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Smart Rail Infrastructure: Onboard Monitoring with Machine Learning for Track Defect Detection

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Abstract

Detecting damages in railways is essential for ensuring the safety and reliability of train operations. This study introduces a methodology for detecting damage in railway tracks by employing an onboard monitoring system installed on a freight wagon. The methodology proposed here adopts a comprehensive approach involving data acquisition, feature extraction, data fusion, and outlier analysis. Initially, data is collected using the onboard monitoring system, capturing diverse responses from both the axle box and carbody during wagon operation. Subsequently, feature extraction is conducted on these acquired responses utilizing continuous wavelet transform techniques. Additionally, feature normalization via principal component analysis is applied to mitigate environmental and operational variations, enhancing sensitivity to damage detection. The Mahalanobis distance is then employed to merge features, yielding a damage index for each scenario. Finally, the fused features undergo classification using appropriate machine learning algorithms to distinguish between undamaged and damaged tracks. This methodology promises to enhance railway maintenance practices by offering an automated and dependable approach for detecting damages in railway tracks.

Keywords: machine learning algorithms, onboard condition monitoring, railway maintenance, train track interaction, defect detection, continuous wavelet transform

1 Introduction

Railway transportation serves as a backbone for global mobility and commerce, facilitating the movement of goods and passengers efficiently and reliably. Central to the seamless operation of railways is the integrity of the track infrastructure. However, continuous exposure to environmental factors, heavy loads, and dynamic stresses inevitably leads to wear, degradation, and potentially dangerous defects in the track structure [1]. Timely detection and mitigation of such damages are paramount for ensuring the safety, reliability, and cost-effectiveness of railway operations [2].

Traditional methods of track inspection primarily rely on manual visual inspections or periodic use of specialized equipment, which often prove to be time-consuming, labor-intensive, and susceptible to human error. In recent years, the advent of onboard monitoring systems integrated with advanced machine learning techniques has emerged as a promising solution to address these challenges [3]. By leveraging real-time sensor data and sophisticated algorithms, these systems can autonomously detect, diagnose, and predict track anomalies with unprecedented accuracy and efficiency [4].

Previous researchers have employed advanced signal processing techniques to mitigate signal interference and diagnose faulty signal patterns indicative of defective rails [5-7]. While extensive investigation has focused on detecting infrastructure defects [8-11], with a particular emphasis on railways [12, 13], literature specifically addressing automatic track defect identification remains limited. Hence, the application of artificial intelligence (AI) techniques holds promise for early detection of track defects, thereby enhancing safety and reducing operational costs.

Numerous researchers [14-17] have employed various machine learning algorithms to analyze data, establish learning frameworks, and make intelligent decisions. These algorithms include artificial neural networks (ANN) [18], convolutional neural networks (CNN) [19], and support vector machines (SVM) [20].

This paper aims to present an application of an unsupervised machine learning approach to detect track defects of the rail. The detection methodology comprises four steps: (1) feature extraction from the acquired responses using the continuous wavelet transform method; (2) feature normalization; (3) data fusion; and (4) damage detection by performing an outlier analysis.

2 Methodology for track damage detection

Figure 1 illustrates the automatic rail defect detection process using an unsupervised learning approach consisting of 5 steps [21-24]: (i) data acquisition, (ii) features extraction from acquired responses using a continuous wavelet transform (CWT) model, (iii) feature normalization to remove the environmental and operational variations (EOVs) by applying a latent-variable method named principal component analysis (PCA), (iv) data fusion, through the implementation of a Mahalanobis distance, to merge the features from each sensor and enhance sensitivity to detect rail defects, and (v) unsupervised feature classification through outlier analyses.

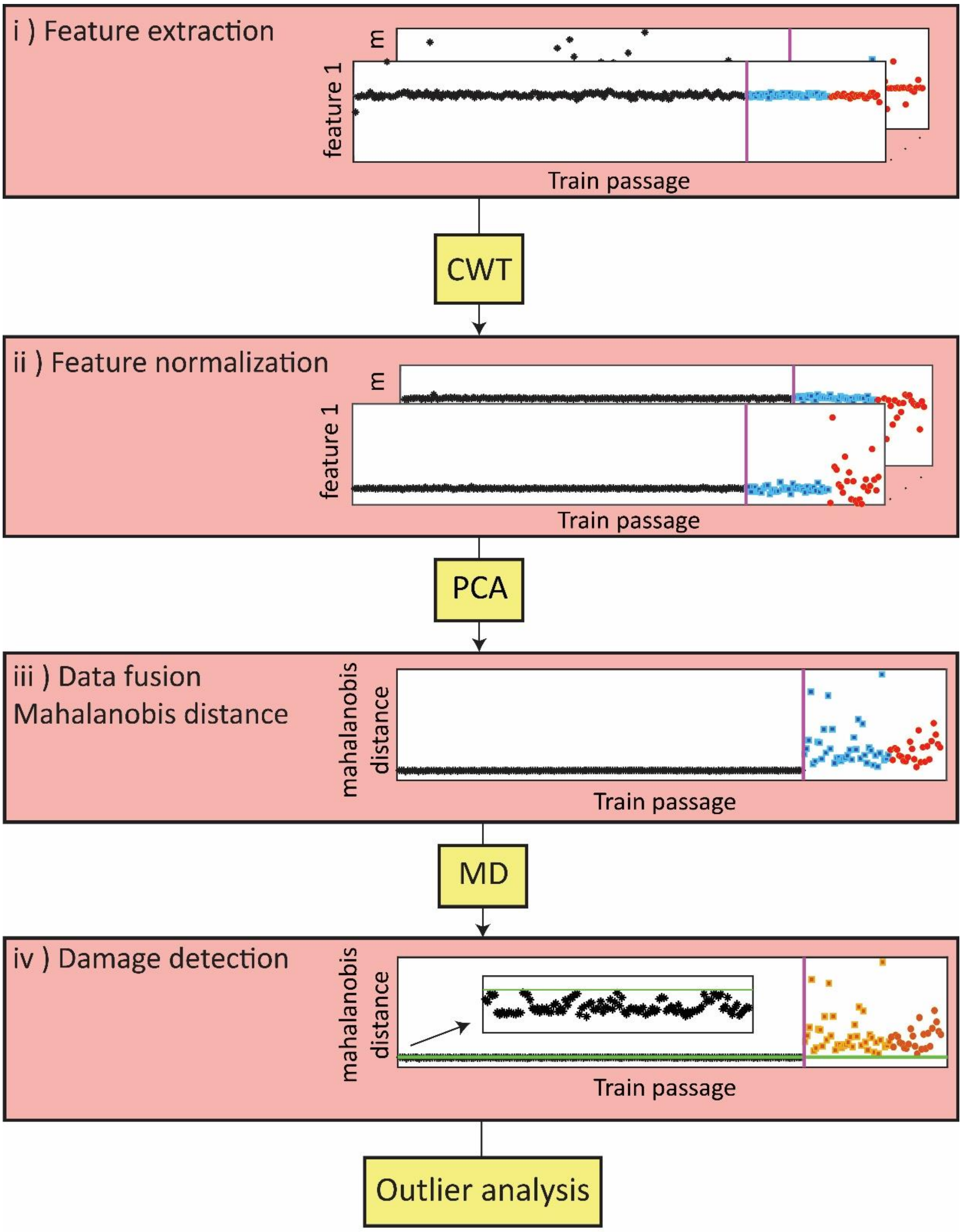


Figure 1: The framework of the proposed methodology for online track damage detection.

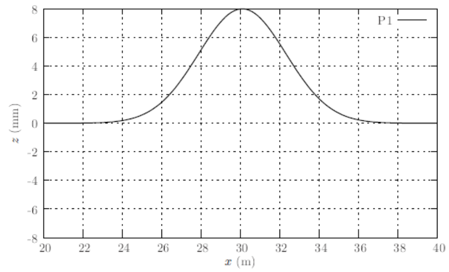
3 Train-Track dynamic interaction modelling

An in-house software program called VSI-Vehicle-Structure Interaction Analysis is utilized for conducting numerical simulations of train-track dynamic interactions, which have been validated and extensively documented in a prior publication [25-27]. Within this model, the train is interconnected with the track via a 3D wheel-rail contact model employing Hertzian theory [28] to calculate normal contact forces and the USETAB routine [29] to compute tangential forces arising from rolling friction creep. MATLAB® [30] is employed to implement this numerical tool, importing structural matrices modeled in a finite element (FE) package for both the vehicle and the track. The track is represented within the computer software [31] using beam elements for the rails and sleepers, spring-dashpot elements to emulate the behavior of flexible layers such as ballast and fasteners, and mass point elements to account for the mass of the ballast. The train is also modeled in ANSYS® [31] utilizing a multibody formulation, employing spring-dashpot elements to replicate the flexibility of the primary and secondary suspension, rigid beams to account for rigid body movements, and mass point elements situated at the center of gravity of each body, including carbodies, bogies, and wheelsets, to simulate their mass and inertial effects. Detailed descriptions of both track and train models are available in the authors' previous publications [7, 32].

4 Simulation of baseline and damaged scenarios

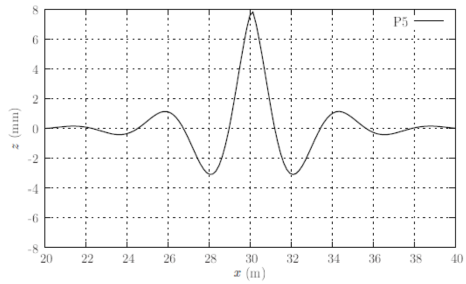
4.1. Description

This study employs a virtual simulation to assess and validate the automatic rail defect detection method, both under normal conditions and in scenarios with damage. Two distinct types of isolated defects, designated as P1 and P5 (refer to Figure 2) are taken into account. The equations representing these defects (depicted in Figure 2) incorporate parameters such as k, determining the defect's wavelength; z, representing defect's vertical extent; and x, indicating its horizontal length. The investigation involves altering the amplitudes and wavelengths of these defects to observe their impact on acceleration. Specifically, amplitudes considered in this analysis are chosen based on predefined thresholds defined in accordance to the European Standard EN 13848-5 [33]: alert limit (A=8 mm), intervention limit (A=10 mm), instant action limit (A=17 mm), and early detection (A=6 mm). Additionally, corresponding variations in wavelet for each amplitude are selected.



P1: $z = Ae^{(1/2)(\bar{k}x)^2}$

(a)



P5: $z = Ae^{-\bar{k}|x|}\cos(\pi\bar{k}x)$

(b)

Figure 2: Track defect geometry [34].

The acceleration of the vehicle is assessed across 7 sensors shown in Figure 3, including various scenarios, for both baseline (undamaged) and damaged conditions to validate the proposed methodology. 4 sensors are installed in the axel box and 3 sensors are installed in carbody.

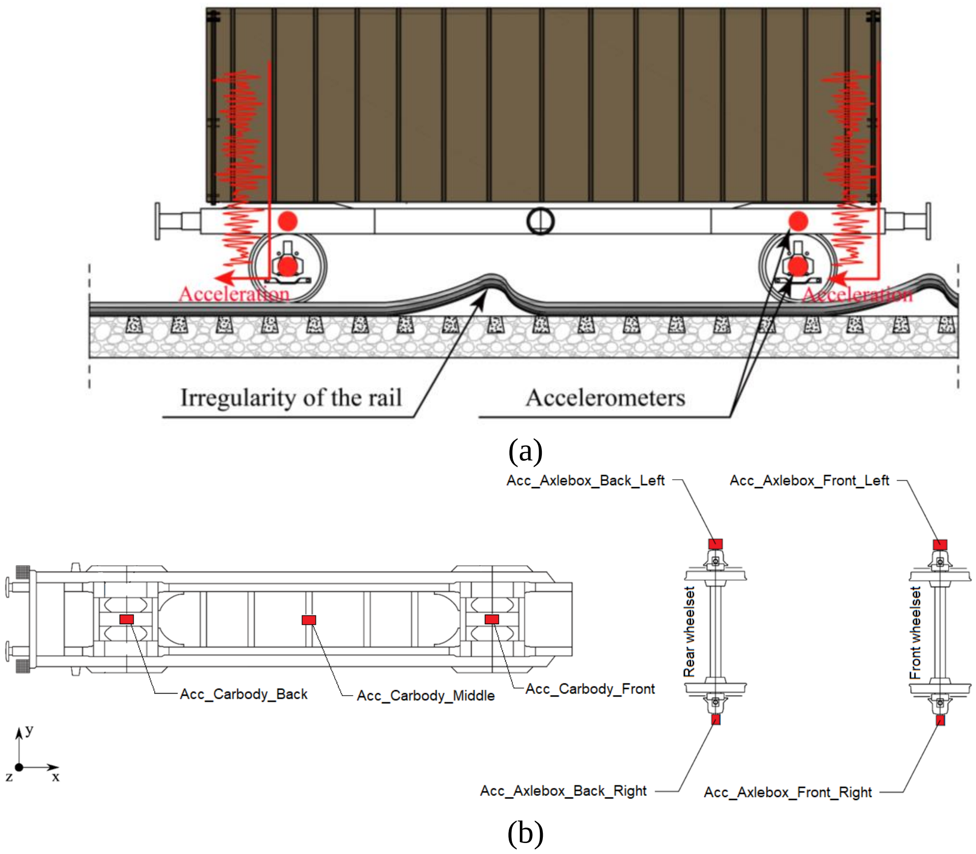


Figure 3: Onboard monitoring system and location of sensors installed on the vehicle

Table 1 provides an overview of the 188 simulations conducted for undamaged scenarios, that aim at reproducing the vehicle's responses across different speeds and rail unevenness profiles.

Table 1: Damaged and undamaged scenarios

	Baseline Scenarios	Damaged Scenarios	
	Healthy track	Damage P1	Damage P5
Irregularity profiles	10	1	
Speed	40-120 km/h	75 km/h	
Noise	5%	5%	
Wavelength	3-25 m	5-25 m	15-25 m
Defect amplitude	-	± 6mm (acceptable) ± 8mm (warning) ± 10mm (intervention) ± 17mm (safety risk)	
Total	188	40	24

5 Automatic track defect detection

5.1 Feature extraction with CWT approach

The initial phase of the automated damage detection methodology involves extracting damage-sensitive features from the dynamic signals. Across 188 baseline and 64 damage scenarios, three-dimensional feature matrices measuring 252-by-432 are obtained for each of the 7 accelerometers (4 sensors installed in the axel box and 3 sensors installed in carbody). Figure 4 shows 4 features out of 432 for all 252 scenarios, focusing on the acceleration registered on the axle-box front left. In damaged scenarios, simulations 189 to 228 depict the passage of a vehicle through the track with an isolated defect referred to as P1, while simulations 229 to 252 depict the passage with an isolated defect named P5.

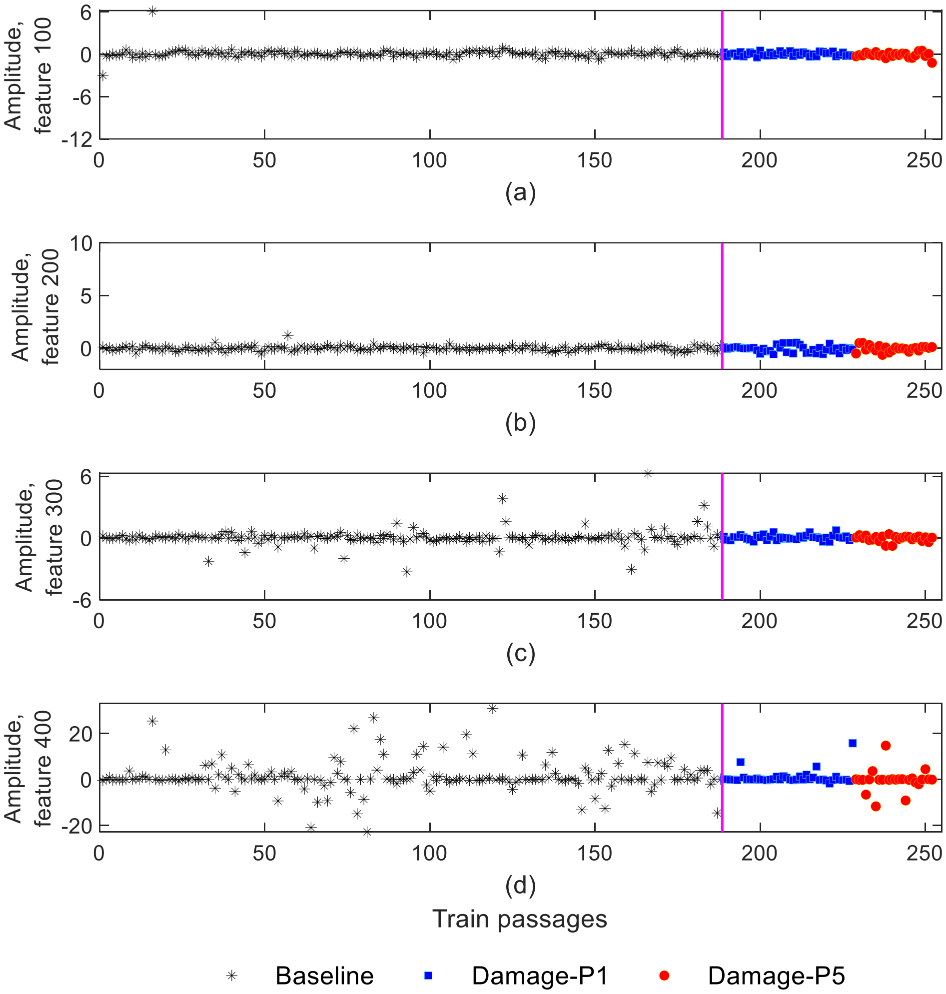


Figure 4. Feature extraction: 4 features out of 432 for all 252 scenarios for the accelerations located on the axle-box front left.

5.2 Feature normalization with PCA

The normalization process of data is crucial for eliminating the influence of environmental and operational factors. Analysis of the CWT-PCA-based features depicted in Figure 4 reveals the complexity of distinguishing defective scenarios from healthy ones. This complexity arises due to the influence of environmental and operational factors, resulting in subsequent changes in the features. Hence, to mitigate these effects and enhance damage sensitivity, it is imperative to appropriately model these features. Utilizing the latent-variable method PCA, feature normalization is executed. In this stage, a PCA-model-based approach is employed on the CWT-PCA-based parameters, yielding a new 252×432 matrix of normalized features for each sensor. Figure 5 displays the modeled features for all baseline and damage scenarios for the accelerometer located on the axle-box front left. During the modeling process, the cumulative percentage of variance components exceeding 80% is disregarded, leading to the exclusion of 9 rows. These findings demonstrate the successful normalization of CWT-PCA-based parameters, effectively reducing operational effects while preserving sensitivity to damage.

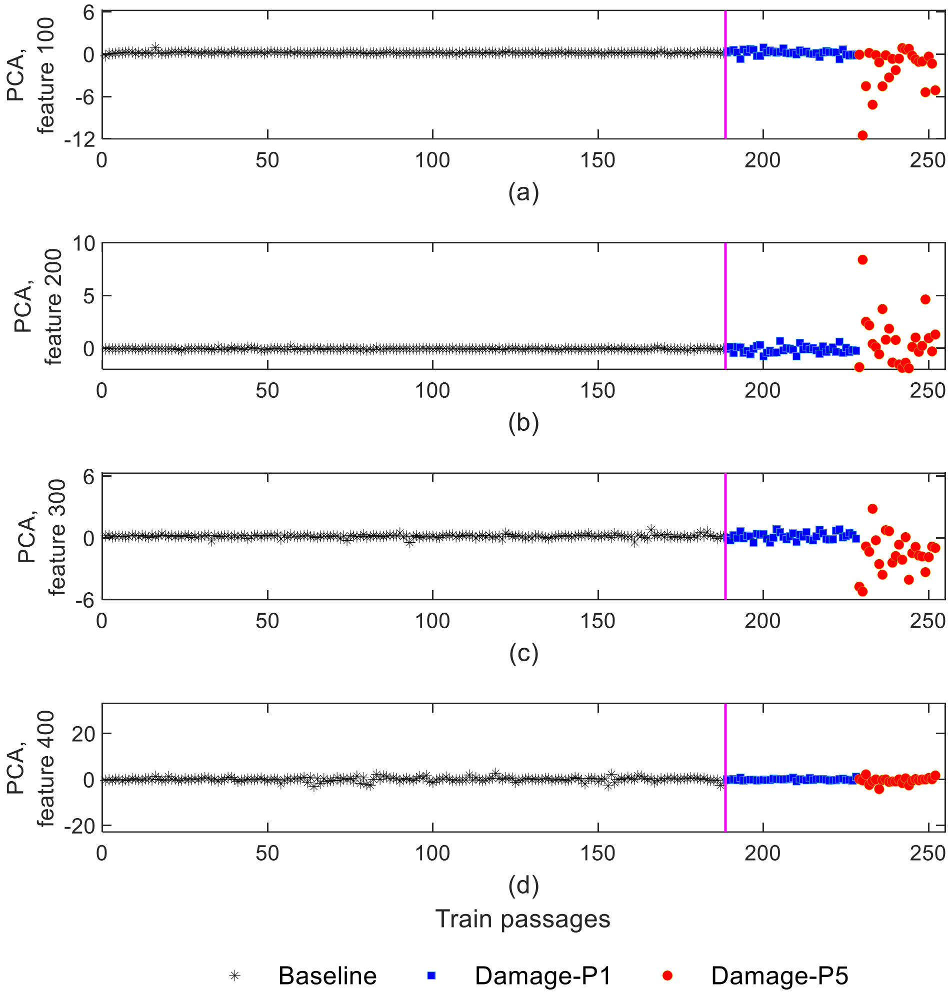


Figure 5. Feature normalization: 4 normalized features out of 432 for all 252 scenarios for the accelerations located on the axle-box front left.

5.3 Data fusion

In order to merge all 432 CWT-double-PCA-based parameters acquired for each sensor, the Mahalanobis distance (MD) method is employed. This approach facilitates the transformation of the 432 parameters into a single damage-sensitive feature for every sensor and train passage. Consequently, a vector of size 252×1 is generated for each of the 7 sensors as the output of this process. Figure 6 illustrates the Mahalanobis distance values across all 252 train passages, considering the responses from various accelerometers. The outcomes show notable sensitivity to damage, as evidenced by the disparity in MDs between the baseline simulations and the damage scenarios.

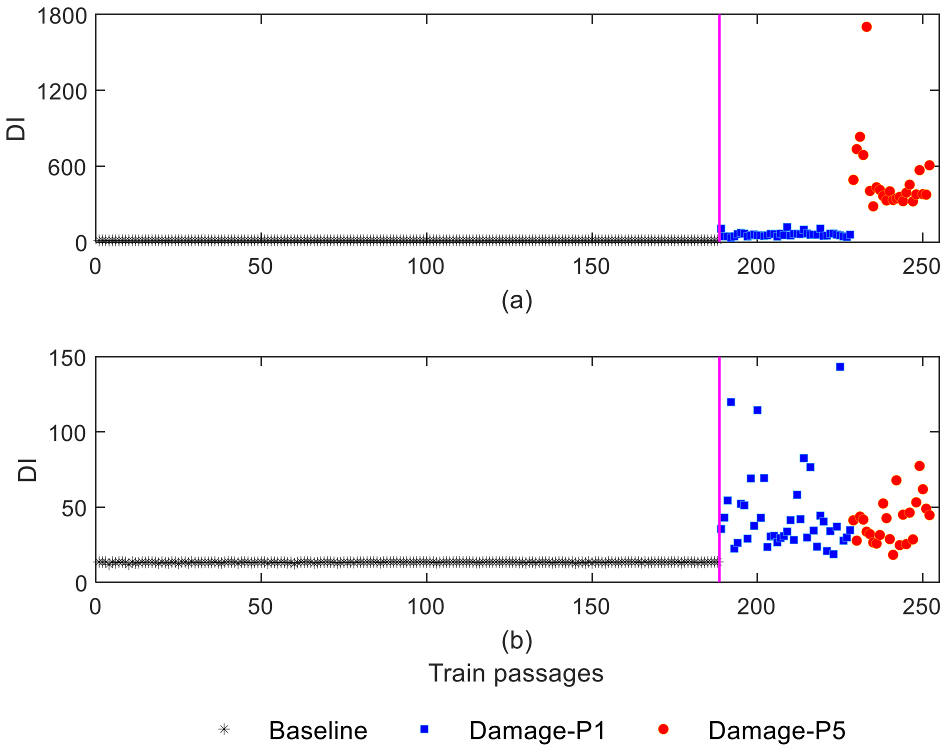


Figure 6. Damage index (DI) for all 252 train passages evaluated by accelerometers located at: (a) axle-box front left, (b) car body middle.

5.4 Statistical-based automatic track defect detection

Figure 7 shows distinct damage behaviors across two intervals, designated as a baseline and damaged scenarios, as captured by accelerometers installed in both axle box and carbody. The results depicted in this figure show that the methodology is capable of detecting all damage scenarios accurately, without any false positives or false negatives. An inherent advantage of this approach is its requirement for only a single sensor, even one installed in the carbody, to effectively detect a defective wheel. Consequently, the proposed methodology offers the benefits of minimizing installation costs while enabling a more automated and simplified implementation process. These findings underscore the significant potential of this innovative application of data mining within the railway industry.

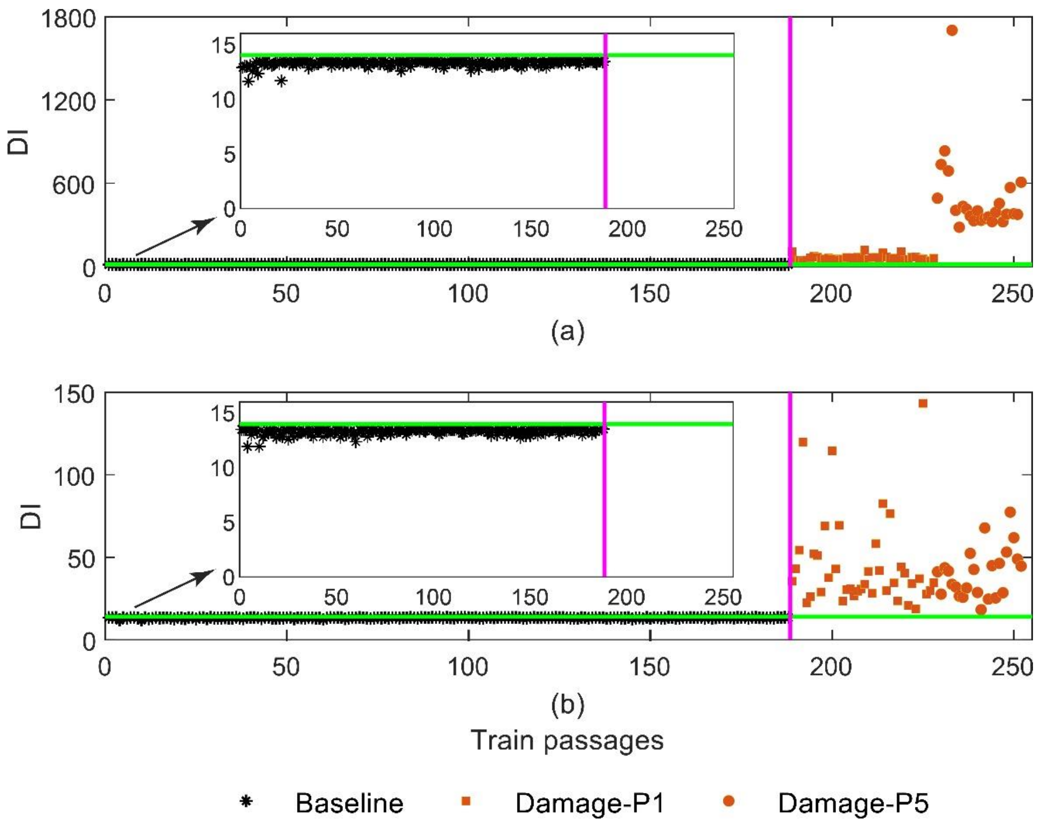


Figure 7. Automatic rail isolated defect detection considering the responses from accelerometers: (a) axle box front left, (b) car body middle.

Conclusions and Contributions

The objective of this paper is to develop an unsupervised methodology for detecting track defects automatically, particularly focusing on detecting isolated defects at their early stage. A significant advantage of this proposed methodology is its ability to detect such defects using just one sensor installed in the car body. This streamlined approach not only reduces the complexity and cost of the installation system but also facilitates a more automated implementation process. Future work will involve conducting field trials to further evaluate the effectiveness of the developed technology. Additionally, to refine the proposed methodology, it is crucial to develop an automatic indicator capable of distinguishing and categorizing track defects based on their severity. Such advancements will enhance the practicality and efficacy of the methodology in real-world railway operations.

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