Recognition of track defects through measured acceleration - part 1

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Abstract. For an optimized maintenance strategy, the early detection of track defects is necessary. Mounted sensors (e.g. acceleration sensors) on in-service trains are very suitable for track monitoring. With the continuous measurement of axle-box acceleration, short wavelength defects can be identified. For example, these defects can be rail breaks or cracks (i.e. rail defects), or local instabilities. Local instabilities can reduce the track quality in a short period of time. For an efficient data analysis of the acceleration signal and classification of different track defects, the development of appropriate methods is necessary. Therefore, a track-vehicle scale model was built to generate acceleration data used to detect typical types of failures. With the generated acceleration data, developed algorithms for pattern recognition can be easily tested. In the first part of this research, the vertical acceleration signals generated by the rail defects and local instabilities are collected, analysed, classified and prepared for being used in a model that can automatically identify these failures. The data is collected in a track-vehicle scale model, and after data analysis, the characteristics of the waveforms associated with each failure are examined using cross correlation. Every failure is classified both manually as well as automatically, and statistical features of the waveforms are extracted to create a database that is used to train a model using supervised learning. This model is described in the second part of the research.

1. Introduction

In this day and age, the demand for mobility using railway transport systems is very high. Most trains operate continuously for almost the whole day long. Hence, track maintenance activities are limited to only a few hours per day when the trains are not in operation [1]. The typical failures such as rail-joints, local instabilities and rail-cracks cause several collisions, fatalities and injuries [2]. Therefore, a good track condition over a long period of time is important to decrease intensive maintenance work. Traditional equipment for inspection such as track recording-vehicles are used by default to determine any track defects [3, 4, 5]. However, these track recording-vehicles are expensive to maintain and may interrupt regular operation. Both the need to occupy the track with regular operations and the small number of track recording cars limit the track geometry measurements. To carry out an efficient maintenance strategy, “continuous track monitoring” is needed. With the use of continuous track monitoring, railway maintenance actions can then be planned in the early stages of track degradation. In order to do this, solutions for the continuous determination of the track condition have to be developed; one solution could be an axle-box accelerometer system mounted on in-service trains.
Particularly short track defects can be recognized very well by using continuously-measured axle-box accelerations. The acceleration signals which are the readout of all the acceleration data collected along the model track are represented as a graph of time versus the value of the vertical acceleration and can be analysed based on their time and frequency to determine the characteristics of the different failure types.

In the course of the research project titled “Frühzeitige Erkennung von punktuellen Instabilitäten bei zyklisch dynamischer Einwirkung an bestehenden Bahnkörpern in konventioneller Schotterbauweise bei bindigen Böden im Unterbau/Untergrund” (EPIB), which is funded by the German Research Foundation (DFG), the early detection of local instabilities is investigated. In this research, a track-vehicle scale model is built to generate acceleration data that is used to detect different failure types by running for several laps. In [6], the local instability in the track-vehicle scale model is successfully recognized with the continuously-measured accelerations using five methods: amplitude range investigation, frequency analysis, cross correlation analysis, wavelength analysis and the failure detection method that is based on the classification of peaks using their ranges in amplitude and wavelength. To extend these five methods to track failure detection, machine learning algorithms were introduced.

This current paper is the first of two papers presenting the approach for track defect recognition using a bagged decision tree algorithm. In figure 1, the complete approach for failure detection (which employs the supervised learning for training data [7]) in the machine learning method is shown. This current paper describes the first two steps: “Data Collection” and “Data Preparation”. The second paper describes the last two steps: “Training Process” and “Prediction Process”.

Figure 1. General approach for failure detection using the machine learning method.

2. Data collection

2.1. Track-vehicle scale model
The track-vehicle scale model simulates an elevated railway that has four sections (two curves and two tangents) that together form an oval route of 4.04 m long (see figure 2). The model has an easy elevation setting due to its spring-screw construction. Track failures with different amplitudes, wavelengths and twists can be generated easily within this model.

In a real track system, there is usually little information about the failure types and their characteristics. According to [8], only a single fault analysis based on defined tolerance and limit values can be carried out on a real track system. Therefore, the main advantage of the track-vehicle scale model is that the failure types, their exact positions in the model and in the acceleration signals are known so that algorithms for pattern recognition can easily be tested [6].

In the track-vehicle scale model, eight failures are installed along the track: Four rail joints, two rail cracks, one local instability and the entrance/exit to the bridge. The position of each failure is marked in figure 2.
The failure types can be classified depending on their wavelength. The following failures, which occur in the vertical profile, can be detected using the axle-box accelerations:

- Rail defects, such as rail cracks and joints
- Track irregularities with a wavelength between 1.00 and 25.00 m, such as cracked sleepers, defect fastener, hanging sleepers and local instabilities

In table 1, pictures of the failure types in the track-vehicle scale model and from a real track are shown. During the data collection, the measuring vehicle generates acceleration data. In the same moment the vehicle passes over a failure, the sensor detects an increase in the vertical acceleration. Because each failure type generates its own typical amplitude and wavelength ranges, the different waveforms for the different failure types can then be used to recognize the type of track defect using the acceleration signal [6]. For example, rail cracks and rail joints produce high amplitudes, short wavelengths/high frequencies and two peaks (vehicle excitation caused by the two axes of the first car). In contrast, the entrance/exit to the bridge and the local instability generate accelerations with low amplitudes and larger wavelengths.

Table 1. Pictures of failure types in the track-vehicle scale model and from a real track system.

| Rail joint [9, 11] | Local instability [12] | Rail crack or brake [9, 13] |
|-------------------|------------------------|-----------------------------|

The track has rail joints at the Positions 1, 2, 5 and 6 (see figure 2).

The track has a local instability at Position 3 (see figure 2), which is generated by a reduced vertical stiffness and a concave deformation of the vertical alignment of the rails.

There are rail cracks or brakes at Positions 4 and 8, which create a high vertical acceleration (see figure 2).
2.2. Local measurement system
The measurement system on the vehicle model consists of a locomotive and two cars. The first car is loaded with a battery and the second with the sensor module that continuously collects the acceleration data with a sample rate of 500 Hz. In order to increase the natural frequency of the measuring vehicle, additional weight is added. The vehicle speed is approximately 0.37 m/s while passing over the track failures. After finishing each lap, the train always stops at the same position for about three seconds before a new lap is started (see figure 2 start point) [6]. As the track-vehicle scale model doesn’t have a suspension system, there are no external influences to the acceleration data measured with the vehicle model. Therefore, the data collected with the vehicle model is comparable to the axle-box accelerations on a real train [6].

2.3. Instability
Local instabilities (also known as mud spots) are often the result of the interaction of several circumstances such as the presence of cohesive soil and water in the sub-ballast/subgrade and a locally increased dynamic impact acting on the track ballast. The interaction of these circumstances can cause a self-reinforcing process, which leads to a rapid deterioration of the track quality in a relatively short period of time [14]. The vertical track stiffness is reduced by soil softening and the ballast stones get pressed into the sub-ballast/subgrade. In combination with hanging sleepers, a pumping effect starts that infiltrates the ballast bed stepwise with fine grade soil.

The main characteristics of the local instabilities are:

- Low vertical track stiffness
- Strong deviation in the longitudinal level
- Deterioration of the track quality in a relatively short period of time

The primary goal of this research is the recognition of the local instability in a real system. The physical similarity between the track-vehicle scale model and the real system has been proven in [6] by dimensional analyses. The local instability in the track-vehicle scale model is also analogue to the real system when considering the shape of the longitudinal level and the reduced vertical stiffness. Furthermore, a pumping effect is generated in the model, which significantly influences the measured acceleration in frequency domain.

2.4. Data generation
The generated data was collected from six tests of several laps (between 11 and 15 laps) around the track-vehicle scale model with a maximum vehicle velocity of 0.37 m/s. The measuring system started and ended at a specific chosen point (see figure 2 “Start point”). More than 1.3 million samples of acceleration data are generated from 139 laps around the track-vehicle scale model in a clockwise direction and are used as training data for the generation of the new machine learning models.

3. Data preparation

3.1. Acceleration signal processing
In the first step of the data preparation, a Savitzky Golay filter [1] is used to smooth the noisy data obtained from the undesired vibrations by fitting a polynomial to a set of input samples and evaluating the resulting polynomial at a single point within the approximation interval.

3.2. Classification
In order to identify each failure in the model, it is necessary to analyse the typical waveforms in the acceleration signal caused by cracks, joints, the local instability and the entrance/exit to the bridge. A unique mapping “pattern in the generated acceleration signal - failure position” can then be made without great effort [10]. According to the failure type, a specific range of sample numbers can be defined. In order to do this, the typical waveforms for the eight failures are analysed by cross correlation
(see figure 4). During the cross correlation analysis, the specific range of the sample numbers is changed stepwise. If the maximum correlation is reached, it can be determined that a failure was found. Subsequently, three classes for failure detection are defined to differentiate between local instabilities, non-track failures (noise) and other types of failures (joints, cracks and entrance/exit to the bridge). Table 2 provides a description of these three classes.

Table 2. Description of the classes [9].

| Class number | Class         | Failure Number in figure 2 |
|--------------|---------------|----------------------------|
| 1            | Non-track failure | ***                       |
| 2            | Joint         | 1,2,5 and 6               |
| 3            | Local instability | 3                         |
| 2            | Crack         | 4 and 8                   |
| 2            | Bridge        | 7                         |

The classification of the failures is first conducted manually by identifying each failure and then the specific sample range is determined in a stepwise approach along the acceleration signal. Figure 3 shows the position of the local instability for a range of 250 samples as identified by manual classification.

Figure 3. Classification of the filtered acceleration signal [9].

Figure 4. Alignment of the filtered acceleration signals at their failure position and sample range definition [9].
After the manual classification is completed, the acceleration signals are cut to separate the individual laps. The starting position of each sample range is determined for the eight failures and every lap by identifying unified peaks (see figure 5). To align the acceleration signals at the position of each failure and lap, the acceleration signal delays are calculated by cross correlation. The output of this process guarantees a proper classification of the failures in the acceleration signal.

Due to the time consuming process of manual classification, an automatic classification process was developed and also used in this study. Figure 5 shows the filtered vertical acceleration signal for two laps where repetitiveness between the laps can be identified. Therefore, it is possible to work with just the features of one lap by detecting local peaks at the unified peaks. The eight failures can then be classified by using the waveforms defined in figure 4.

For the automatic classification process, a moving-average filter is used to filter the vertical acceleration signal in order to smooth out any noisy data. Based on the calculated absolute values of the vertical accelerations, peaks are detected automatically when the peak acceleration is higher than a defined acceleration threshold and a set peak distance. After a dataset with the peak position, the maximum peak acceleration and the sample distance between two consecutive peaks is generated, a specific sample range is designated from the unified peak position according to figure 4. The acceleration data outside the ranges are classified as Class 1 (non-track failure), while the data inside each sample range is classified as either Class 2 (crack or joint) or Class 3 (local instability); the results are verified after classification.

Figure 6 shows the results of the automatic classification process. The bold black line shows the class of each acceleration value and the dark dots show the unified peaks for each failure type. The automatic classification process works only for the generated training data because each lap shows a large similarity and a kind of periodicity. If the starting point or the direction of movement is changed, the use of the automatic classification process is no longer possible.
3.3. Statistical features
In order to generate the predictors that Matlab requests for creating the model, the classified acceleration data is grouped into ten batches of equal length analogous to [16], creating a numerical matrix of 139,500 x 10 values (see figure 7). Every row contains ten sample numbers, which are used to calculate six statistical features. These statistical features are: the mean value, root-mean-square, 12 spectral peaks, 5 spectral power features, standard deviation and principal component analysis.

4. Conclusions
- In this study, more than 1.3 million sample numbers are generated as training data, which are based on the vertical acceleration of 139 laps of data from the track-vehicle scale model.
- The waveforms (specific sample range) of the eight failures in the track-vehicle scale model are defined by cross correlation, their amplitudes and wavelengths.
• The acceleration data is automatically classified into three classes: Class 1 are non-track failures; Class 2 are joints, cracks or the entrance/exit to the bridge and Class 3 is the local instability.

• Statistical features are developed by using the statistical characteristics of the acceleration signals with approximately 1,395,000 sample numbers. These characteristics are: the mean value, root-mean-square, 12 spectral peaks, 5 spectral power features, standard deviation and principal component analysis.

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