In-service condition monitoring of rail tracks

On an on-board low-cost multi-sensor system for condition based maintenance of railway tracks

Preventive maintenance, Condition monitoring, Vehicle-based sensors, Sensor fusion, Anomaly detection

Low-cost on-board sensors provide the possibility of cost-effective in-service rail track monitoring. This will allow a major step forward towards condition-based preventive maintenance that might reduce maintenance cost significantly compared to today's corrective maintenance schemes. Here, we present a prototype multi-sensor system for quasi-continuous track condition monitoring. This system has been tested in operational environment since 2015, allowing the development and verification of multi-sensor-fusion and processing techniques as presented in this article.

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Maintenance costs amount to approximately half of the life cycle costs of railway infrastructures today. In order to reduce them, a transition from periodic or corrective maintenance towards condition based preventive maintenance is indispensable. The latter maintenance strategies require a more or less continuous track monitoring. However, today's inspection methods are based on visual inspection and on, depending on the size of the railway network, either dedicated service trains or handheld measurement devices. These approaches are time consuming, require the closure of the track segment and are hence expensive. In contrast, on-board sensor systems installed on in-service trains provide a quasi-continuous track inspection without track downtime [1]. Continuous analysis of the acquired data enables the early detection of track defects. Furthermore, the high data acquisition frequency makes preventive maintenance statistically feasible [2]. Simply adopting the sensor setups of inspection vehicles to in-service trains is not economical, especially for small to mid-size railway network operators. This is mainly due to the high costs of the sensors, special operating conditions (e.g. vehicle speed, distance to rail) and sensor maintenance requirements. Sensor systems based on components of the shelf (COTS) provide a low-cost alternative. Particularly, inertial sensors have become increasingly popular for track monitoring from in-service trains [3]. It has been proven that vibration signals measured by Axle-Box Accelerometers (ABA) provide valuable insights on the vehicle track interaction and can be linked to track irregularities such as corrugation, squats, defect welded joints or hollow sleepers [4, 5]. In *Figure 1* a time series of ABA data is exemplified, that reflects the vehicle-track-interaction related to the track characteristics.

In order to extract information about the track condition from ABA data, multiple challenges have to be addressed. On the one hand, an on-board sensor system for in-service trains needs to be suitable for the harsh environment on railway vehicles and for the retrofit of legacy vehicles. On the other hand, the costs of the system need to be low enough to make it economical, particularly if the installation on many vehicles in the network is necessary to provide high frequency track monitoring. The sensors then need to be tested during operation. Data need to be collected that cover different rail conditions temporally as well as spatially and are big enough for statistical data analyses. Track-selective georeferencing is necessary to relate monitoring data to tracks and positions. Last but not least, appropriate data analysis algorithms need to be developed and tested. The above challenges are discussed in the following sections.

ZUSAMMENFASSUNG

Kostengünstige, nachrüstbare Multi-Sensor-Systeme auf Schienenfahrzeugen ermöglichen die kontinuierliche Zustandsüberwachung des Gleisoberbaus im regulären Betrieb. Veränderungen und Schäden können somit frühzeitig erkannt, Wartungsarbeiten dementsprechend durchgeführt und teure Ausfälle vermieden werden. Vom Deutschen Zentrum für Luft- und Raumfahrt (DLR) wird seit 2015 ein Prototyp-System auf einer Rangierlokomotive im Braunschweiger Hafen im operativen Einsatz erprobt. Dieses Sensorsystem ermöglicht die georeferenzierte Aufnahme von Achslagerbeschleunigungen, die Aufschluss über den Zustand des Schienennetzes geben. Der so gemessene, umfangreiche Datensatz ist die Grundlage für die laufende Entwicklung und Erprobung von Sensorfusions- und Datenverarbeitungsalgorithmen am DLR. In diesem Artikel werden einige dieser Ansätze vorgestellt und Datenbeispiele aus dem operativen Einsatz gezeigt. Die Ergebnisse zeigen, dass relevante Streckeneigenschaften erkannt und lokalisiert werden können.

Low-cost multi-sensor system

DLR is developing and testing low-cost multi-sensor systems based on COTS hardware [5, 6]. A software framework developed at DLR realises the autonomous operation of the monitoring system, the data acquisition and the communication to the background data management system [7]. The collected data are firstly stored on a local storage medium and can later be sent to a server at infrastructure facilities (e.g. train yards) via a wireless local area network (WLAN). Additionally, smaller amounts of data such as status information or position coordinates can be sent through the mobile network. The software framework is modular and can hence be upgraded with additional functionalities and algorithms for e.g. real-time condition monitoring. The georeferencing sensor unit comprises a Global Navigation Satellite System (GNSS) receiver and an inertial measurement unit (IMU) for acceleration and angular rate measurements. Here, readily available low-cost components from the automotive industry are used.

For research purposes three-component broadband ABAs are employed. The broad bandwidth (0.8 Hz to 8000 Hz) allows the investigation and determination of relevant frequency ranges that will determine the sampling rate for future, probably cheaper sensors with narrower bandwidth for commercial operations.

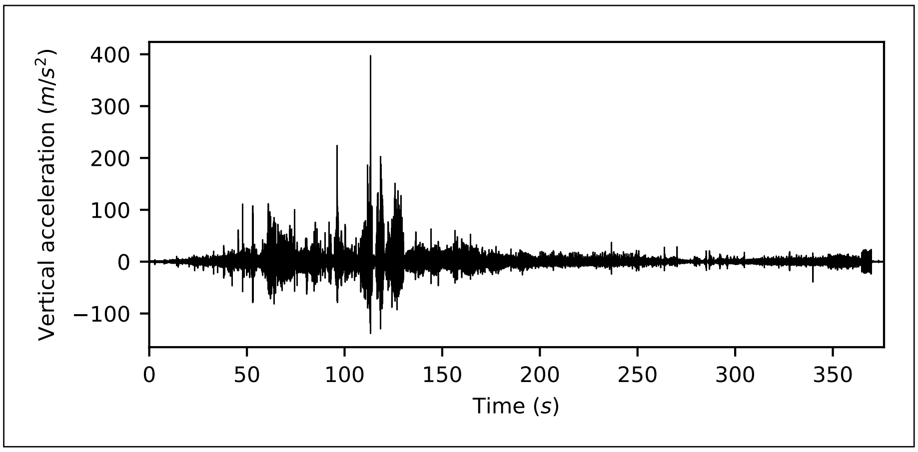

Figure 1: Exemplary time series of vertical acceleration data.

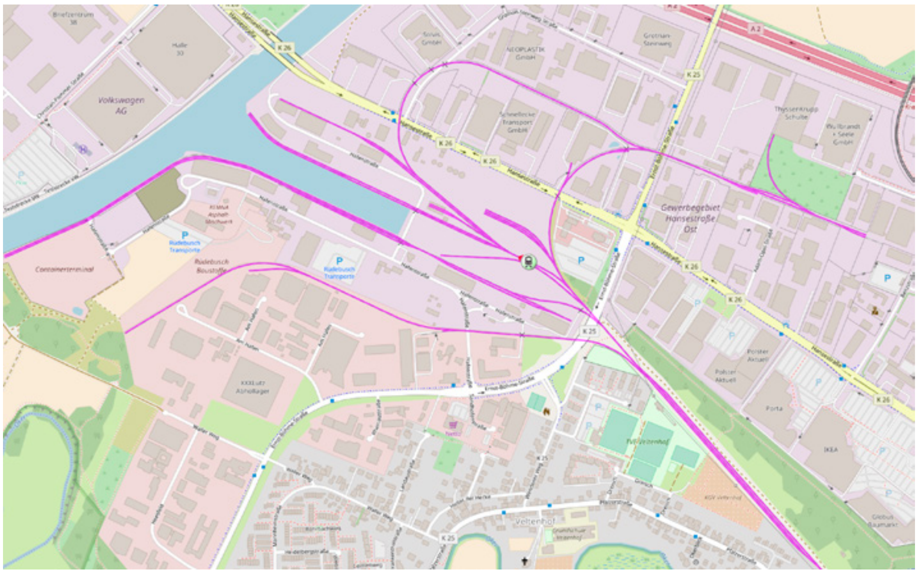

Figure 2: Braunschweig harbour industrial railway network indicated by magenta lines, green symbol indicates position of the locomotive (background image from [15]).

Test site (Braunschweig harbour)

To develop, test and improve the sensor system as well as data processing and analysis algorithms, data acquired from in-service railway vehicles under operational conditions are essential. Therefore, DLR is running prototypes of the multi-sensor systems on an industrial rail work network (*Figure 2*). This local railway network belongs to the "Hafenbetriebsgesellschaft Braunschweig mbH" situated at the inner harbour of Braunschweig, Germany, providing freight handling between railway and inland water transport. On the approximately 15 km long network, two shunter locomotives operate on a daily basis. Both are equipped with multi-sensor systems that have been continuously gathering data since 2015. Thus, ABA data of more than 700 hours or 1300 km of operation have been acquired, building a unique data set of more than 1 TB. The repeated passing over each section of track allows the investigation of track condition changes with time. The operating speed of the shunter locomotives is lower than 30 km/h. This together with the high-sampling rate of the sensor provides a sub-millimetre range spatial resolution with decimetre range positioning accuracy.

Georeferencing

Georeferencing refers to the assignment of position coordinates to the ABA data, in order to facilitate the location-dependent analysis that is required for infrastructure monitoring. In addition to geographic coordinates, the position in the railway context also comprises the track ID from a given track data base and the one-dimensional position on the track.

In the present work the georeferencing relies on the GNSS position and speed, the IMU acceleration data from the multi-sensor system, and a digital map of the railway infrastructure. The highly accurate map has been developed within the Application Platform for Intelligent Mobility (AIM) [8] based on own measurements and aerial photographs provided by the city of Braunschweig [9]. For several reasons, the combination of the different sensors with the map is essential. First, the low-cost GNSS receiver provides measurements at a maximum rate of only 5 Hz, which gives position stamps with 1.5 m distance at a speed of 7.5 m/s (27 km/h). In contrast, the IMU can be sampled at 200 Hz, which translates to a spatial resolution of 3.75 cm and fulfils the demands for the analysis of georeferenced ABA data. Second, GNSS requires unobstructed sky view for accurate positioning and exhibits large errors in e.g. underpasses. Also, reflections of the satellite signals (multipath effects) corrupt the GNSS data. Alternatively, the IMU data (accelerations and turn rates) can be integrated to obtain velocities and positions. However, such dead-reckoning approaches suffer from vastly increasing errors without absolute position measurements at regular intervals. The map information is vital in order to exploit the rail-constrained locomotive motion for improved accuracy [10].

The implemented georeferencing uses statistical sensor fusion methods [11] to compute the on-track positions in a post-processing setting. After investigation of several approaches including advanced RTK-GNSS with base station information [12], a simple two-stage procedure has been found to be most suitable. It is based on a prior division of the data into journeys from start to stop, which can be achieved by investigation of the GNSS speed. First, the GNSS data from such a journey and the railway map are employed to generate path hypotheses, that is, sequences of tracks. The map and all track connections are here represented as a mathematical graph. In most cases only a single path hypothesis complies with the measurement data, otherwise a set of likely hypotheses must be maintained.

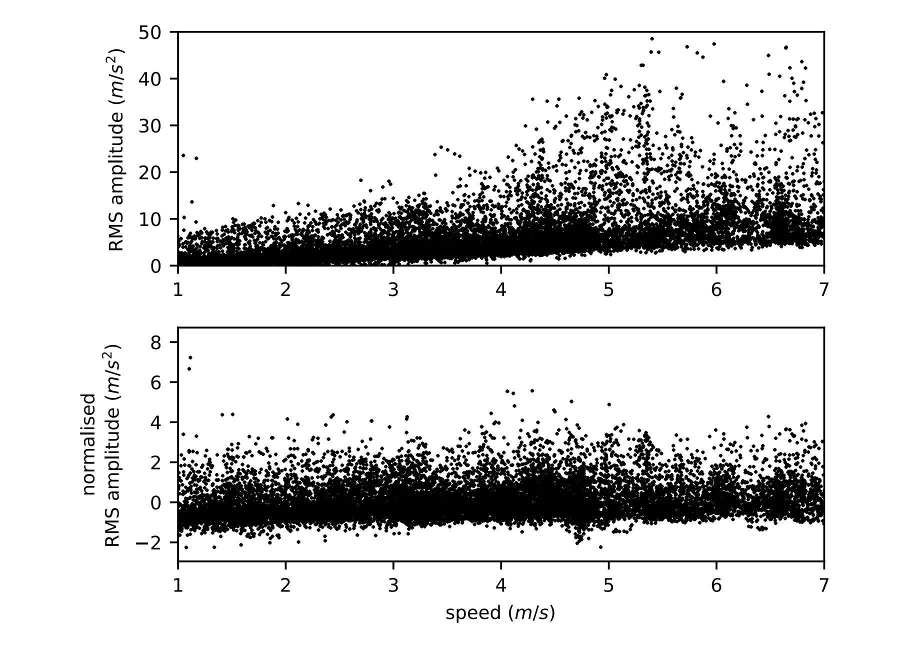

Figure 3: ABA RMS amplitude versus train speed before (top) and after (bottom) normalisation.

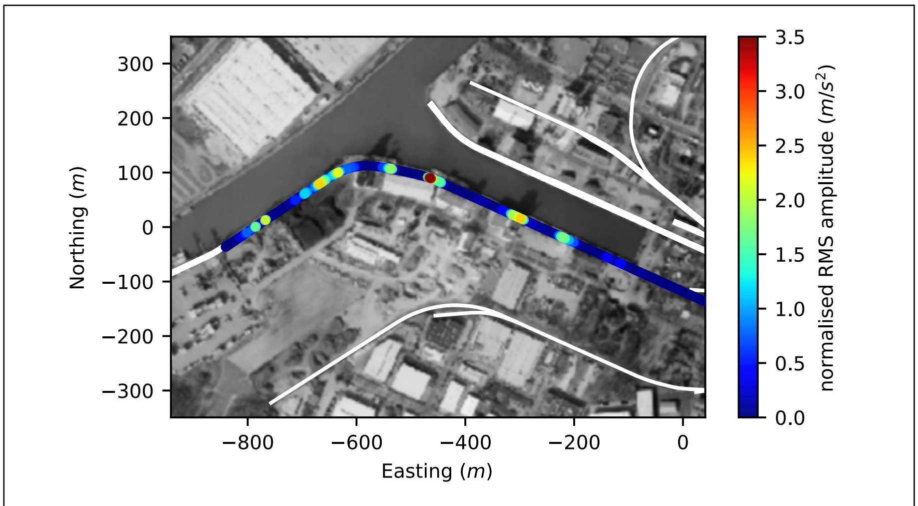

Figure 4: RMS amplitude of ABA data in an embankment area for bulk material loading and dumping operations (background image from [9]).

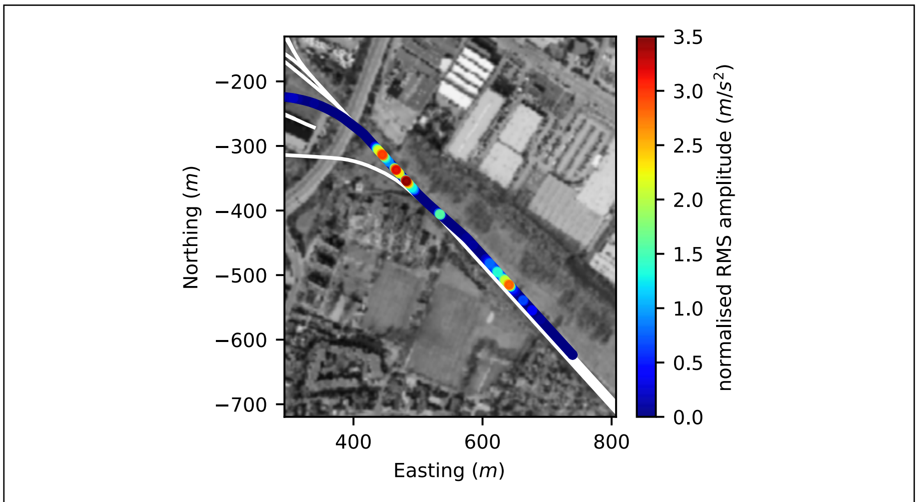

Figure 5: RMS amplitude of ABA data in an area with weld joint defects (background image from [9]).

Given a path hypothesis, the positioning is reduced to a one-dimensional problem in the respective path coordinate frame. An offline version of the Kalman filter (a Rauch-Tung-Striebel smoother) is finally employed to combine the IMU and GNSS data with a mathematical model of the on-track locomotive motion.

Results of the georeferencing are smooth and accurate on-track position stamps with a sampling rate of 200 Hz. Velocities and accuracy information (covariance matrices) are provided as by-products. GNSS speed and position errors due to intermittent satellite signal loss are eliminated, even in challenging GNSS environments and with low-cost sensors.

Data analysis

The analysis of ABA data for condition monitoring of rail tracks from dedicated inspection vehicles or in-service trains has been widely discussed in the literature. However, analysis and interpretation of ABA data is still challenging. The main issue is the complexity of the dynamic wheel-rail interaction, namely the superposition of different vibration signals related to wheel and rail characteristics and noise in the data. Additionally, vehicle-specific and time-varying parameters such as train speed, load and different locomotive/waggon types affect the acceleration data and hence make direct interpretation (e.g. clustering and classification) of acceleration data difficult.

Conventionally, there exist three different types of data analysis algorithms. The first type comprises purely data driven approaches that extract features which can be used as track condition indicator. Algorithms of the second type try to reconstruct the track profile by solving an inverse problem [13] and the third type is a mixture of type one and two [14]. All three types have their own advantages and drawbacks that depend on a priori knowledge of the train and the track, the amount of data and finally the problem to be solved.

Here, we show that already simple energy related features offer valuable information on the track condition. However, those features are strongly affected by the speed of the train.

Since the train speed varies for different track segments and different passes, features that depend on train speed are hardly comparable. Those features therefore need to be corrected for train speed variability. Since each feature point is georeferenced and has a certain speed associated to it, we can represent the features as function of speed. We can then normalise the features in the speed-feature-value domain over a sliding window. This is done by successively subtracting the mean and dividing by the standard deviation. The resulting values then represent the deviation from the average feature value at similar speed.

This approach is only feasible if the range of different track conditions is similar in each velocity window. Strictly speaking, all track segments need to be passed at all different speeds. Clearly, this is impossible to realise during normal operation. However, continuous measurements provide data that reflect the different track conditions at a wide range of speeds and therefore minimise the speed-position correlation. *Figure 3* shows the root-mean-square (RMS) amplitude of the ABA signal before and after normalisation. It can be seen that the standard deviation as well as the mean of the RMS amplitude is increasing with speed. After the speed correction, the mean approaches zero and the signal variance becomes speed-invariant. The normalised RMS amplitude can then be represented in the spatial domain using the track position derived from the georeferencing (*Figure 4* and *Figure 5*). High RMS values are striking at distinct positions of the track. In *Figure 4* high amplitudes are mostly observed at locations where loading and dumping of bulk material takes place. Here, the high amplitudes indicate the accumulation of dirt and related track defects. Visual inspection of the rail segment in *Figure 5* showed that high RMS amplitudes in this area coincide with rail head deformation at welded joints.

Conclusion and outlook

Condition monitoring systems installed on in-service trains offer a quasi-continuous data acquisition that enables the timely detection of track defects. Hence, their use can improve the safety and reliability of operation, and reduce maintenance costs by means of condition-based preventive maintenance strategies. Additionally, the short monitoring periodicity of the same track segments has the potential to allow the prediction of changes in the track conditions.

The use of low-cost COTS makes our systems economical and hence especially interesting for small to mid-size network operators that currently rely on visual inspections only. Those inspections could be complemented by the information retrieved from the on-board condition monitoring, which could improve their efficiency significantly already today. The quality and usability of the retrieved information for network operators will significantly increase in the future as ongoing research activities steadily improve and extend the capabilities of the applied data analysis algorithms.

For the localisation and the investigation of the temporal evolution of rail defects, a precise and track selective georeferencing is mandatory. Appropriate strategies were presented. DLR developed a low-cost multi-sensor system for the acquisition of georeferenced axle-box acceleration data. Since 2015 this system has been used to acquire data on two shunter locomotives operating at the inland harbour Braunschweig, Germany, covering a total distance of more than 1300 km. The collected data build the basis for the development of data analysis algorithms that are subject of past, current and future research at DLR. We showed that energy-related features such as the RMS amplitude are highly correlated with the train speed. We provided a simple strategy to compensate those feature for speed variations. The compensated features then represent known track irregularities well. The data analysis algorithms will be continuously improved and the system tested in different operational environments. ■

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