Detecting singular track defects by time-frequency signal separation of axle-box acceleration data

Benjamin BAASCH[1], Michael ROTH[2], Patrik HAVRILA[2], Jörn C. GROOS[2]

[1]Institute of Transportation Systems, German Aerospace Center (DLR e.V.), Berlin, Germany
[2]Institute of Transportation Systems, German Aerospace Center (DLR e.V.), Braunschweig, Germany
Corresponding Author: Benjamin BAASCH (benjmain.baasch@dlr.de)

Abstract

Singular railway track irregularities, such as squats and corrugation have a major impact on the ride stability, noise emission, comfort and safety of freight and passenger trains. Therefore, the detection and monitoring of such defects play an important role in railway track maintenance. Embedded low-cost sensors on in-service vehicles provide the opportunity of quasi-continuous condition monitoring of railway tracks and can thus enhance existing track maintenance strategies.

In this paper we demonstrate a processing sequence to detect singular track defects from noisy axle-box acceleration (ABA) data. The data are acquired with a multi-sensor prototype measurement system on a shunter locomotive operating on the industrial railway network of the inland harbor of Braunschweig (Germany).

A blind signal separation (BSS) algorithm based on non-negative matrix factorization is applied to the ABA data in the time-frequency domain. It is completely data-driven and hence does not rely on a priori knowledge or physical models. The algorithm makes use of different time-frequency characteristics of the signal components and is thus able to separate quasi-continuous band-limited signal components from transient broad-band components. The magnitude of the transient components reflects the strength of track singularities along the track and can hence be used to detect and quantify short track defects. Through georeferencing the identified defects can be localized, mapped on the track and be used to guide specific maintenance actions. Additionally, the BSS algorithm shows the potential to reduce the dimensionality of the data without significant loss of information.

Keywords: condition monitoring, blind signal separation, axle box acceleration, track defects, dimensionality reduction

1. Introduction

Singular track defects can excite high wheel/rail forces that can cause further track and wheel deterioration and may lead to serious railway accidents. Therefore, the early detection of such defects is vital in order to ensure secure, stable, and economic operation. Monitoring the track using embedded sensors on in-service trains is considered to allow the timely detection of track defects. Additionally, this quasi-continuous monitoring builds the data basis for condition-based and predictive maintenance strategies. Due to their relatively low price and robustness to harsh environmental conditions, mainly inertial sensors (accelerometers and gyroscopes) come into consideration for in-line freight and passenger trains [1]. In the past, axle-box acceleration has been successfully measured and analyzed in order to monitor short track defects [1–4], such as squats [5], corrugation [6] and defective rail welds [7]. However, the detection of railway track defects from axle-box acceleration data is still challenging for several reasons. Simulation of the dynamic wheel-rail interaction using simplified models often fails due to the complexity of the physical system to be described and the superposition of different vibration signals. Vibrations originate mainly form the wheel and rail but also from the bogie and sleeper as well as from the engine and other rotating devices. Additionally, ABA measurements are influenced by environmental conditions and vehicle-specific and partly time varying vehicle parameters, such as train speed, load, suspension system etc. [8]. Information on these factors is often missing and/or their impact on the measured acceleration is not fully understood. Measuring ABA at

low vehicle speeds, as in case of e.g. monitoring tracks of industrial railway networks, results in poor signal-to-noise ratio [1] compared to measurements on main-line trains. Another challenge is the broad frequency range of the accelerometers that is required to detect short-wave track defects of a few millimeters to centimeters. The corresponding high sampling rate produces big datasets that can get too large for on-board processing with embedded computers, which often have limited CPU power and memory. Furthermore, the online data transfer may be restricted due to bandwidth and electric energy limitations. Therefore, feature extraction as a dimensionality reduction process might be desired, where the selected features are supposed to contain all relevant information from the original data, so that the reduced representation can be used for further analyses instead of the large input data.
Features can be extracted in the time-domain (e.g. root-mean-square and maximum amplitude) [2, 3], frequency and time-frequency domain [2, 8]. Time-frequency techniques are widely used in noise and vibration analysis including rail track [9–11] and wheel condition monitoring [12].
In this paper the authors present a BSS algorithm to separate the ABA signal in its different vibration components with the goal to extract features indicating track defects.

2. Methods

2.1 Data acquisition

The German Aerospace Center (DLR) is developing and testing low-cost multi-sensor prototype systems based on components of the shelf (COTS) for in-service condition monitoring [2, 3]. The hard and software is modularly designed. The sensor setup used for this study includes a low-cost global navigation satellite system (GNSS) receiver (with GNSS raw data acquisition), an inertial measurement unit (IMU) at the car body (above suspension) measuring accelerations and turn rates at 100 Hz sampling rate. The IMU and GNSS data are fused with a digital map of the railway infrastructure for georeferencing [13], which means the assignment of locations (track ID and distance on track) and train speed to the measured data. The ABA is gathered with a broad-band (0.8 – 8000 Hz) triaxial accelerometer at 20625 Hz sampling rate. A multiband antenna is used to acquire GNSS data, for communication and data transmission. The unit sends position and status information to a central data management system every second and can thus be maintained remotely. If a broad-band internet connection is available, measurement data can also be transferred. The entire system is run with an open-source software framework based on the robotic middleware ROS, the programming languages Python and C++. The data presented here have been acquired at the Braunschweig (Germany) harbor industrial railway network on an operating shunter locomotive (Figure 1) at maximum train speed of 25 km/h. At this railway network, over 5000 train journeys with a total duration of approximately 136 hours have been acquired and georeferenced till now.

Figure 1: DLR prototype of multi-sensor-measurement system (right) installed on a shunter locomotive (left) with triaxial accelerometer at the front right axle box (middle), modified from [2].

2.2 Blind signal separation

Blind signal separation (BSS), also called blind source separation, is a machine learning technique to separate a set of mixed signals into their source components. A classic example is the so called *Cocktail Party* Problem, which describes the challenge to extract a single voice from a mixture of several superimposed voices at a crowded party. It can also be used to achieve a low-rank approximation or dimensionality reduction of the original signal and hence reduce the amount of data while keeping the same amount of information. This is a crucial aspect especially for on-board real-time monitoring where the amount of data that can be transferred from the train to the back office is limited. Principal component analysis (PCA) and independent component analysis (ICA) are among the most popular BSS techniques. Here, in contrast, a non-negative matrix factorization (NNMF) is used, which assumes that the data and its components are non-negative [14]. Unlike PCA and ICA, the NNMF represents the data in an additive fashion, by superimposing the components, without subtracting. Such additive models are especially efficient for representing images and text [14], but finds also applications in e.g. end-member analysis [15] and audio signal processing. The NNMF decomposes the non-negative input data matrix **X** into two matrices **H** and **W** of non-negative elements. The approximation of **X** by the matrix product **HW** is achieved by minimizing the objective function:

$$\frac{1}{2}\|\mathbf{X}-\mathbf{HW}\|_{Fro}^{2} \; ,$$

where $\|\cdot\|_{Fro}^{2}$ is the squared Frobenius norm.

In this study, the goal of BSS is to separate the unwanted vibration components of the vehicle from the vibration component related to track defects. Here, NNMF is applied to the vertical component of the ABA data in the time-frequency domain. The processing sequence is as follows: firstly, the data are transformed into the time-frequency domain by applying the short-time Fourier transform (STFT). Here, a time window of 1024 samples or approximately 0.05 s is used. The logarithm of the amplitude spectra is taken and its minimum value subtracted to achieve positivity. Then, NNMF is applied to separate the signal into N components with characteristic amplitude spectra. The underlying mixing model can be expressed as $\mathbf{X} \approx \mathbf{HW}$, where $\mathbf{X}$ is an $F \times T$ matrix containing the data in the logarithmic time frequency domain. The number of rows F represents the number of frequency windows (i.e. half the time window length) and the number of columns T represents the number of time windows. The $F \times N$ matrix $\mathbf{H}$ with the column vectors $\mathbf{h}_i (i = 1, \dots, N)$ contains the amplitude spectra of the N components and $\mathbf{W}$ is an $N \times T$ matrix with row vectors $\mathbf{w}^j (j = 1, \dots , N)$ that hold the weights of the N components. Thus, the logarithmic amplitude spectra of the data at each time window can be represented as a weighted sum of the spectra of the different signal components. In this study we set $N = 2$ to separate the signal into two components. Since the ABA data are corrupted with noise, dedicated optimization need to be used. Here a mixture of L1 and L2 regularization, also known as elastic net regularization, is applied to the components and the weights. The problem to be optimized then reads:

$$\frac{1}{2}\|\mathbf{X}-\mathbf{HW}\|_{Fro}^{2} + \alpha\|\mathbf{H}\|_{1} + \alpha\|\mathbf{W}\|_{1} + \rho\|\mathbf{H}\|_{Fro}^{2} + \rho\|\mathbf{W}\|_{Fro}^{2} \, ,$$

where α and ρ control the elementwise L1 and L2 penalty, respectively.

3. Results and discussion

BSS has been applied to the vertical component of a 370-second-long ABA data record (Figure 2). The data in the time-domain reveal distinct peaks with ABA of up to nearly 400 m/s^2 between 100 s to 150 s (Figure 2a) that can be attributed to track irregularities. The logarithmic amplitude spectrum in the time-frequency representation (Figure 2b) shows high amplitudes for a wide frequency range in this region. This broad frequency spectrum corresponds to the impulsive wheel-rail contact force excitation at the track defects. In contrast, at the end of the record (between 370 s and 376 s) a different type of vibration signal is present. From the time-frequency representation it can be seen that this signal is very band limited (roughly between 4000 Hz and 4500 Hz) and lasts for a few seconds. These high accelerations are caused by wheel vibrations during breaking of the train and produce high pitch squeal noise. The time-frequency representation also reveals horizontal bands of high amplitudes that appear at constant frequencies of up to 5000 Hz. The amplitude of these bands varies only slowly with time. It can be shown that these "long-wave-length" amplitude variations are directly related to the speed of the train. Since the horizontal bands represent quasi-stationary signal components they can be linked to vibrations caused by components of the vehicle, in particular wheel irregularities and wheel roughness as well as vibration of the engine of the locomotive.

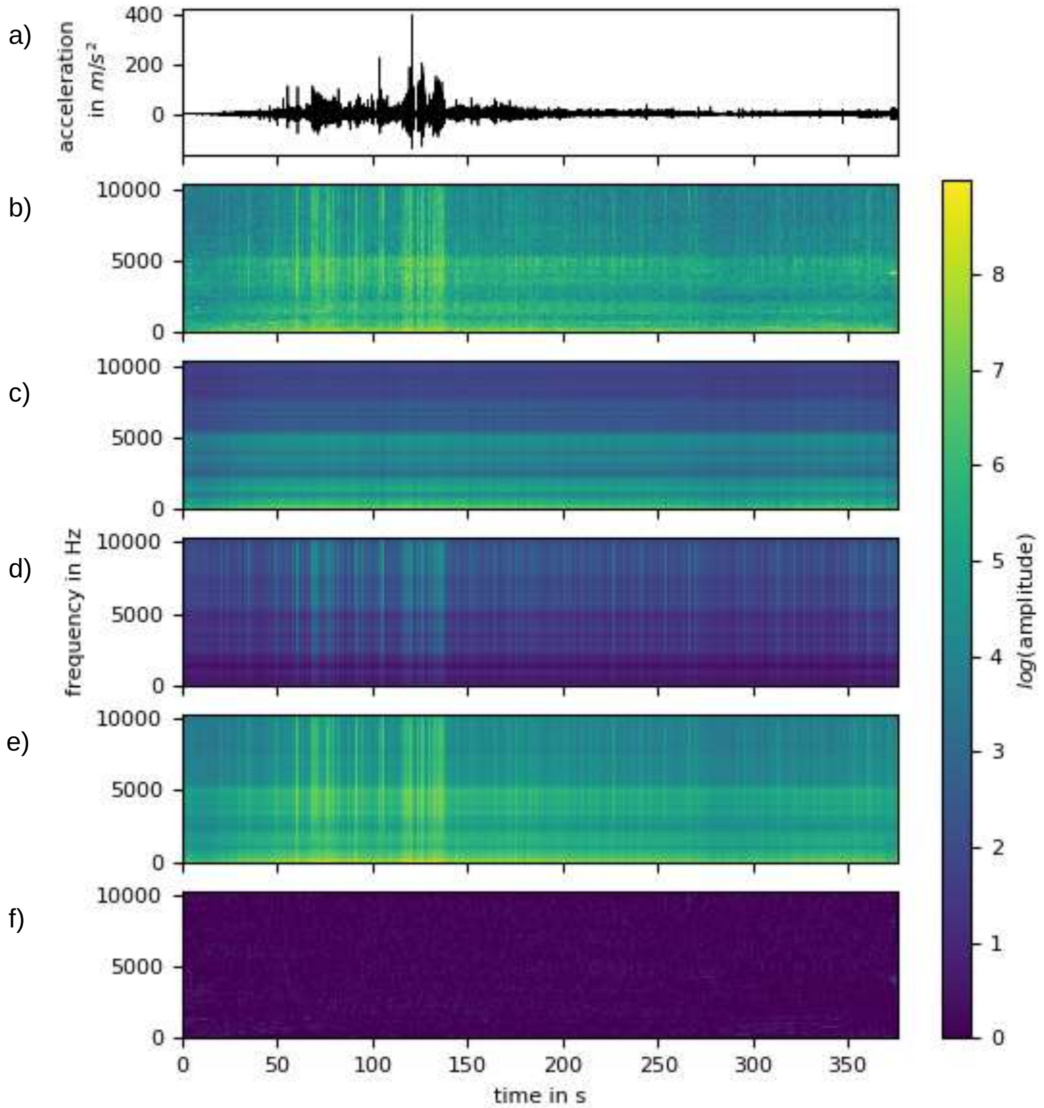

Figure 2: a) original ABA time series; b)-f): time-frequency representations of b) the original logarithmic ABA signal, c) the first component multiplied by the weights of the first component ($\mathbf{h_1} \times \mathbf{w^1}$), d) the second component multiplied by the weights of the second component ($\mathbf{h_2} \times \mathbf{w^2}$), e) the approximated signal, i.e. weighted sum of the two components ($\mathbf{H} \times \mathbf{W}$), f) the residual (difference between original and approximated signal). The coloring of the time-frequency representations corresponds to the shifted logarithmic amplitude values.

Simply speaking, the time-frequency image consists of two main patterns vertical lines and horizontal bands. The vertical lines are considered to be related to transient singularities, hence related to the track while the horizontal bands represent stationary vibration components related to the wheel and other rotating components of the vehicle. The goal of the BSS algorithm is then to separate these two components, which was successfully done as shown in Figure 2c-f. The reconstructed time-frequency representation (Figure 2e) represents the original data (Figure 2b) well and the residual (difference between the original and reconstructed signal, Figure 2f) contains mainly white noise and only little coherent signal. This shows that the NMF can be used as a low-rank approximation of the original signal without loss of significant information and is therefore a powerful tool to reduce the dimensionality of the data, which can be very important for on-board processing and communication where the size of the data may be restricted.

The representations of the individual components after BSS show that each component represents one of the two main patterns described above. The first component (Figure 2c) mainly consists of the horizontal bands that can be linked to the vibrations caused by the vehicle. This component could hence be further analyzed to detect for instance wheel defects. The second component (Figure 2d) consists of the vertical lines that represent the transient broad band components and hence indicates track singularities. The weights of this component provide an indirect measure of the magnitude of track irregularities and can thus be used to detect singular track defects. By means of georeferencing the identified defects can be localized, mapped on the track and be used to guide specific maintenance actions (Figure 3). The highest amplitudes in Figure 3 are indicated in red and appear at a track segment, which is one of the oldest segments of track with partly rotten wood sleepers and ballast in bad condition. The high amplitudes in the south-east of that indicated by the red arrow correspond to two welded rail joints with gentle depressions of the rail surface of several centimeter lengths [2].

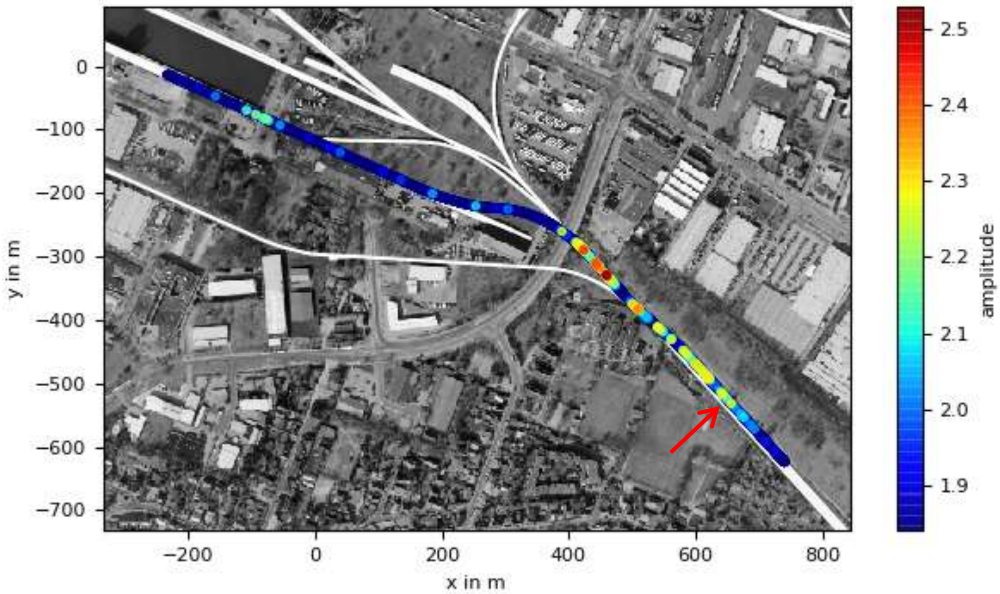

Figure 3: Weights of the second component indicating track singularities.

In this example the same regularization is applied to the components and the weights. Further fine tuning of the regularization by using different parameters for the components and the weights may be used to further constrain the results. For example, it might be desired to increase the sparsity of the weights of the transient component by adding additional constraints such as Lasso-regularization, while keeping the weights of the static components smooth through L2-norm-regularisation.

4. Conclusions

We showed that the presented BSS algorithm based on NNMF is able to extract the main components of ABA data originating from different vibration sources. Continuous vibration signals could be separated from transient signals related to short track irregularities. The extracted features can be used to detect and quantify track singularities from ABA data acquired on in-service trains. Therefore, this approach might help to improve safety and reliability of train operations and reduce maintenance

costs.
Additionally, the algorithm provides an accurate low-rank approximation of the original data and can hence be used as a dimensionality reduction process.
Since the algorithm is completely data driven, it is independent from sensor specifications, sensor location and rolling stock and hence can be readily adapted to other kinds of wagon borne accelerometers.

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