Advances in Train and Rail Monitoring with DAS

Gregor Cedilnik, Ryan Hunt, Gareth Lees
AP Sensing GmbH, Herrenberger Str. 130, 71034 Boeblingen, Germany
info@apsensing.com

Abstract: DAS resembles thousands of microphones along the sensing fiber. In railway applications, only a small fraction of all DAS data carries information about the train-rail interaction. Transforming the data to a rail view or train view simplifies analysis and reveals valuable rail and train properties.

OCIS codes: (060.2370) Fiber optics sensors; (280.4788) Optical sensing and sensors; (290.5870) Scattering, Rayleigh

1. Introduction

Distributed Acoustic Sensing (DAS) can detect and locate mechanical vibrations along long structures in real time, so is naturally suited for rail and train monitoring. In railway applications, various acoustic sources can reach the sensor fiber, allowing the detection of events like TPI (third party interference, including walking, digging and theft activities), vehicles, rock fall and many more [1,2,3].

A prominent source of acoustic signals are the trains themselves. Their acoustic emission can carry information about the train condition. In addition, the interaction between the train and the rail can generate acoustic signals which contain useful information. A flat wheel for example will create a characteristic acoustic signal. In this case the rail is being used to interrogate the condition of the wheel. At the same time a rail joint or damaged rail creates sound when a wheel passes that point. In this case, the wheel is interrogating the rail.

In a classical waterfall representation of DAS data, such signals are transient, i.e. the flat wheel travels along the position- and time axis of the waterfall, which adds complexity to the interpretation of the information. Similarly, welds/joints are mostly not audible and appear only as a small set of events within the data set while a train is passing there.

We propose two transformations of the DAS acoustic data. One is the “rail view”, where the trains act as repeated stimuli on the rail and where the acoustic data from the train over its whole length and optionally from multiple trains is considered for each rail position. The other transformation leads to a “train view”, where the position axis of the transformed waterfall reduces to the train length. For each position along the train the acoustic response from the (same) rail section acts as a probe for the train in the time domain.

Machine learning techniques can be useful to identify rail and train events. We think that also these can benefit from data transformed in a way described here.

2. Data Transformation

A common visualization of DAS data is using a waterfall diagram which displays the acoustic amplitude per sensor position over time, see figure 1(a).

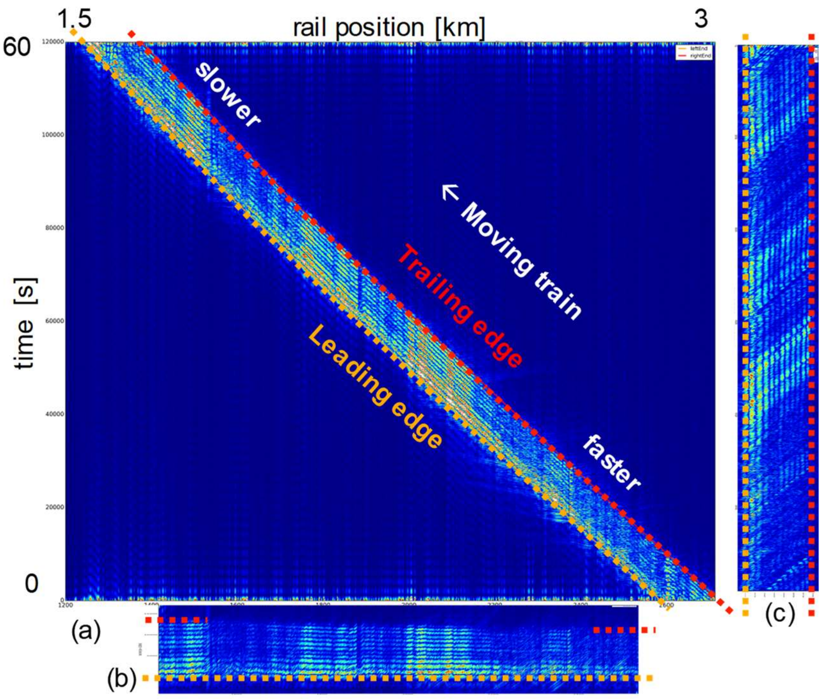

Fig. 1 Waterfall diagram (a) and transformation example for rail view (b) and train view (c).

In this case, a moving train appears as a diagonal signal pattern where the slope depends on the speed. The pattern width (along the position axis) corresponds with the train length and is therefore usually constant. The height (along time axis) changes with the train speed. The simplest transformation would be to cut out the train pattern from the waterfall and to warp it so that e.g. the train front over time transforms to a horizontal line, rail centered figure 1(b) or vertical line, train centered figure 1(c).

3. Properties of Transformed Data

In the rail centered view, figure 1(b), the horizontal axis again shows the rail position, but the zero position on the time axis indicates when the leading edge of the train reaches the respective rail position. In that simple transform the trailing edge of the train moves as the train changes its speed. A further enhancement to this transform would also maintain the trailing edge of the train horizontal by scaling the time with the current train speed. This would also compensate acoustic frequency shifts caused by a change of the train speed. Without such time re-scaling, spectral shifts can be used to derive changes of the train speed by frequency analysis, see figure 2. We could extract changes of the train speed by less than 1 km/h this way.

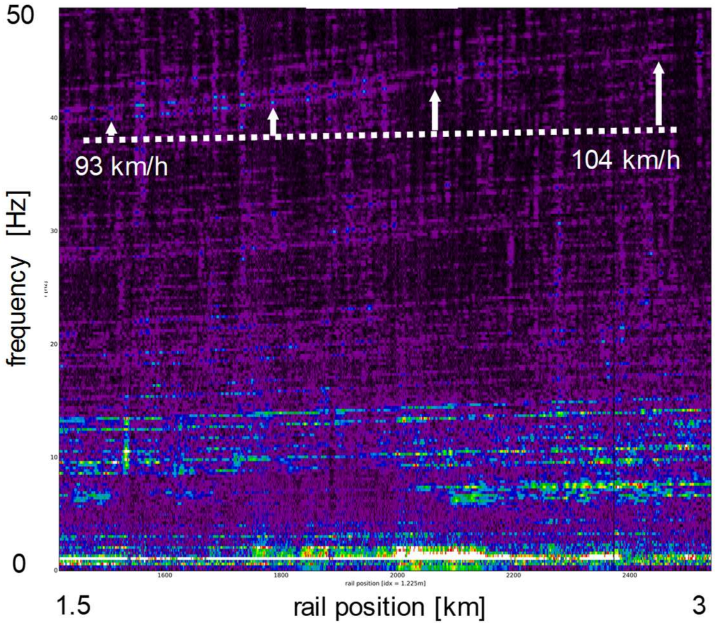

Fig. 2 Spectrum of the rail view data. Frequencies increase along the rail (due to increasing train speed), indicated by the white arrows.

In the train centered view of figure 1(c), the horizontal axis corresponds to the position along the train, i.e. ease to follow a single wagon or axis by following a vertical line. Following the line in the transformed acoustic data shows the phasor (amplitude and phase) over a moving position in time, i.e. it resembles a moving microphone. This means that data at the train engine location for example shows the acoustic signal at a fiber location that moves in parallel with the engine. One resulting effect is that the engine sound or a train horn is monitoring without the Doppler effect which would happen when monitoring from a static point of the fiber.

4. Rail Properties

The rail view becomes the basis for easy extraction of rail properties. Every rail location is “sampled” by the same “stimulus”, i.e. the train over its full length. The stimulus varies along the train front to rear because different axles with different weights and different rolling noise stimulate different amplitudes and frequencies on the rail. But the stimulus is the same for every rail location which allows a comparison of the response between different positions on the rail to be made.

Averaging the acoustic response along the time axis (e.g. the acoustic power within a certain frequency range) gives a curve which is determined by (a) the amplitudes and frequencies emitted by the train and (b) the train-rail interaction (rolling noise) and (c) the transfer function from the rail via the ground to the sensing cable and fiber.

The train stimulus (a) is the same for each rail location if the train runs at constant speed (which is often not the case), in which case the relative shape of the curve does not depend on the train (its length, speed, weight…) as long as the whole system can be regarded as linear which we assume to be true to some degree. Where the train changes its speed, the detected acoustic signal changes its spectrum (as seen in fig. 2), which is not compensated in our examples and which has little impact where the analysis includes a wider acoustic frequency range (like in the presented examples).

The rail-train interaction (b) in general depends on the position along the rail. Welds, road crossings, rail defect, rail bed etc. will impact the acoustic responses at respective position. A parallel track will in general have a different interaction pattern as demonstrated below.

The transfer function (c) via ground to the fiber in general also depends on the position along rail and fiber. The distance between rail and cable may vary or the mechanical coupling of the cable to its environment (e.g. trough) or the signal damping by other cables per locations. Also, soil consistency (sand content, moisture content, rocks in the path, concrete objects) will vary, to give some examples.

Contributions (a), (b) and (c) show that the averaged acoustic relative response along the trail depends only little on the stimulating train, making it a kind of “signature” of the rail-sensor system. Figure 3 show the signature for different trains of different lengths, speeds and at different days. It also shows the average from these signatures used as a “reference”. The cross-correlation values of the single signatures to the reference is >90%, indicating a pronounced similarity.

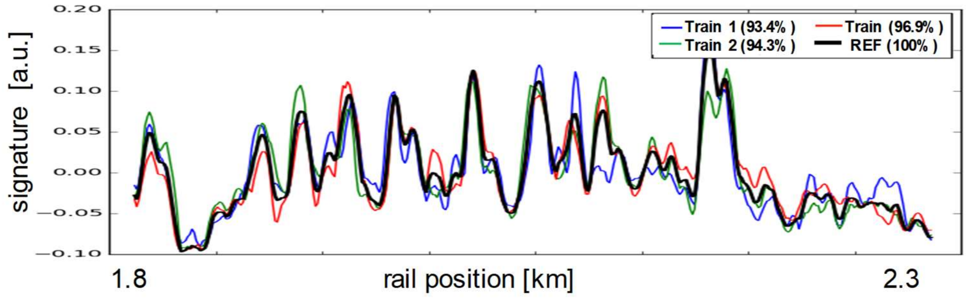

Fig. 3 Signature of 3 different trains. “REF” is the average signature. The legend numbers show the cross-correlation value (auto-correlation in case of REF).

It turns out that this signature can be used to determine on which track a train is going. Figure 4 shows the reference signature of two parallel tracks, each derived from few trains running on respective track. The cross-correlation value is about 53%, so well below the values seen between trains on the same track, indicating significant differences in the signature features, mainly attributed to differences in contributions (b) and (c).

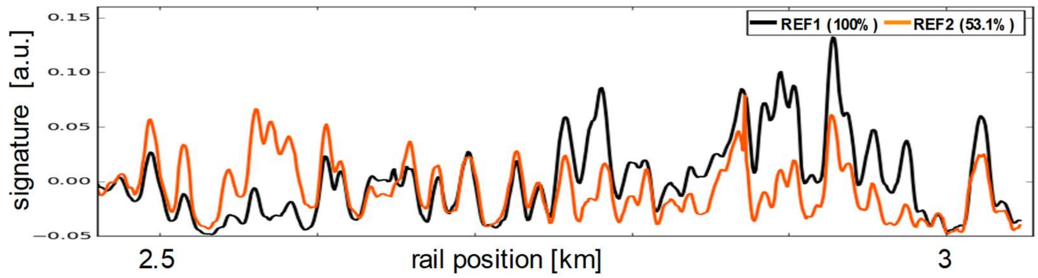

Fig. 4 Reference signatures of track 1 (black) and track 2 (red). Remove DC and curves normalized.

5. Train Properties

The train view focuses on signals obtained when moving in parallel to the train. Averaging the acoustic response over time (which in this case means over an extended rail range as stimulus) gives a train signature as shown in figure 5.

The signature naturally depends on the acoustic spectrum analyzed. At low frequencies (below 50 Hz), 12 peaks become clearly visible, figure 5(a). Visual counting of the bogies (axle pair) gave the same number of 12 of that specific train, suggesting that this low frequency signature can reflect the number of bogies.

The signature at higher frequencies (above 50 Hz), figure 5(b), provides a different picture. In this case the train has a significantly increased emission near the engine and near bogie 8. The first can be explained by the higher weight and noise of the engine. The second suggests a problem with at least one wheel. When this train passed the DAS instrument location, an experienced engineer nearby heard a flat wheel on that train. This suggests that from the train view, wheel defects can be detected and localized. Experts or moitoring software can extract further information from the Fourier transform of the train view matrix.

6. Long Range (80km)

All tests were performed with a prototype of a new commercial DAS system from AP Sensing GmbH. It allows monitoring trains beyond 80 km distance with a “basic” DAS system on standard fiber, i.e. without additional components such as optical amplification along the sensor path or FBGs within the fiber, see figure 6. This reach is unprecedented to our knowledge.

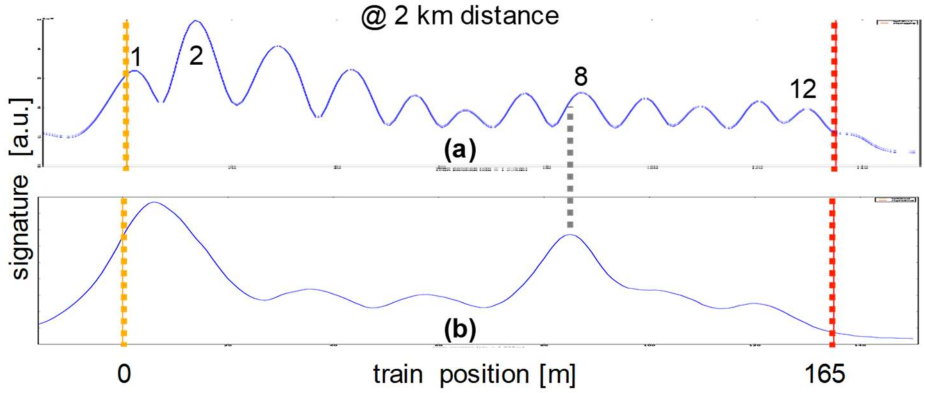

Fig. 5 (a) Train signature over 0.5 to 50 Hz; train with 12 bogies (engine and 5 wagons; 24 axles), (b) Signature over 50 to 250 Hz.

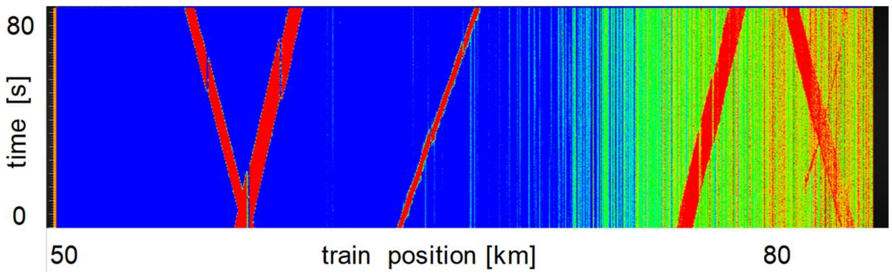

Fig. 6 Waterfall diagram showing several moving trains at long distances.

One interesting question is how well the described view separation and information extraction operates on longer distances. For that, data from trains at about 60 km distance were analyzed. Building up a reliable fingerprint requires the knowledge of the track for each train, which we unfortunately didn't have. But the train view shows a clear signature of the train. In the example of figure 7 the ICE train shows 16 clear peaks, suggesting 16 bogies with 32 axles.

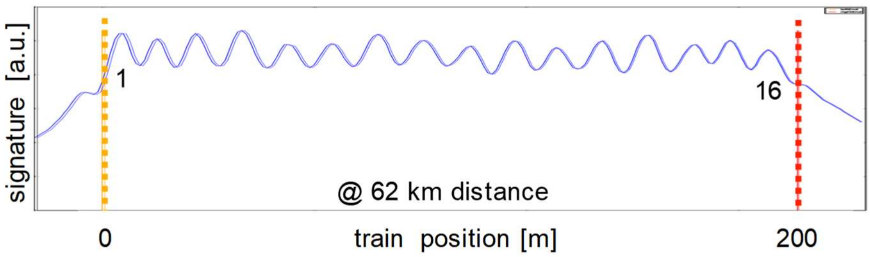

Fig. 7 Signature of an ICE train at far distance, 16 peaks.

7. Conclusions and Outlook

These first results on separating DAS data into a rail view and a train view demonstrate to our knowledge a new approach to extract rail and train properties e.g. for track discrimination and detection of train anomalyies.

Further analysis and statistics from more trains will demonstrate the reliability and confidence of DAS track identification. We expect that selecting locations with well distinguishable signatures and focusing on relevant acoustic frequency ranges will increase the confidence in track detection. Also, for detecting train anomalies from the train view, we want to analyze and optimize suitable frequency ranges for different train failure modes.

8. References

[1] G. L. Duckworth, "Distributed sensing applications of Rayleigh scattering in fiber optic cables," pp. 3–5, 2013.

[2] US Department of Transportation, "Feasibility Study of Fiber-Optic Technology for Broken Rail Detection," 2013.

[3] A. V Timofeev, "Monitoring the Railways by Means of C-OTDR Technology," *Int. J. Mech. Aerospace, Ind. Mechatronics Eng.*, vol. 9, no. 5, pp. 586–589, 2015.