Proceedings of the Fifth International Conference on
Railway Technology:
Research, Development and Maintenance
Edited by J. Pombo
Civil-Comp Conferences, Volume 1, Paper 27.15
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.1.27.15

A Structural Health Monitoring Approach for Rail Fastening Systems

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Abstract

A novel fault diagnosis strategy for rail fastening systems is proposed. Its key feature is the compensation of environmental and operating point dependent distortion effects on the fault residuum. This results in a robust and effective basis for a fault diagnosis strategy which requires little data for calibration.

Keywords: Structural Health Monitoring (SHM), Fault Diagnosis, Operating Point, Rail Fastening Systems.

1 Introduction

Bridges and their components are designed for different lifetimes. The prevention of catastrophic failures as well as the lifetime extension can be reached by monitoring their structural heath. This paper deals with railway bridges and specifically with the monitoring of their rail fastening systems (RFS) with the goal to reliably detect failures as early as possible.

For this reason the University of Siegen has been commissioned by Deutsche Bahn AG to carry out continuous structural health monitoring (SHM) of a steel railway overpass in Berlin. The relative horizontal deformations of the elevated rails (in both directions) are measured during each train crossing. For this purpose, magnetic inductive sensors were installed at a spacing of 1.2m (Fig. 1), which measure the relative deformation of the rail against the derailment guard. Acceleration sensors at the beginning of the bridge structure serve as triggers. Furthermore, the temperature of the bridge deck as well as the ambient temperature is recorded. The measurement data is transferred via internet to the University of Siegen and evaluated there. At the moment, the measured deformations are simply compared to given fixed deformation limits. In the event of a given limit value being exceeded, the client must be notified to check the rail fastening system which may have suffered damage [1].

Figure 1: Magnetic inductive sensors were installed at a spacing of 1.2m at the elevated rail.

However, with more than 60 trains per day and 196 sensors to be evaluated, procedures must be found that facilitate reliable automated evaluation. On the one hand, faulty sensors must be detected so that they are not used for the analysis. Most frequently, loose contacts occur in the extended connection cables, which lead to maximum peak deflections in the measurement. Furthermore, sensors can be displaced or torn off by passing trains - this also must be detected. On the other hand, to improve fault detection, additional features like train speed and axle loads have to be extracted from the data. This will allow variable deformation limits for fault detection instead of fixed ones, depending on influences like the afore mentioned features. This approach is described in the next section in more detail.

State-of-the-art methods for SHM of railway bridges can be found in [2]. For a more general overview of fault detection methods applied to railways, see e.g. [3] and [4]. Methods using machine learning approaches in context of computer vision can be found in [5] while complete track circuit diagnosis with recurrent networks are addressed in [6].

2 Methods

The idea of the proposed fault detection method is to measure the rail displacements and to assume a fault if the displacement gets too large. Just defining an allowed maximum value for the displacement is insufficient, though, since the displacement is not only influenced by a fault in the RFS, but also by the axle load of the railway cars, the train speed, and even the temperature of the rail. The consequence would be that a fault is more likely to be detected under the rare condition of a heavy, fast train crossing the track on a hot day. To avoid this, a model is trained from sensor data to predict the nominal displacement given the afore mentioned influences. The model represents the reference/undamaged state of the RFS and allows the compensation of environmental and operational conditions on the rail displacements. This approach leads to an adaptive displacement limit with a lower value e.g. for light and slow trains, permitting an earlier detection of the fault. See [7] for an overview of fault detection methods.

The basic concept is depicted in Fig. 2. In a first step, the available sensor information is pre-processed, e.g. to remove noise, but mainly to identify the speed and axle load from the data. In a second step, faulty sensors are identified and excluded from further calculations. However, the detection of sensor errors is not treated in this paper. In the next step, a machine learning algorithm, is used to predict the displacement using speed, load, and temperature (directly measured) as inputs. The allowed displacement limit can then be defined relative to the predicted displacement.

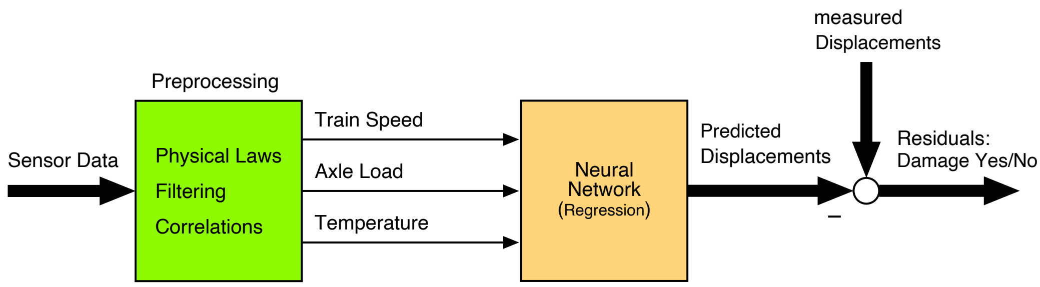

Figure 2: Fault detection concept.

The remaining task is to determine speed and axle load. The speed can be estimated by cross-correlation of the signals of two adjacent sensors. With the time-shift determined by cross-correlation and the known sensor distance the speed can be calculated. The load can by determined by the different displacements the different axles cause on the same sensor. Different sensor calibrations can be corrected by the fact that the same axle should cause the same displacement on all sensors. Averaging over the available sensors and axles increases the robustness of the operation. The displacement measurements of 10 consecutive sensors for a typical train crossing (16 cars) is shown in Fig. 3. The time-shift of the sensor data can clearly be seen, also the 32 displacement peaks caused by the 32 axles.

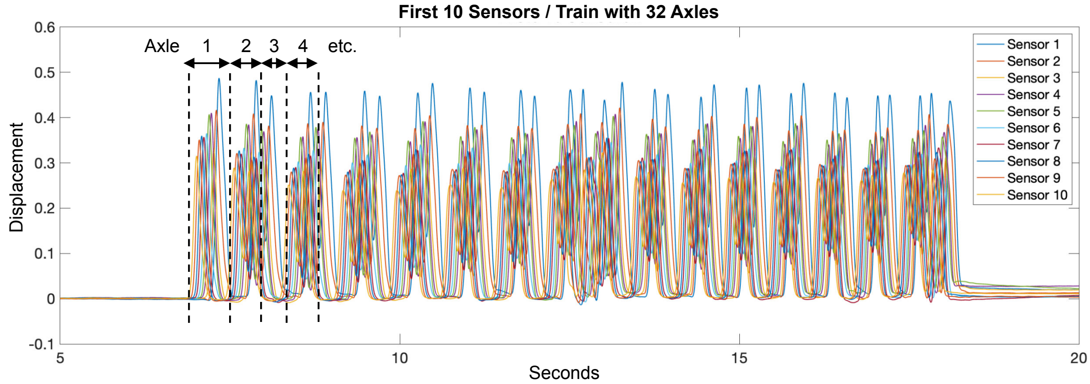

Figure 3: Example for the measurement of the first 10 sensors on the bridge.

3 Results

The calculation of the train speed using the time-shift at the maximum of the correlation function proved to be very reliable, especially when using the average from all consecutive sensor pairs.

More difficult is the determination of the peak values of the rail displacement for every train axle. The most promising method is based on finding local maxima in the data set by searching all groups of 3 consecutive measurements, where the middle measurement has the highest value. To avoid errors due to noise only values over a certain threshold are considered. While this method is quite robust, sometimes unusual sensor disturbances cause false peak detections as shown in Fig. 4 for one sensor (the red circles). These can be corrected in almost all cases by a sensor majority vote since they occur only in a few of the available sensors. For the majority of the sensors the correct number N of peaks is detected and therefore only the N highest peaks in the disturbed measurements are used.

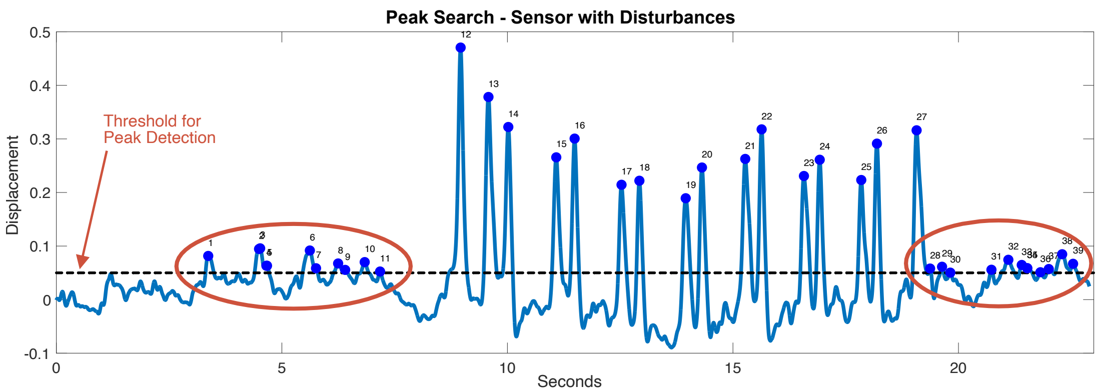

Figure 4: Example for unsuitable threshold for peak search with sensor disturbances.

The estimation of the axle load is depicted in Fig. 5. In the ideal case, the same axle should cause the same displacement on all (fault-free) sensors. Therefore, all lines (one per axle) in the left diagram should have the same displacement for all sensors. This can be compensated by calculating the mean displacements for all sensors over all axles and using them to adjust the measurements. The result is shown in the right diagram. This still does not lead to constant values over all sensors but the mean value represents an acceptable estimation of the axle load.

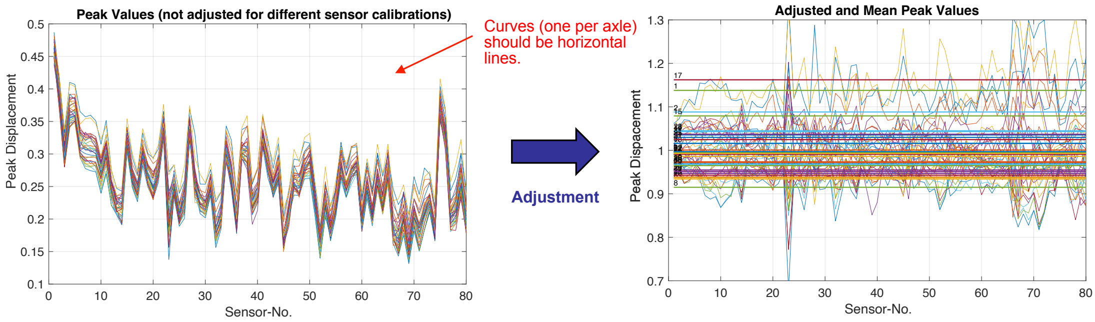

Figure 5: Estimation of axle load.

Figure 6 shows a simple linear model (dashed plane) for the prediction of the rail displacement using speed and axle load. It can be seen that the load and speed have an influence on the displacement. The red points represent data from one unreliable sensor. These points can clearly be separated from the others at certain trains speeds. Thus, sensor faults are detectable by this approach as well as defects of the rail fastening system.

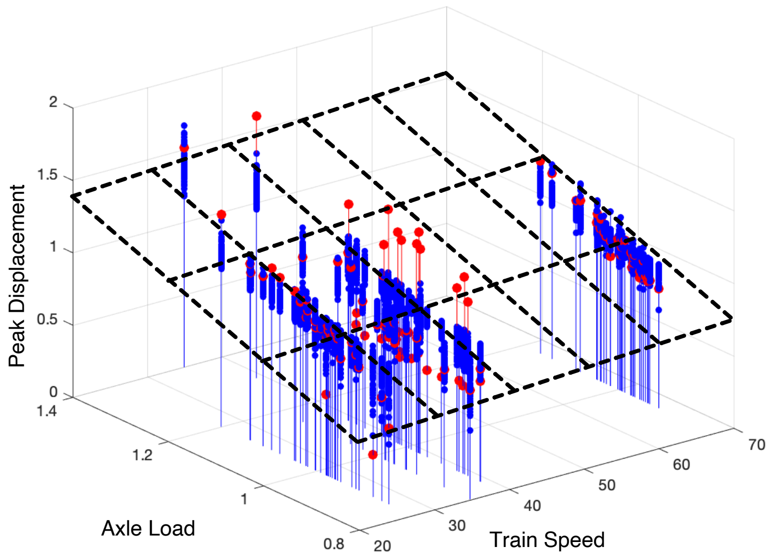

Figure 6: Simple linear model for displacement. Red points show faulty sensor.

4 Conclusions and Contributions

The first results show that the proposed strategy is a promising approach for fault detection of rail fastening systems. The distorting effects on the fault residuum due to environmental changes (temperature) and operating point changes (axle load and train velocity) can be compensated effectively. As this compensation is carried out in an explicit manner, only very few data are required and the transparency is high.

When more data is available more sophisticated methods to predict the rail displacement for fault-free fastening systems using machine learning will be investigated. Also more complex nonlinear models to estimate the axle loads from the displacement measurements will be considered [8]. Of course the fault detection concept has to be developed and tested using faults of the fastening system in simulation and finally during real-world operation.

It was noticed during the data analysis that the trains often break or accelerate on the bridge. This also could influence the displacement and should probably be taken into account in the future. Also sensor faults seem to occur quite often. Therefore, additional methods will be considered to detect them quickly and independently from the fault detection strategy used for the rail fastening system. Comparison of the data between adjacent sensors could be one approach for this [9], [10].

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