Spectral characterization of the rail surface in urban environments using in-service vehicles

Benjamin Baasch[1,3], Judith Heusel[2], Alexander Lähns[1], Michael Roth[2], and Jörn Groos[2]

[1] German Aerospace Center (DLR), Rutherfordstr. 2, 12489 Berlin, Germany
[2] German Aerospace Center (DLR), Lilienthalplatz 7, 38108 Braunschweig, Germany
[3] benjamin.baasch@dlr.de

Abstract. Rail monitoring using in-service vehicles enables the fast detection of surface defects, which are often responsible for high noise emission. In this paper a processing sequence is presented that converts axle box accelerations into rail condition indicators based on spectral characteristics of the rail surface. The methodology is exemplified with data acquired with a shunter locomotive operating at an inland harbour in the city of Braunschweig, Germany.

Keywords: railway, condition monitoring, rail roughness, axle box acceleration, rolling noise

1 Introduction

Railways play an important role for urban transportation and mobility. However, railway noise is a considerable challenge in urban environments and its minimization is an important task. The continuous monitoring of the rail surface can help to identify track segments that are potential sources of increased noise emissions. Traditional methods of rail condition monitoring are based on visual inspections and manually operated measurement equipment. These are accurate and reliable but relatively expensive and slow. They cannot be carried out during railway operations and thus are performed only at dedicated time intervals. Vehicle-based condition monitoring (VBCM) in contrast is fast and cost efficient, especially if carried out with in-service vehicles. It provides data of entire track networks continuously. Therefore, there is a growing interest in VBCM with in-service vehicles for urban railway networks. However, urban railway operations present unique challenges for VBCM compared to mainline railways [4]. Highly variable vehicle speeds, short travel intervals and frequent stops complicate vehicle positioning and data analysis. This results in a special demand for dedicated data processing and analysis algorithms. In this paper we present a combination of signal processing, data fusion and machine learning techniques for the spectral characterisation of the rail surface in urban environments. Specifically, georeferenced axle-box accelerations (ABA) are analysed and decomposed in different spectral components. The use of accurate speed information from vehicle positioning allows to transform the data from a time-frequency representation to an equivalent representation in the spatial domain, which reveals speed independent information on the wavenumber spectrum of the rail surface. In this spectral domain unsupervised feature extraction is performed. The features can then be linked to rail surface defects such as corrugation.

2 Materials and Methods

The goal of the VBCM methods described here is to find and extract spectral patterns that can be linked to characteristics of rail surface irregularities. The following sections describe the complete process chain from data recording through signal processing to the extraction of characteristic features for rail condition monitoring.

2.1 Data Acquisition

Onboard data have been acquired with a shunter locomotive operating at the Braunschweig (Germany) Harbour. Condition monitoring of the track is carried out by using analogue broadband three-component accelerometers, which measure the ABA with a working frequency band of 0.8-8,000 Hz. The accelerometers are mounted on the axle boxes on the left and right side of the shunter's front axle. The resulting six ABA channels are digitised by an analogue-to-digital converter and sampled with 20.625 Hz. A central data processing unit is used to collect and process the data. The multi-sensor system further comprises GNSS (global navigation satellite system) receiver and antenna and an IMU (inertial measurement unit) for vehicle positioning tasks.

2.2 Georeferencing

In this context georeferencing refers to the association of actual locations in the track network to the ABA recordings. It facilitates the track-dependent analysis of monitoring data from repeated runs and is crucial for tracking the development of rail defects over time. Furthermore, accurate velocity estimates are important.

The actual georeferencing is performed using an advanced processing pipeline that is based on [6]. It employs map data and Kalman filters. In brief, the following steps are performed. First, the GNSS and IMU data of entire measurement days (sessions) are processed in a Kalman filter and smoother to provide accurate estimates of the vehicle velocity, longitudinal acceleration, and the IMU acceleration bias. Based on these results, the session is divided into single journeys from vehicle start to stop (without changes of direction). For each journey the driven path in the network is then found from a graph of the network and comparing different path hypothesis with the GNSS measurements. Finally, the GNSS and IMU are re-processed using an on-path Kalman filter and smoother that encodes the vehicle position as a one-dimensional on-path distance. The georeferencing results comprise position and velocity estimates with covariance matrices. The 100 Hz output rate translates to a spatial resolution of ca. 0.14 m at 50 km/h.

2.3 Signal Processing

When a train travels along a track with a defect characterized by a specific wavelength λ at a constant speed v, it undergoes a vertical movement, and the excitation frequency of the resulting vibration is given by $f = v/\lambda$ [7].

Time-frequency representations are powerful tools to analyse these frequency patterns in the ABA data [2, 5]. The task of the signal processing here is to transform the time domain data to a space-wavenumber representation that facilitates the extraction of characteristic wavelength patterns of rail surface irregularities.

First, the data is transformed from the time domain to a time-frequency representation using a Short-Time-Fourier-Transform (STFT). The discrete STFT of the signal $y[n]$ with the window $w[n]$ can be expressed as

$$\mathbf{STFT}\{y[n]\}[m,f] \equiv Y[m,f] = \sum_{n=1}^{n=N} y[n]w[n-m]e^{-i2\pi fn}, \tag{1}$$

where n, m and f are discrete time and frequency steps, respectively.

In the time-frequency domain the frequency response of the wheel-rail system is removed employing log-spectral averaging as follows:

The wheel-rail interaction can be modelled by a linear time-invariant system in form of the convolution of the source (rail roughness) function $r\,(t)$ and the impulse response of the rail-wheel system $s\,(t)$:

$$y\,(t) = s\,(t) * r\,(t)\,. \tag{2}$$

The logarithmic amplitude of the STFT of $y\,(t)$ can then be expressed as

$$\log|Y\,(m,f)| = \log|S\,(m,f)| + \log|R\,(m,f)|\,. \tag{3}$$

If the rail roughness function is considered spatially non-stationary and the rail-wheel response stationary, by averaging the log-spectra of the overlapping segment of the STFT, the log-spectra of the rail roughness will average out and the resulting estimate of the log-spectrum of the rail-wheel system

$$\log\left|\hat{S}\,(m,f)\right| = 1/M \sum_{m=1}^{m=M} \log|Y\,(m,f)| \tag{4}$$

can then be subtracted from $\log|Y\,(m,f)|$, which yields an estimate of the logarithmic amplitude of the STFT of the rail roughness:

$$\log\left|\hat{R}\,(m,f)\right| = \log|Y\,(m,f)| - \log\left|\hat{S}\,(m,f)\right|. \tag{5}$$

Finally, the time-frequency representation of the rail roughness function is transformed to a distance(x)-wavenumber(k) representation using vehicle speed obtained from georeferencing with $x = tv$ and $k = f/v = 1/\lambda$.

This representation serves as input to the feature extraction via machine learning, which is explained in section 2.4. Fig. 1 shows the raw onboard data from one journey in the time-domain (top) and after signal processing as distance-wavenumber representation (bottom).

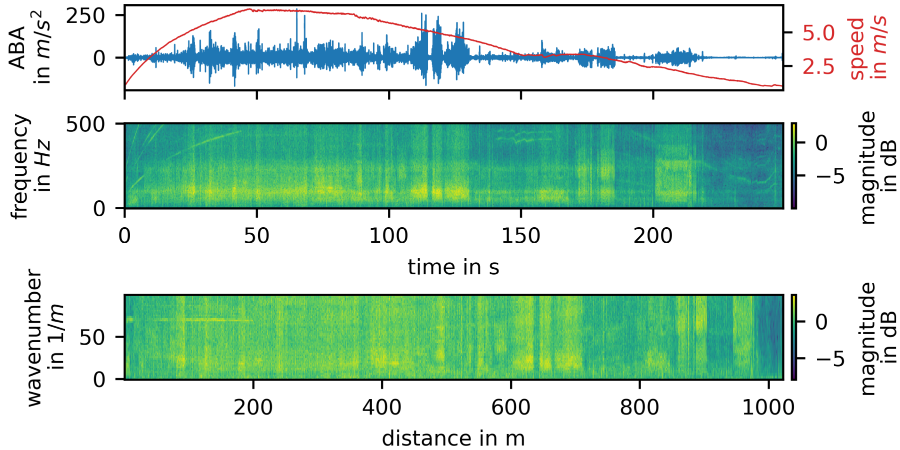

Fig. 1. ABA data in the time domain (top), in the time-frequency domain (middle) and distance-wavenumber domain (bottom).

2.4 Machine Learning

An unsupervised machine learning approach is used to extract characteristic spectral patterns from the distance-wavenumber representation of the ABA data. Specifically, an undercomplete sparse dictionary is learned that represents the actual input data in a lower-dimensional space. The atoms of the dictionary represent characteristic spectra of the rail surface. The weights of the atoms can then be used to find and describe rail surface defects. The dictionary H and the weights W can be found via the following optimization problem:

$$\arg\min_{W,H} \frac{1}{2}\|Y - WH\|_{\text{Fro}}^2 + \alpha\|W\|_{1,1}, \quad (6)$$

where $\|.\|_{\text{Fro}}^2$ stands for the Frobenius norm and $\|.\|_{1,1}$ stands for the element-wise matrix norm, namely the sum of the absolute values of all the entries in the matrix.

3 Results

Onboard data acquired with a shunter locomotive as described in section 2.1 are used to exemplify the results of the proposed methodology. In Fig. 1 the time frequency representation of the raw data is compared with the distance-wavenumber representation of the data after signal processing. It can be seen how, after signal processing, the rail-wheel system's response and spectral components of rotating parts of the wheelset and engine are suppressed, whereas the spectral components associated with the irregularities of the rail surface stand out. In the distance-wavenumber domain, characteristic spectra are extracted by sparse dictionary learning. Eight atoms representing wavenumber spectra of the rail surface are found (Fig. 2). The low wavenumber atoms (dark blue lines) represent track geometry anomalies with longer wavelength, whereas atoms in high wavenumber ranges (light-green and yellow lines) represent short-wavelength rail irregularities. The sparsity constraint on the weights ensures that mainly frequency components from relatively strong track and rail irregularties are considered. The weights of these atoms can be mapped on the railway network (Fig. 3). The high-wavenumber anomalies indicated by yellow and light-green dots at a rail segment in the north-west of the map reflect known corrugation defects.

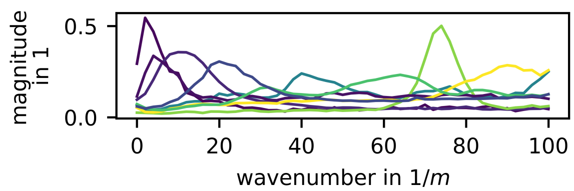

Fig. 2. Different atoms of the learned dictionary. Brightness of lines increases with increasing wavenumber of the maximum magnitude of the different atoms.

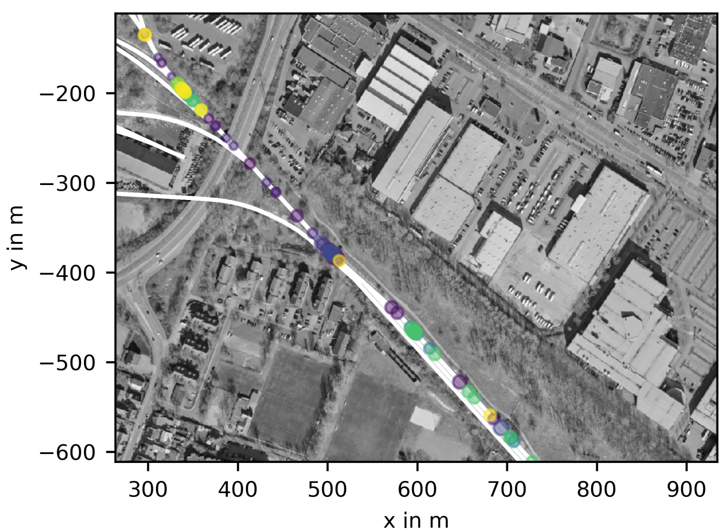

Fig. 3. Map of the railway network [1]. Dots indicate rail surface anomalies. The color represents the atom according to Fig. 2 that best approximates the wavenumber spectrum of an anomaly. The size represents the magnitude of the corresponding weight.

4 Conclusions

A methodology to monitor the rail surface condition using in-service vehicles has been presented. It includes sensor fusion, signal processing and machine learning approaches that are suitable to extract information from ABA data in challenging environments. Real-world data from a shunter locomotive operating at an inland harbour in the city of Braunschweig, Germany were presented and analysed. The results indicate the great potential of the presented methodology to detect and describe rail surface irregularities with in-service vehicles. The conditions of the shunting operations pose typical challenges that are shared by other urban railway systems such as light rails and trams. Therefore, the methodologies presented here are readily applicable to other kinds of urban rail transportation systems.

Acknowledgements

This research is part of the OnboardEU [3] project funded by mFund, an innovation initiative for digital data-based applications for the mobility of the future of the German Federal Ministry for Digital and Transport (BMDV) .

References

[1] Aerial photograph: City of Braunschweig (Department of Geoinformation).

[2] Benjamin Baasch et al. "Detecting singular track defects by time-frequency signal separation of axle-box acceleration data". In: *WCRR 2019*. URL: https://elib.dlr.de/121517/.

[3] DLR Verkehr. *OnboardEU - mit KI Schäden am Gleis automatisch erkennen*. Ed. by DLR Verkehr. 2022. URL: https://verkehrsforschung.dlr.de/de/news/onboardeu.

[4] J. Heusel et al. "Detecting corrugation defects in harbour railway networks using axle-box acceleration data". In: *Insight - Non-Destructive Testing and Condition Monitoring* 64.7 (2022), pp. 404–410. ISSN: 1354-2575. DOI: 10.1784/insi.2022.64.7.404.

[5] Julia Niebling, Benjamin Baasch, and Anna Kruspe. "Analysis of Railway Track Irregularities with Convolutional Autoencoders and Clustering Algorithms". In: *Dependable Computing - EDCC 2020 Workshops*. Vol. 1279. Communications in Computer and Information Science. Springer International Publishing, 2020, pp. 78–89. DOI: 10.1007/978-3-030-58462-7_7.

[6] M. Roth et al. "Map-Supported Positioning Enables In-Service Condition Monitoring of Railway Tracks". In: *21st International Conference on Information Fusion (FUSION)*. July 2018, pp. 2346–2353. DOI: 10.23919/ICIF.2018.8455377.

[7] Pablo Salvador et al. "Axlebox accelerations: Their acquisition and time–frequency characterisation for railway track monitoring purposes". In: *Measurement* 82 (2016), pp. 301–312. ISSN: 02632241. DOI: 10.1016/j.measurement.2016.01.012.