 and 9;
- based on these results, it is expected that in situations of greater proximity to damaged axles, the methodology will have difficulty in counting the damage;
- in addition to the characteristics of each damage, simulated scenarios were included with different severity levels in the same passage. That fact provides a simple relationship between damage states, as an effect caused by more advanced wear overlaps the early defect, making it less pronounced in the dynamic response.

These results demonstrate the immense potential of this new methodology in the railway sector, especially regarding infrastructure management. The main challenge of this work was to establish the best criteria to localize the damage on the vehicles with a wayside monitoring system. Given the difficulty in obtain real train passage records, due to the high costs associated with their installation, this methodology was validated with numerical models. However, as part of future research, there are plans to conduct a dedicated experimental campaign involving vehicles equipped with predefined and thoroughly characterized out-of-round (OOR) defects. This experimental setup aims to provide precise validation of the methodology proposed in this work.

Acknowledgements

This work was financially supported by: Base Funding - UIDB/04708/2020 with DOI 10.54499/UIDB/04708/2020 (https://doi.org/10.54499/UIDB/04708/2020) and Programmatic Funding - UIDP/04708/2020 with DOI 10.54499/UIDP/04708/2020 (https://doi.org/10.54499/UIDP/04708/2020) of the CONSTRUCT - Instituto de I&D em Estruturas e Construções - funded by national funds through the FCT/MCTES (PIDDAC).

References

1. Sun, Q., et al., *An on-board detection framework for polygon wear of railway wheel based on vibration acceleration of axle-box.* Mechanical Systems and Signal Processing, 2021. **153**: p. 107540.
2. Amini, A., M. Entezami, and M. Papaelias, *Onboard detection of railway axle bearing defects using envelope analysis of high frequency acoustic emission signals.* Case Studies in Nondestructive Testing and Evaluation, 2016. **6**: p. 8-16.
3. Dwyer-Joyce, R., et al., *An ultrasonic sensor for monitoring wheel flange/rail gauge corner contact.* Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 2013. **227**: p. 188-195.
4. Shaikh, M.Z., et al., *State-of-the-Art Wayside Condition Monitoring Systems for Railway Wheels: A Comprehensive Review.* IEEE Access, 2023. **11**: p. 13257-13279.
5. Mosleh, A., et al., *An approach for wheel flat detection of railway train wheels using envelope spectrum analysis.* Structure and Infrastructure Engineering, 2021. **17**(12): p. 1710-1729.
6. Lai, C., et al., *Development of a Fiber-Optic Sensing System for Train Vibration and Train Weight Measurements in Hong Kong.* Journal of Sensors, 2012. **2012**.
7. Salehi, M., S.A. Bagherzadeh, and M. Fakhari, *Experimental detection of train wheel defects using wayside vibration signal processing.* 2023. **22**(5): p. 3286-3301.
8. Sun, Z. and J. Lu, *An Ultrasonic Signal Denoising Method for EMU Wheel Trackside Fault Diagnosis System Based on Improved Threshold Function.* IEEE Access, 2021. **9**: p. 96244-96256.

9. Amini, A., et al., *Wayside detection of faults in railway axle bearings using time spectral kurtosis analysis on high frequency acoustic emission signals.* Advances in Mechanical Engineering, 2016. **8**.
10. Deilamsalehy, H., et al., *An automatic method for detecting sliding railway wheels and hot bearings using thermal imagery.* 2017. **231**(6): p. 690-700.
11. Iwnicki, S., J.C.O. Nielsen, and G. Tao, *Out-of-round railway wheels and polygonisation.* Vehicle System Dynamics, 2023. **61**(7): p. 1787-1830.
12. Han, L., L. Jing, and L. Zhao, *Finite element analysis of the wheel–rail impact behavior induced by a wheel flat for high-speed trains: The influence of strain rate.* 2018. **232**(4): p. 990-1004.
13. Wu, X., et al., *A study of formation of high order wheel polygonalization.* Wear, 2019. **424-425**: p. 1-14.
14. Ye, Y., et al., *Multislice Time-Frequency image Entropy as a feature for railway wheel fault diagnosis.* Measurement, 2023. **216**: p. 112862.
15. Yan, G., et al., *Structural damage detection using residual forces based on wavelet transform.* Mechanical Systems and Signal Processing, 2010. **24**(1): p. 224-239.
16. Liu, J.-L., et al., *Time-varying damage detection in beam structures using variational mode decomposition and continuous wavelet transform.* Construction and Building Materials, 2024. **411**: p. 134416.
17. The MathWorks Inc (2018) MATLAB®, R.a.N., Massachusetts, USA.
18. Rosso, O.A., et al., *Wavelet entropy: a new tool for analysis of short duration brain electrical signals.* Journal of Neuroscience Methods, 2001. **105**(1): p. 65-75.
19. Hess-Nielsen, N. and M.V. Wickerhauser, *Wavelets and time-frequency analysis.* Proceedings of the IEEE, 1996. **84**(4): p. 523-540.
20. Jolliffe, I., *Principal Component Analysis Springer Verlag.* 2002.
21. ANSYS®. C, P., USA: Academic Research, Release 19.2. 2018.
22. Mosleh, A., et al., *Railway Vehicle Wheel Flat Detection with Multiple Records Using Spectral Kurtosis Analysis.* 2021. **11**(9): p. 4002.
23. Montenegro, P.A., et al., *Wheel–rail contact formulation for analyzing the lateral train–structure dynamic interaction.* Computers & Structures, 2015. **152**: p. 200-214.
24. Jorge, T., et al., *Early identification of out-of-roundness damage wheels in railway freight vehicles using a wayside system and a stacked sparse autoencoder.* Vehicle System Dynamics: p. 1-26.