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Intelligent clustering-based approach for railway wheel flat detection

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Abstract

The main goal of this paper is to present an unsupervised methodology to identify railway wheel flats. This automatic damage identification algorithm is based on the acceleration evaluated on the rails for the passage of traffic loads and deals with the application of a two-step procedure. The first step aims to build a confidence boundary using baseline responses evaluated from the rail, while the second step involves the damages' classification based on different severities levels. The proposed procedure is based on a machine learning methodology and involves the following steps: (i) data acquisition from sensors, (ii) feature extraction from acquired responses using an AR model, (iii) feature normalization using principal component analysis, (iv) data fusion and (v) unsupervised feature classification by implementing outlier and cluster analyses. The obtained results show that the proposed methodology is a reliable and cost-effective method that can be successfully used for the wheel flats identifications and considering different operating speeds.

Keywords: Machine learning, Damage identification, Railway wheel flat, Wayside condition monitoring.

1 Introduction

Rail infrastructure and vehicles can be damaged by defective wheels, especially on freight railway wagons. Wheel flats happen when a wheel locks and slides over the rail. Wheel flats are the main causes of wheel bearing damage, axle fractures, as well as rail and concrete sleeper fractures since the impact loads due to damaged wheels, are higher than the static load of the wheel. The probability of detecting a defective wheel by visual inspection depends on various conditions (e.g., darkness/lightning) and the visibility of wagon components due to access or contamination. In addition, a tiny defect that experienced inspectors does not even detect remains in the wagon for a long time, leading to inescapable adverse effects such as excessive periodic effects on the wagons and track.

Researchers have proposed onboard and wayside measurement methods to detect defective wheel during the past decades. Mostly, onboard damage detection methods are commonly used to monitor the condition of the track and are not suitable to monitor the wheel condition [1]. In contrast, wayside measurement systems are now an ideal solution to identify wheel defects, as the condition of all wheels is assessed during the passage of in-service trains [2].

Typically, several operations are required to identify a defective wheel, including [3]: (i) data acquisition, (ii) feature extraction, (iii) feature normalization, (iv) feature fusion, and (v) feature classification [4-6]. In recent years, advanced signal processing and machine learning methods have been used to distinguish between a healthy wheel and a defective wheel [7]. To determine the best combination of features/classifier in making intelligent decisions regarding the presence of wheel flats, several researchers tested different classification methods, such as k-means, Naive Bayes, and k-Nearest Neighbor (kNN) [8].

According to the authors' knowledge, only a few studies have been conducted on automatic wheel flat detection and classification due to flat severity based on analysis of the aforementioned studies. There are still many studies to be performed to identify a defective wheel, and the contribution of intelligent algorithms is very valuable and needed. As a result, one of the novelties of this research study is to propose an unsupervised machine-learning-based methodology to automatically identify defective wheels based on the severity of the flats.

2 Methods

The main objective of this paper is to present an unsupervised method for identifying railway wheel flats. This automatic damage identification algorithm is based on the acceleration evaluated on the rails (as presented in Figure 1) for the passage of traffic loads and deals with the application of a two-step procedure. A confidence boundary is created in the first step based on baseline responses evaluated from the rail, while the second step involves the classification of the damages based on severity levels. Machine learning is used to develop the proposed procedure, which involves the following steps: (i) data acquisition from sensors, (ii) feature extraction from acquired responses using an AR model, (iii) feature normalization using principal component analysis, (iv) data fusion and (v) unsupervised feature classification by implementing outlier and cluster analyses.

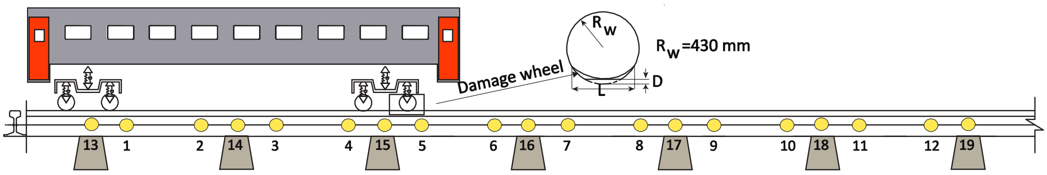

Figure 1: Virtual wayside monitoring system

Due to different lengths of wheel flats, damage on a wheel is defined by three intervals and nominated as L1, L2 and L3. The uniform distributions U (10, 20) [mm], U (25, 50) [mm] and U (55,100) [mm] define the lower and upper limits of the wheel flat length for each interval L1, L2 and L3 respectively. Considering various rail speeds, loading schemes, and unevenness profiles, the 100 simulations of the undamaged scenarios are summarized in Table 1. Additionally, 150 simulations are conducted for the damaged scenarios, considering a variety of flat properties for defective wheels as a result of an Alfa Pendular vehicle circulating at 60 m/s.

	Undamaged scenarios	**Damaged scenarios**
Train	Alfa Pendular	Alfa Pendular
Number of Loading schemes	3 types	1 type
Unevenness profile	10 profiles	1 profile
Speeds	20-60 m/s	60 m/s
Noise ratio	5%	5%
Flat characteristics	-	Flat lengths: 10-20 mm (L_1), 25-50 mm (L_2), 55-100 mm (L_3)
Total analyses	**100**	**150**

Table 1. Damaged and undamaged scenarios

3 Results

The first step of the proposed methodology is to build a baseline scenario and obtain a confidence boundary (CB) for each sensor considering 100 passages of the vehicle. In stage 2, additional vehicle passages are considered (150 passages), and once again, AR model, PCA, and data fusion are applied to obtain a damage index (DI). Figure 2 presents the effectiveness of the proposed methodology to distinguish a defective wheel from a healthy one by comparing the confidence boundary (considered only 100 passages) with different damage indexes (250 passages). Since the DIs for the first 100 passages are less than CB, the algorithm can detect a defective wheel. Figure 2 also allows observing different damage behaviors between three intervals, namely L1, L2 and L3, corresponding to low, median and severe wheel flat lengths.

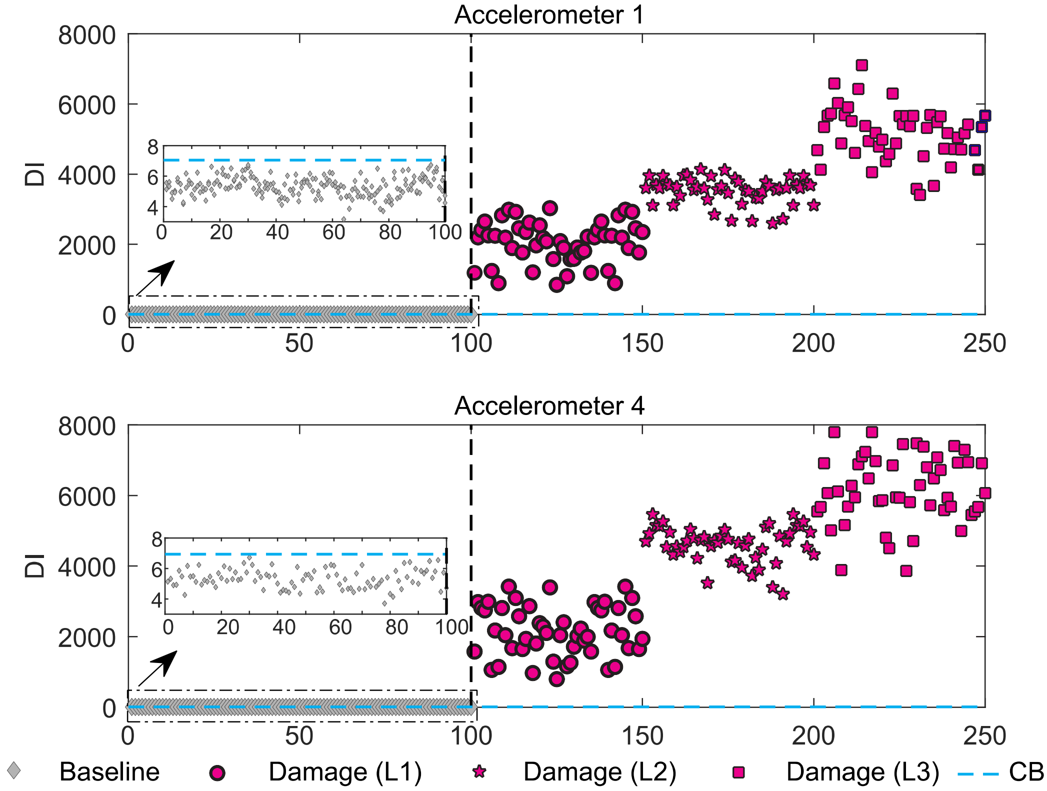

Figure 2: Wheel flat detection

As shown in Figure 2, the proposed methodology is capable of detecting a wheel flat automatically. However, to classify the wheel flat based on flat severity, user intervention is required to: (i) find the first cluster, which is the baseline scenario, and (ii) classify the damaged clusters of the defective wheel based on the wheel flat severity. Therefore, the SIL indicator is extracted from five cluster partitions, showing the maximum for 4 clusters (K=4). Figure 3 presents the corresponding features' allocations automatically generated by the k-means method for three of the nineteen sensors. Moreover, the centroids are calculated for each cluster and then organized in ascending order (CD1 to CD4). The centroid with a value less than CB (presented in Figure 3) is defined and nominated as CD1, and the corresponding partition is considered cluster 1, which corresponds to baseline scenarios. Furthermore, the k-means algorithm generates centroids higher than CB if the damage is observed. Therefore, the partitions related to centroids CD2 to CD4 are associated as cluster 2 to cluster 4, respectively. CD2 corresponds to damaged wheel interval L1, CD3 corresponds to damaged wheel interval L2 and CD4 corresponds to damaged wheel interval L3.
The diagrams in Figure 3 demonstrate that the clustering method is able to divide features without any intervention from the user. Moreover, the diagonal diagrams of this figure show that the first cluster found for each sensor is compressed over time and separates as the wheel defect begins.

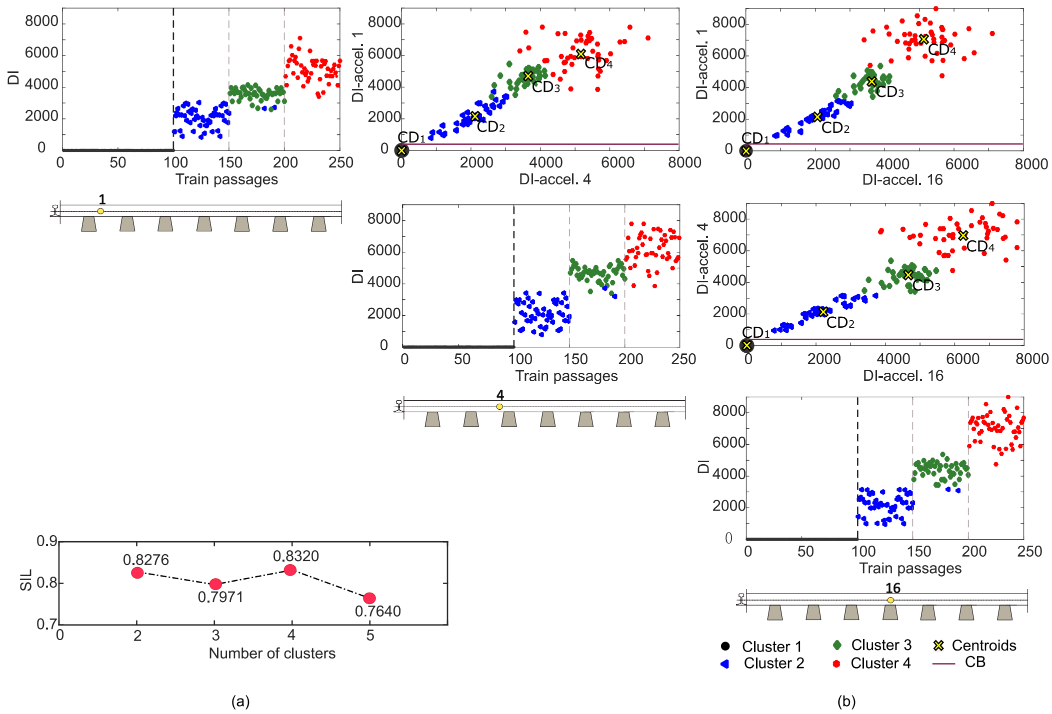

Figure 3: Allocation of damage-sensitive features into clusters: a) silhouette index (SIL), b) clusters and their centroids defined for 3 sensors

4 Conclusions and Contributions

The objective of the research study is to propose the damage identification methodology to automatically detect railway wheel flats and classify them based on different severities. The features are extracted by applying AR to the acceleration measurements. Moreover, PCA and Mahalanobis distance are used for feature modelling and data fusion, respectively. Finally, a combination of outlier and cluster analyses is applied for feature discrimination. The following conclusions can be drawn from the research work herein presented:

- The results show that the proposed methodology is robust and cost-effective to be used under real-world conditions to identify wheel flats for different train speeds.
- It was demonstrated that outlier analysis is capable of distinguishing automatically between the healthy and damaged wheel at an early stage based on a confidence boundary.
- k-means method can analyse the feature set and separate it according to the wheel conditions in a completely automatic way.

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