Detecting corrugation defects in harbour railway networks using axle box acceleration data

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Abstract

Sea- and inner ports are intermodal traffic nodes which play an important role in transportation, especially in the transportation of goods. Track defects appearing in a harbour railway network have negative impacts on safety, cost and comfort (e.g. noise emission). The analysis of data obtained by embedded acceleration sensors, which are installed at the axle box of an equipped in-service vehicle, allows for continuous condition monitoring of the track infrastructure. The German Aerospace Center (DLR) develops prototypical modular multi-sensor systems that are used in different operational environments, among others on a shunter locomotive operating in an industrial harbour railway network in Braunschweig (Germany). Within the research project *HavenZuG* extensive rail longitudinal profile and track geometry measurements have been performed with established inspection methods to obtain the true underlying condition of the railway network. In the present paper methods for gaining relevant information from the axle box acceleration (ABA) data are presented and validated with the given reference data. The focus is on detecting defects which are visible in the rail longitudinal profile, mainly rail corrugation. It can be shown that ABA data gathered during every day shunting operation can be used for detecting corrugation and for inferring rail longitudinal profile parameters.

1. Introduction

The railway sector plays an important role towards a sustainable and environmentally friendly transportation. With the objective to increase its availability, reliability and cost efficiency, condition-based and predictive maintenance become important tools. Overall, until now a large share of maintenance and repair activities are done either at set time intervals (preventively) or after a defect is found (correctively). Especially in small railway infrastructures like industrial networks and feeder lines, state-of-the-art condition monitoring relies on time-based inspections, visual inspections by field workers. In this context, advantages of automated condition monitoring approaches using on-board sensors on in-service vehicles are given by the possibility to quasi-continuously monitor the track quality and thus being able to detect emerging defects early and to monitor the development of the asset's condition. In addition, by supporting the existing maintenance strategies and partly replacing them in the future, it can contribute to lower work load for operators, improve cost efficiency of assets and increase the availability of the infrastructure.

Numerous rail, track and wheel defects affect the dynamic interaction of an operating vehicle and the track[1]. The induced vibrations can be captured by measuring the accelerations at car body, bogie or the axle boxes of a carriage or the locomotive. Their analysis can be used for deriving information on the conditions of vehicle and track infrastructure, e.g. on the existence of several defects regarding the wheel (e.g. wheel flats[2-3]), track geometry[4-7] and track surface[8-11]. As shown in these references, using inertial sensor data has already been investigated and found to be suited for detecting several track and rail defects. However, the known studies have been conducted on main or tram lines where operating speeds are much higher than in industrial railway networks or marshalling yards like harbour railways. To our knowledge, besides the publications presented in the next paragraph, there are no publically available experiments and analysis applied to harbour or other small-size networks. The application for shunting operations in harbour areas poses additional challenges for both positioning and condition monitoring.

With the objective to investigate the potential and applicability of sensor configurations and newly developed algorithms, the Institute of Transportation Systems (TS) of the German Aerospace Center (DLR) develops and operates low-cost multi-sensor boxes which are being used in different operational environments and with different research questions in focus. These comprise online and offline positioning of railway vehicles[12], condition-monitoring of wheel[13] and rail[14] in main lines for passenger traffic and in industrial railway networks like harbour areas[15]. Each of these applications has its own challenges. The usage in harbour areas comes with low vehicle speeds, numerous accelerating and decelerating actions and shocks caused by shunting operations which increase the noise ratio and other unwanted components in the measured signals. In addition, vehicle positioning is impeded by lack of reception near bridges and cranes or multi-path effects and the existence of close parallel tracks in shunting sides. Recent work mainly made use of unsupervised machine learning methods and addressed e.g. the separation of vibration components caused by vehicle and rail using blind signal separation[16] or clustering of anomalies by usage of convolutional autoencoders[17]. In this paper, the set-up allows for supervised learning since the processed ABA data can be compared to reference data. It investigates an approach for deriving qualitative information concerning the rail longitudinal profile from ABA data collected at low speeds in a harsh industrial shunting environment. The pre-processed acceleration data is transformed to vertical profile via double integration, synchronised and analysed with respect to specific wavelength components. Track segments are classified with respect to the existence and severity of periodic profile defects and trained and validated by means of reference data.

2. Reference data

The status quo of condition monitoring in industrial railway networks like harbour railways is, depending on the size of the network, relying on interval-based inspections that are manually performed using measurement trolleys. Various parameters related to the quality of rail and track geometry are typically captured. These are often complemented by visual inspections of the operating staff. Performing these inspection measurements requires the closure of the track sections under consideration and a high amount of manual labour. Therefore, time intervals between inspections are comparably long, especially for small networks. Maintenance actions are frequently taken correctively.

2.1. Data acquisition

With the described state-of-the-art methods for obtaining and assessing the track quality, ground truth data were collected for a large part of the railway network in Braunschweig harbour in form of measurements of the rail longitudinal profile and track geometry parameters, namely track gauge, cant and twist. Measurements were performed twice, i.e. in two subsequent years, for the main tracks and once for tracks that are not passed frequently. The data basis was complemented by several visual inspections where visible, e.g. surficial, defects and track features such as welds were recorded.

2.2 Data description

The part of the aforementioned reference data used in the present paper concerns the rail longitudinal profile measurements. The device records a height value every 2 mm and so provides a height profile of the measured rail where vertical surficial defects as rail corrugation become detectable. The measurements were assigned to positions in the railway network (identifiable via track identifiers specifying the track segment and track positions giving information on the longitudinal position with respect to a segment-specific reference point, e.g. the frog of the turnout). To obtain high-accuracy and track-selective positions of the reference data, the positions of the measurement start and end points were logged with a differential GNSS-receiver. They were projected onto the related tracks and used to assign track positions to all measurement points.

Figure 1 shows the rail longitudinal profile of one of the tracks showing strong vertical dips where welds were detected as result of the visual inspections. The given track is heavily affected by rail corrugation on several track sections that are alternating with sections where no rail corrugation is found. In Figure 1 one example of a transition from non-corrugated to corrugated parts of the track can be seen at the welds at position 40 meters on both rails.

Corrugation is a periodic surficial rail defect that can develop from different mechanisms. It is characterised by its wavelength and amplitude. Corrugation induces high dynamic loads on both rail and vehicle and can, depending on the wavelength, cause strong noise disturbance(18). The corrugated segments in Braunschweig harbour originate from main lines as old rails from main lines have been re-used and put together from different sources. This represents a typical situation especially for small industrial networks. The development of corrugation due to operation in industrial networks is especially known for transfer lines with higher average train speeds in mid-size networks (> 50 km total track lengths).

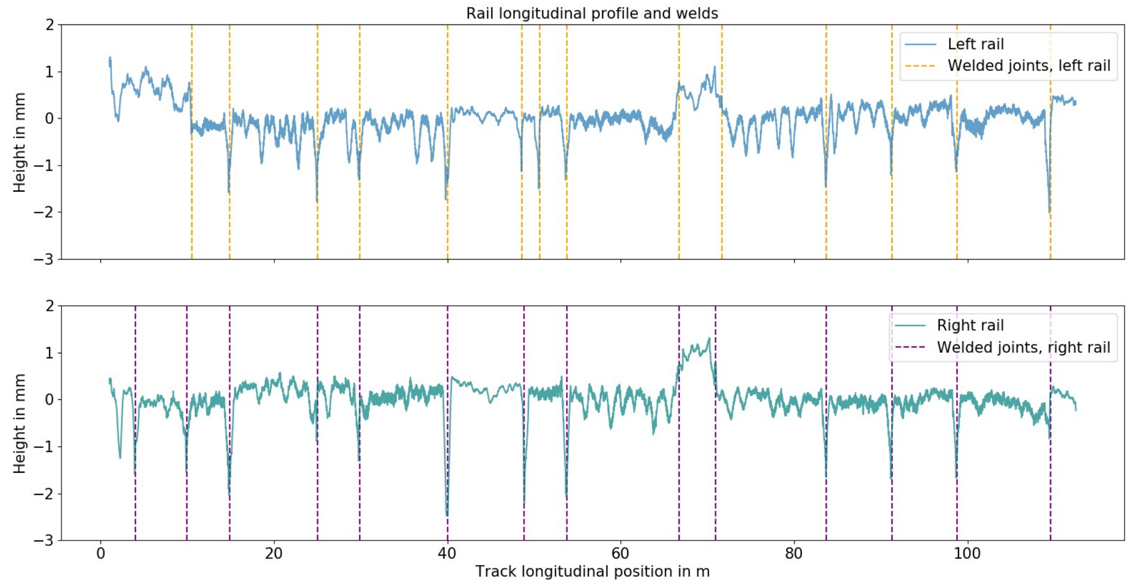

Figure 1: Longitudinal profile of both rails belonging to one of the tracks in Braunschweig harbour and recorded positions of welds on the given track. Left and right are defined with respect to the measurement direction (coinciding in this case with the track direction, i.e. with increasing position values).

2.3. Data processing

The profile measurements are bandpass filtered to different wavenumber components in order to assess the track quality respective to periodic defects with specific wavelengths. Acceptable amplitudes differ for different wavelength domains and so different assessment rules are applied. One approach is to classify track segments into normal and defective according to the fulfilment of the condition that the ratio of points where the absolute amplitude exceeds a threshold is above a certain quality threshold. This corresponds to track segment assessment of German Railways (DB AG, corporate policy rule (RIL) 824.8310) and international standard EN 13231-3:2012.

3. Axle-box acceleration data

3.1. Data acquisition

The data are collected by a modular multi-sensor system installed on a shunter locomotive and composed of various low-cost sensors[15, 19]. Axle Box Accelerations (ABA), representing the dynamic vehicle-track-interaction, are captured by tri-axial broadband accelerometers covering a frequency range from 0.8 to 8000 Hz attached to the front axle of the shunter locomotive. The six acceleration channels are sampled with 20,625 Hz. The sensors used for condition monitoring are complemented by a Global Navigation Satellite System (GNSS) receiver and an inertial measurement unit (IMU) used for offline vehicle positioning and hence positioning of the collected ABA data. It is completed by cameras in front and on the back of the locomotive which can be used for landmark recognition, weather condition estimation or dirt detection (e.g. near container terminals where coal is loaded near the tracks). Results from camera data analysis can complement the work on ABA data but are beyond the scope of this paper.

Figure 2 shows the locomotive with one of the installed sensors and the sensor box (without external sensors).

Figure 2: Mounted acceleration sensors on the front axle box of the shunter locomotive (left side, overall view and close up), shunter locomotive (upper right), sensor box without external sensors (bottom right)

3.2 Data pre-processing: Positioning

To make use of the ABA data in terms of condition monitoring of the track infrastructure, the data have to be assigned to positions in the harbour railway network with high a priori accuracy. In particular, the positions have to be track-selective and with preferably small longitudinal deviation along the track. The GNSS receiver offers first global positions and speed which have to be refined in order to be track selective. In addition, the lack of positional and speed information due to no or compromised reception (bridges, high buildings, cranes) has to be compensated. This objective is reached by fusing GNSS (position, speed) and IMU (acceleration) data with a digital map of the railway network(12). In a first step the data is split into journeys defined from standstill to standstill. Using the start and end positions of a given journey and a graph modelling the network (track segments are represented by vertices and allowed connections between tracks correspond to edges connecting the respective vertices), path hypotheses covering all allowed paths which connect the given start and end position are created. Then one path is selected for further processing by comparing the projection errors of the provided GNSS positions on these paths and choosing the minimiser. Speed and longitudinal position then are obtained using a Kalman filter based on GNSS position and speed as well as longitudinal accelerations provided by the IMU. Finally, the results can be improved by applying a Rauch-Tung-Striebel smoother.

Final improvements can be made by using the ABA data itself and are obtained from the analysis of the rail longitudinal profile as described in section 3.3.

Aside from assigning georeferences to the ABA data, positioning of the railway vehicle can give an impression of track loads in form of the number of segment crossings and driven speeds which can be used for further purposes, e.g. for deciding on inspection or maintenance prioritisation or determining estimations for suited inspection intervals.

3.2 Data set description

The data used for this publication comprises passages of the track described in Chapter 2. For the first analysis, journeys were chosen where the track is crossed as a whole. Data of all driven speeds such that the minimum speed on the track segment is larger than 1 m/s and with speed variations up to 0.5 m/s are considered. The data comprise 100 journey-sensor combinations and a time interval of approximately 10 months. Figure 3 shows the raw ABA data for seven journeys collected by the acceleration sensors attached to the right side of the axle with respect to the track direction.

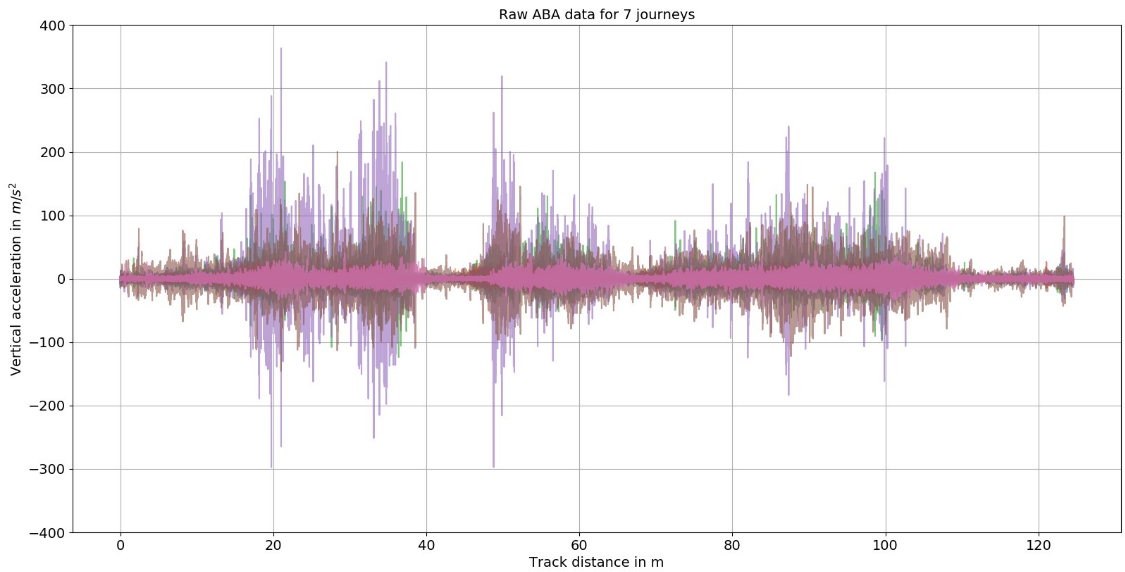

Figure 3: Vertical acceleration along one of the tracks in Braunschweig harbour, measured during seven different journeys by the acceleration sensor placed on the wheel bearing on the right side of the vehicle with respect to track direction.

3.3 Data processing

The goal of the present research is to analyse and to evaluate the potential of extracting information on relevant parameters and quality measures of the rail longitudinal profile from data acquired by on-board acceleration sensors. To this end, several processing steps are necessary. In the given set-up, the data are processed as follows:

1. Low-frequency components below the cut-off frequency of the acceleration sensors are removed by a zero-phase high pass filter to avoid low frequency

noise caused by non-linear transfer function and corrupting the output of the double integration.

2. A journey-specific low pass filter removing high frequency components is applied. The cut-off frequency is defined by half the smallest wavelength of interest, using the driving speed of the journey.
3. Linear trend is removed from the data.
4. The pre-processed acceleration signal is integrated twice and linear trends are removed.
5. The integrated signals are sampled equidistantly in the distance domain and down-sampled to the same sampling frequency of 500/m as the one used for collecting the reference data (rail longitudinal profile measurements).
6. Positioning is refined (relative spatial signal alignment).

Concerning the last processing step, the a priori positioning provides good track selective and longitudinal positions with an accuracy of up to a few meters, often below 1 m. Small deviations in position and speed occur and are not uniformly distributed along the track segment or journeys. For further analysis, these positions can be improved by comparing the processed ABA data to the rail longitudinal profile or, if the latter is not available, by comparing it to a reference journey and to obtain an improved estimate of the absolute position by averaging over all journeys.

In this application the alignment is done by a two-step approach. The data used for synchronising is the pre-processed (double integrated) ABA data. Other methods and input data, that is, different stages of processed data to be used for synchronisation, are possible. In this context, the described method has proven to be most successful and adequate for the presented analysis. Comparing a new journey to a reference one (or the reference data), the input data are split up into larger segments of tens of meters and the cross correlation with subsets of the reference data is calculated. The best shift for each subsegment is determined and the obtained longitudinal profile is shifted by the mean value of all segment shifts (linear interpolation between varying shift values is not applied since it is done in the next step using local minima). The new distance information already provides a very good result that depends on the resolution of the shifts for which the cross correlation is calculated. The last step is done by comparing distinctive local minima in the data which are especially given by welds. The a priori position is then good enough to avoid incorrect minima mappings. The profile is stretched and compressed linearly between the known shift positions. After this processing step, the data are again resampled to an equal and identical distance resolution. Figure 4 shows the vertical rail profile obtained from several crossings (more precisely: from the raw ABA data shown in Figure 3) that have been synchronised with respect to the reference data. It can be seen that the results are, beside a certain variation in the absolute heights, indeed similar and repeatable for different journeys.

Figure 4: Processed ABA data (obtained vertical profile) on a subsection of length 25 meters. Before (upper row) and after (bottom row) alignment and removal of linear trend.

3.5 Data analysis

The desired results from the ABA data processing and analysis concern several aspects. First, qualitative information is of large benefit, especially from the user (habour) perspective. Classes obtained by reference data-based assessments should be obtained from ABA data with high accuracy. In addition, detection of welds and other distinctive spots or anomalies is of interest. As can already be seen from the alignment process, the detection of welds and strong anomalies can be obtained from the sensor data. Estimating their depth and additional quantitative information on the profile is content of current research and beyond the scope of this paper.

Concerning the first aspect which will represent the focus of this paper, track sections are assessed to be normal (i.e. no corrugation is present on the section) or abnormal. More precisely, reference data-based assessment mainly involves amplitudes of bandpass filtered components of the rail longitudinal profile; track segments are classified based on the resulting amplitudes. Thus, the classification of track segments is performed with respect to the wavelengths. Corrugation can appear in wavelengths from 25 to 1,500 mm, where corrugation of 25-80 mm is called short wavelength corrugation(18). Furthermore, as already discussed in Chapter 2, the considered track is composed of several sections of used rails from main lines partly affected by corrugation and therefore offering a well-suited example for the analysis. The corrugation on the track considered in this analysis is of wavelengths about 50 mm. Hence the wavelength bands including this wavelength are of special interest.

For assessing track segments of a given length, multiple yet similar options have been tested. The assessment is based on segments of 1 m length, with 10 % overlap. Possible input parameters are given by the absolute amplitudes of the bandpass filtered components or by their envelope. The envelope is given by the instantaneous amplitude, this is, as the absolute value of the analytic signal of the input. In order to evaluate track segments, e.g. the ratio of data points where the input parameter exceeds a wavelength-specific threshold or the mean value per track segment can be considered. Segments then are found to be normal/abnormal by comparing these values to additional thresholds. Assessment rules and thresholds may be adopted from international standard or rules of main line operators, but should be handled flexibly to take needs of the infrastructure operators in focus into account.

The final task is to handle multiple journeys. The output parameters obtained for each journey are averaged. The assessment is performed on basis of the mean values of the included journeys.

3.6 Results

The ground truth assessment of the considered track is done by using the envelope of the bandpass filtered rail longitudinal profile and comparing its window mean to the wavelength-specific threshold applied to monitor main lines in Germany. Alternatives as utilising absolute amplitudes or ratio of threshold exceedance yield very similar yet slightly worse results. The ABA data is processed analogously. For training, i.e. choosing a classification threshold, a subset of half of the journeys only using data in forward direction is used (6 journeys out of overall 38 journeys for the sensor on the left side; 11 out of 62 for the sensor on the right side), covering a wide speed range. The threshold is determined to maximise accuracy, for each side separately. For the wavelength band covering 0.03 to 0.08 m and the threshold 0.01 mm for the reference data, an optimal threshold of 0.023 mm is determined for the sensor on the left side, resulting in an accuracy of 1 if only journeys used for training are considered, and 99.2 % for journeys in forward motion not considered in training (6 journeys); finally, 98.4 % accuracy for assessment based on all journeys where the locomotive was moving backwards (40 journeys) is reached. For the right side the optimal threshold equals 0.016 mm with accuracies 96.8 %, 96 %, 96.8 %, respectively. Considering the wavelength band 0.1 - 0.3 m, where no corrugation is present on the given track but nevertheless sometimes the threshold (0.05 mm) is exceeded in the reference data, the optimal thresholds are given by 0.076 mm (left, 99.2 % - 96 % - 98.4 %) and 0.0755 mm (right, 92 % - 91.2 % - 92 %), using the same journeys for optimisation as in the first example. Figure 5 and Figure 6 show the obtained mean values of the envelope of the bandpass filtered profile per window for the left rail and journeys in forward direction, the mean of all these journeys, the corresponding values obtained from the reference data of the left rail and the classification based on the named thresholds.

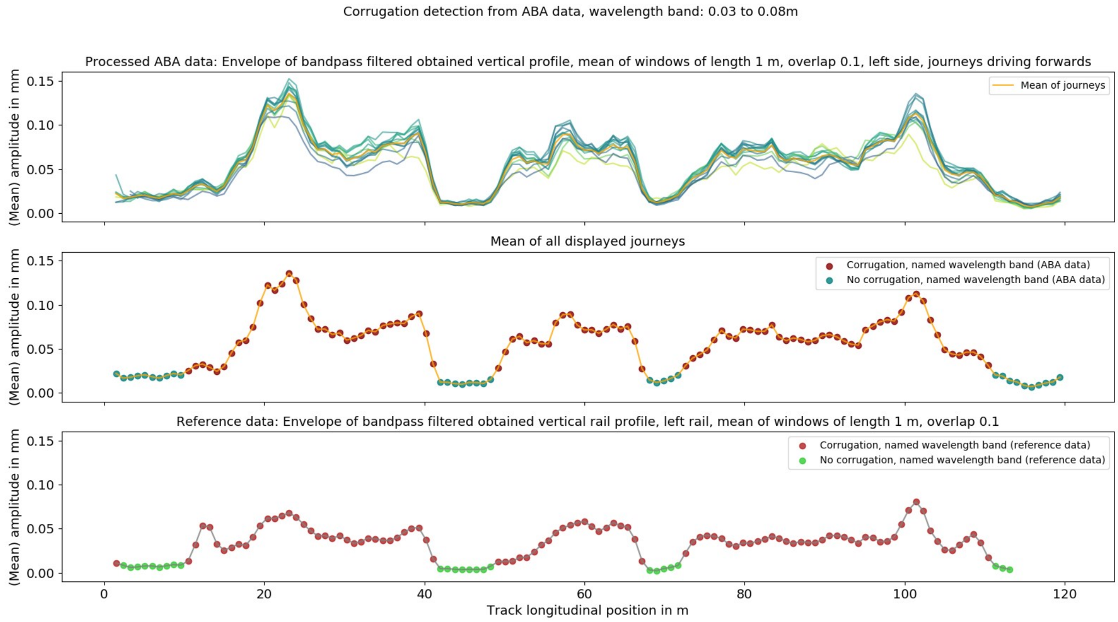

Figure 5: Mean values per window (1 m, 10 % overlap) of the filtered profile's envelope, obtained by different journeys and their mean (first row), the latter and assigned assessment (second row), reference data (mean of 1 m windows with 10 % overlap of the envelope of the filtered profile) and corresponding assessment (bottom row). Thresholds are given by 0.01 mm (reference data) and 0.023 mm (ABA data). Wavelength band: 0.03 – 0.08 m.

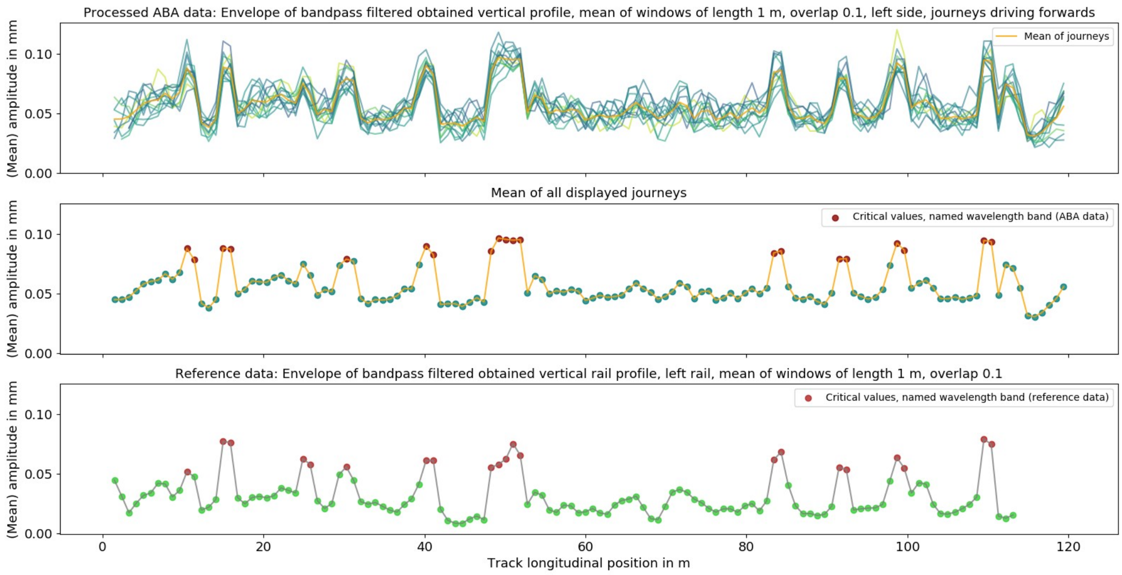

Figure 6: Analogously to Figure 5, wavelength band: 0.1 – 0.3 m. Thresholds: 0.05 mm (reference data), 0.076 (ABA data).

4. Conclusion

The present paper has investigated the potential of deriving qualitative information concerning the rail longitudinal profile from axle-box acceleration data collected in an inland harbour network during shunting operations. An approach based on double integration of the acceleration data was tested on a data set comprising sensor data together with reference measurements reflecting the true underlying condition of the track. The data was synchronised and analysed with regard to corrugation detection and wavelength-specific track section classification. Despite the presence of small vehicle speeds and strong noise components in the data, the results show that the approach is indeed suited for this small harbour network. Corrugation and abnormal track sections can be determined with high accuracy. In addition, as exemplified on the considered track, weld detection is possible by the usage of ABA data.

Future research will focus on evaluating the results on a larger dataset. Furthermore, the collected data show that defects which appear only on one of the two rails also are visible in the accelerations measured by the sensor on the opposite side of the vehicle due to vibration transfer via the axle. This fact has to be included in the evaluation process. Finally, a speed dependency is observed for particular wavelengths that is assumed to originate from resonance effects at certain speeds. Quantitative estimation of the profile via wavelength-dependent regression of multiplication factors and its validation is content of current research. Finally, instead of involving absolute thresholds, relations of the amplitude magnitudes of different wavenumber components of the longitudinal profile can be tested and used for detecting corrugated segments more robustly in future.

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