Railway Track Geometry Irregularity Assessment Using Smartphone Accelerometers

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Railway Track Geometry Irregularity Assessment Using Smartphone Accelerometers

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Cover: Photo from smartphones used in the thesis, with the Phyphox app active.

An electronic version of this thesis is available at `http://repository.tudelft.nl/`.

TU Delft

Preface

This thesis was written as part of the fulfillment of the MSc. of Civil Engineering for Wessel Cornelis Roodenburg, at the Delft University of Technology. The work for this thesis took place in 2024, and took approximately 6 months to complete, excluding preparations.

Mobile crowd-sensing technology is a topic I have found interesting for quite a while. The idea of using passively sourced data from non-dedicated monitoring devices, and retrieving meaningful relations based on that data, is a puzzle I find fascinating. This thesis provided me an opportunity to apply this concept on one of my favourite civil engineering systems: railways. The main driver of me choosing this topic was assisting in the development on a universally accessible and affordable method of monitoring railway systems.

For me, this thesis was meant as a final learning opportunity for my master in civil engineering. This thesis encompassed a broad range of different topics and methods, each posing their own unique challenges. By facing, and at times overcoming, these challenges, I have gained a significant amount of expertise to put to use in my future career as an engineer. Amongst other things, I got to:

- Apply and extend my knowledge on data and signal processing.
- Improve my skills on analysing academic literature to understand the state of the art knowledge.
- Set up a survey for industrial partners to get insights in developments in the railway sector.
- Design and lead a measurement campaign with a team of researchers on in-service trains.
- Conduct tests in a laboratory setting and in a measurement vehicle, using high-end equipment.
- Obtain insights in key challenges in the development of mobile crowd-sensing technology for railways.

Some of these topics were newer to me than others, and I can only express my greatest gratitude that I could grow in so many different ways.

Access to the measurement data produced for this thesis can be requested by contacting Dr. A. A. Núñez Vicencio (a.a.nunezvicencio@tudelft.nl), associate professor at the railway engineering section of the Delft University of Technology.

W.C. Roodenburg
Delft, July 2024

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I would like to express my gratitude to a number of parties and individuals who were of invaluable assistance to me during this process. Without their support, I do not see a way I could have delivered the product with such a high level of detail and quality within the short timeframe.

First and foremost, I would like to thank my committee members: Prof. Dr. Zili Li , Dr. Kumar Anupam and Dr. Alfredo Núñez Vicencio for their clear feedback and sound advice at our progress meetings. I got to enjoy additional supervision by Dr. ir. Arjen Zoeteman and ProRail BV. I wish to thank them for providing me with a position to conduct this research. Another supervisor is found in Dr. Yuanchen Zeng, who I want to thank for his limitless support, patience and willingness to assist with the experiments conducted for this thesis. Additionally, I would like to thank Ing. Jan Moraal, Ir. Jurjen Hendriks, Siwarak Unsiwilai and José Alberto Stradi for their support during the measurement campaigns.

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W.C. Roodenburg
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Abstract

Smartphones have become widely accessible and advanced, pocket-sized computers capable of sensing, sending, and processing an ever-increasing variety of data. Modern phones are, for example, equipped with sensors such as accelerometers and GPS-sensors. Meanwhile, an increase in rail traffic leads to an increase in the need of having a reliable and comfortable railway system, an objective which can be achieved through additional monitoring. Through mobile crowdsensing, the smartphone data from passengers could potentially provide an additional and almost continuous information source on the railway system health state.

This thesis explores to what extent smartphone accelerometer measurements on board of in-service passenger trains can be used to monitor railway track quality. The thesis contains a literature review and a survey with European infrastructure managers. They identify that repeatability, as a result of operational variance, is a key research gap and challenge in the implementation of this technology. The thesis assesses accelerometer characteristics from a set of contemporary smartphones through laboratory tests. The tests uncover limitations and heterogeneity in the sensing capabilities such as sampling frequencies, low-pass filters and eigenfrequencies of the devices. The thesis also makes use of a case study, in which different smartphones are placed in various positions on different in-service passenger trains, running over the same tracks in the Netherlands. The vertical acceleration signals are analysed and compared. The vehicle speed and the position of the smartphone within the car body are found to significantly influence both the frequency content and vertical acceleration amplitudes measured. Finally, the different signals are related back to a Track Quality Index based on the standard deviation of the Longitudinal Level D1 track parameter. A degree of consistency in identifying locations with a low relative track quality is displayed, albeit with a significant degree of variance due to the previously mentioned factors.

Contents

1

Introduction

The title of this thesis is “Railway Track Geometry Irregularity Assessment Using Smartphone Accelerometers”. The thesis is about how vertical accelerations measured by smartphones in the car body of in-service passenger trains can be utilised to retrieve information on the railway track quality. The study focuses both on the data quality acquired by the smartphones, as well as the repeatability of measurements. This chapter is meant to provide an initial outlook in the contents of this thesis. Firstly, the context of the research is set out in Section 1.1. This section explains why this concept is interesting to develop. Secondly, information on current practice on track quality assessment is provided in Section 1.2. This section introduces the Track Quality Index used in this thesis. Thirdly, an explanation of the concept of mobile crowdsensing is given in Section 1.3. Section 1.3 displays some of the key variables in a conceptual framework. Fourthly, the thesis outline and scope is presented in Section 1.4. Lastly, Section 1.5 introduces the case study used in this thesis.

1.1. Context of Research

In 2019, the European Union published “The European Green Deal” , which “resets the Commission’s commitment to tackling climate and environmental-related challenges that is this generation’s defining task” [9]. In this document, it is specified that transport accounts for over a quarter of the greenhouse gas emissions, and thus this sector has a significant contribution to deliver when it comes to the achievement of climate neutrality in 2050. One way the Green Deal specifies this contribution is by shifting freight traffic from road to railways [9]. This leads to an increase in the transport demand on the railway network, which puts a higher pressure on infrastructure managers on the effective use of the available railway transport capacity.

However, humans and animals living along the tracks are constantly exposed to the noise and vibrations caused by the mechanical dynamic interactions of the railway system. As formulated in the EURAIL Master Plan, railways need to reduce its noise and vibrations impact, to allow for further development of railway infrastructure and maintain the acceptance for rail in society [8]. Besides this, the Sustainable and Smart Mobility Strategy specifies that the European Union should create appropriate conditions to make sustainable transport alternatives competitive [10]. A way this could be achieved is through maintaining the comfort levels high. These reasons provide ground for additional, more frequent monitoring of the railway tracks.

The need for both effective use of capacity and frequent infrastructure monitoring poses a challenge in itself. Infrastructure managers conventionally use dedicated measurement vehicles to monitor the state of the tracks. These require reserved timeslots and train paths which then reduce the infrastructure capacity for transport purposes. Additionally, due to the relatively long intervals between measurements, track defects can go unnoticed, resulting in discomfort of passengers, as well as noise and vibrations for non-users. An opportunity therefore lies in reducing the reliance on these dedicated measurement vehicles with long measurement intervals. This could be achieved by supporting them with real-time condition monitoring under normal operational conditions.

Another development is the rise of the mobile phone. Mobile phones have become widely accessible, and have become advanced, pocked-sized, computers which are capable of measuring, sending and receiving an ever-increasing variety of information. Modern phones are, for example, equipped with GPS-sensors and accelerometers. Could passenger smartphones perhaps provide a continuous source of track-condition information? Earlier studies have looked into the applications regarding frameworks in assessing ride comfort [28] and track quality [24]. The reported results in earlier works showed promise for further development in using this “mobile crowdsensing” technology for railway infrastructure condition monitoring. This would turn the threat posed by a higher intensity of trains into a near-continuous railway infrastructure monitoring opportunity.

1.2. Track Quality Assessment

This thesis focuses on assessing the track quality of railway lines through smartphone accelerations from in-service passenger trains, specifically the assessment of vertical irregularities of the railway track geometry. It is required to understand first how railway track quality is assessed in current practice.

Conventional ways to assess the track quality involve geometry measurements. Current practice in the Netherlands for geometry monitoring is that a dedicated measurement vehicle runs along the network [26]. It records the track geometry with a measurement system conforming to European Norm EN13848 at a frequency of 1 to 4 times per year [26]. These measurements can then be used to assess the track quality. The longitudinal level is a track geometry parameter specified in NEN-EN 13848-1 [17] and represents deviations in vertical direction of the rail along a reference line. The Longitudinal Level is a track geometry parameter. It is split into 3 wavelength ranges, of which the D1 wavelength is the focus of this thesis.

The state of the art assessment of the LL D1 parameter is provided in NEN-EN 13848-6 [16], and is commonly assessed by the following Track Quality Index: Calculating the standard deviation of the LL D1 parameter over a length of 200 meters. This thesis works with the standard deviations of the combined or mean LL D1 parameters for both rails (mean of LL D1 value of the left and right rail). A sketch of this mean LL D1 parameter is displayed in Figure 1.1.

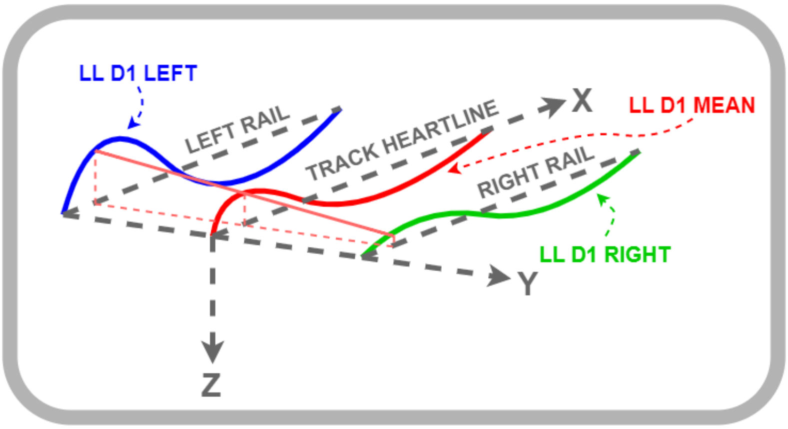


Figure 1.1: Sketch of the mean LL D1 used for track quality in this thesis. The x-, y- and z-axes correspond to the longitudinal, lateral and vertical axes respectively. The LL D1 parameters are the deviations in z-direction. The x-axis is used to denote the kilometer positions of the measured LL D1 parameter.

1.3. Conceptual Framework of Smartphone-Based Monitoring

This thesis is based on the concept of mobile crowdsensing. In [12], mobile crowdsensing is defined as applications “where individuals with sensing and computing devices collectively share data and extract information to measure and map phenomena of common interest”. The sensing and computing devices are considered in the context of the thesis to be smartphones, while the “common interest” is the monitoring of the railway track quality. The concept of monitoring track quality through smartphones from passengers onboard in-service passenger trains would also involve measurements from a moving railway vehicle similar to the current practice. There are however notable differences.

- The first difference is that in current practice, track geometry measurements are conducted by a small fleet of dedicated vehicles. The geometry measurements these vehicles conduct comply with European standards, which implies a significant amount of information is known on the vehicles. This should limit the variance in the geometry measurements as a result from the state and characteristics of the vehicle. When using in-service passenger trains, vehicles are part of a much larger fleet. Variance in the measurements is expected as a result of this.
- The second difference is that, in current practice, measurements take place on a relatively low frequency (1-4 times per year in the Netherlands [26]), whereas most lines see passenger trains pass by every hour [31]. Smartphone measurements therefore have a much higher measurement frequency. In addition to a higher frequency in train passes, data could be retrieved from multiple mobile phones on board of the vehicle.
- Another differentiating aspect is that for conventional monitoring systems. The sensors can be selected by the monitoring system designer, based on available sensor characteristics, making the sensor suitable for that monitoring purpose. In case of using accelerations recorded by the smartphones of passengers, the sensor characteristics used in the monitoring system are unknown. Furthermore, the sensor characteristics are usually not directly available and may vary per device. These factors lead to a degree of uncertainty regarding data quality, because characteristics such as the accuracy, noise and sensitivity of the measurement devices is unknown.
- Finally, although smartphones of passengers are restricted to the inside of the car body, these smartphones can be everywhere within this space. When retrieving data this way, the exact position in the car body is unknown, in contrast to a dedicated measurement set-up. Additionally, the orientation and the damping conditions to which the smartphone is subjected are unknown and may vary (e.g. a smartphone placed on a seat may record different measurements than a smartphone on a rigid surface).

The way that information on the assets (tracks) travels to the mobile phones in the car body of a passenger train is depicted in Figure 1.2. The geometry of the tracks is transferred to the train by track-train interaction in the form of vibrations, and proceeds to pass to the car body through the suspension system. This suspension system enforces comfort and is meant to dampen out undesirable vibrations for passengers and the vehicles, limiting the amount of information extracted from the car body. The vibrations travel to the position of the smartphone within the car body, and may be subject to further damping due to furniture (e.g. soft surfaces) and position in relation to the bogies. Finally, the accelerometer sensor of the smartphone records these vibrations as a digital acceleration signal. The sensor characteristics of the smartphones may influence the final measured signal.

A conceptual framework on how track geometry is translated into information on the track geometry through the smartphones is displayed in figure 1.3. The influence of the aforementioned additional sources of variance and uncertainty are included alongside with some other inherent variables of the measurement system, such as vehicle speed.

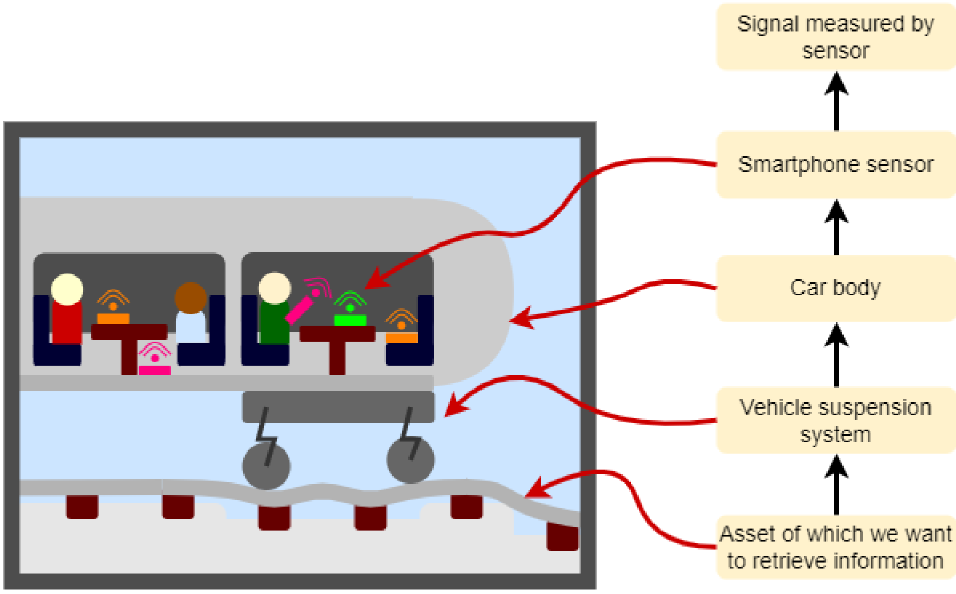


Figure 1.2: Figure of how information of the asset (track quality) travels through the vehicle and mobile phones to an acceleration signal measured by the sensor.

1.4. Thesis Outline and Scope

This thesis seeks to answer the question: To what extent can smartphone accelerometer measurements on board of in-service passenger trains be used to monitor railway track quality? The following questions are posed in order to provide an answer to this research question:

- **Research Question 1**: What research regarding onboard ride and track quality measurement techniques (especially smartphones) have already been conducted and what experience is already present in the industry?
- **Research Question 2**: In which ways do the sensor characteristics of different contemporary smartphone devices differ?
- **Research Question 3**: In which ways do different recorded acceleration signals from smartphones on in-service passenger trains differ?
- **Research Question 4**: To what extent can (repeated) onboard smartphone accelerometer measurements reflect differences in track quality?

Chapter 2 answers the first research question through a literature review on studies involving smartphone accelerometers for railway condition monitoring. Additionally, a survey is conducted among European infrastructure managers, to identify experience and attitudes in the industry. Chapter 3 answers the second research question through a series of laboratory and in-situ tests to identify sensor characteristics. To assess the heterogeneity, a set of contemporary (2023) smartphones is acquired and tested. Chapter 4 answers the third research question. This question is answered through a case study and subsequent analysis. The smartphones of the aforementioned set are placed on different positions in the car body, and their vertical acceleration signals are processed and analysed. Both global observations (over the entire case study) as well as local observations around irregularities are discussed. Finally, 5 answers the last research question and couples the vertical accelerometer signals back to the Track Quality Index. Chapter 5 also reflects upon the encountered variance between different signals and its consequences for the assessment of railway track quality. Chapter 6 summarises the main conclusions and provides recommendations for future research.

Due to limited time available, as well as in accordance with the state-of-the-art literature, the thesis is limited by some scoping decisions. This thesis makes use of a case study to demonstrate empirical relations between smartphone acceleration signals and track quality. This means that observations are limited to the tracks between Delft Campus and Schiedam Centrum. Only one railway vehicle type was used, the Nederlandse Spoorwegen: Sprinter Nieuwe Generatie. The Track Quality Index evaluated is

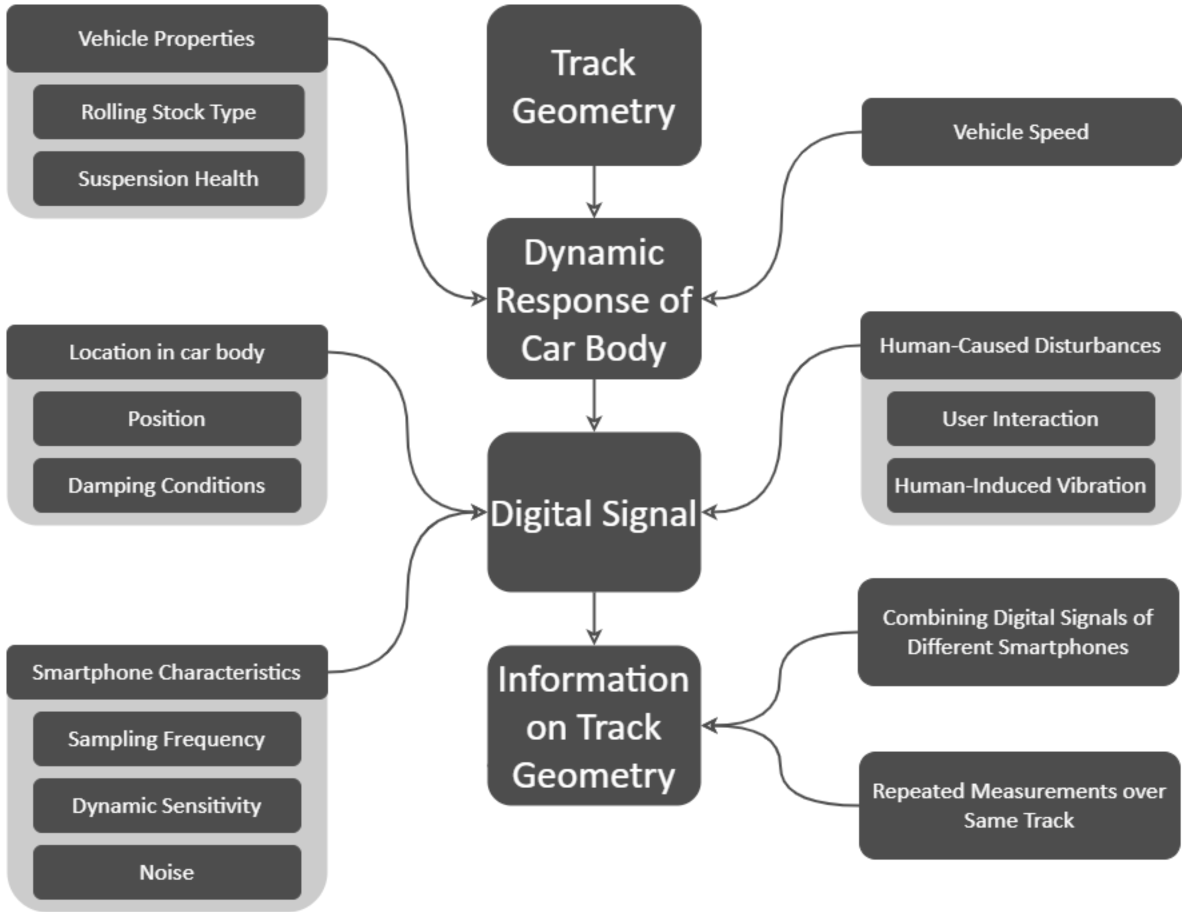


Figure 1.3: A selection of processes and variables involved in how information is obtained through smartphone accelerations.

limited to the one specified in Section 1.2. Measurements on the trains were conducted on 2 different days, spaced 1 month apart, and this thesis does not include an analysis of how signals change over time. Furthermore, only the track quality assessment ability of contemporary (2024) smartphones is evaluated, with the smartphones being in a “fixed” position in the car body, on a rigid surface. The thesis only includes analyses on the vertical accelerations recorded from the car body.

1.5. Case Study Description

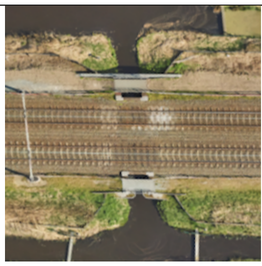
The selected case study is a 5 kilometer long section of railway line between Delft Campus station and Schiedam Centrum station. It is a frequently used route: passenger services are operated by NS, and on weekdays up to 24 passenger trains per hour pass on this route per direction [31]. The line is one of the oldest in the Netherlands, is situated on the weak soils in the west of the country, and is thus subject to settlements. Additionally, the line contains a lot of bridges and joints. These locations are prone to degradation, especially transition zones. Different track quality states are therefore likely to be encountered. For this case study, only track between kilometers 73 to 78 of the southern track (from Delft Campus to Schiedam Centrum) is considered.

The joints, fishplates and transition zones in the selected track segment are added manually and projected onto the track kilometer positioning system used by ProRail. A number of these can be found in Table 1.1 The following elements were added:

- Elements containing transition zones (changing track support structures) such as bridges, viaducts, level crossings, underpasses, culverts.
- Insulated joints and fishplates.

The selected rolling stock is the NS Sprinter Nieuwe Generatie or SNG for short. These trains run

Table 1.1: Selection of Elements in case study

Name	Type	Image	Name	Type	Image
C1	Culvert		J7	Insulated Joint	
B3	Bridge		U1	Underpass	
LC1	Level Crossing		RV1	Railway Viaduct	

Images are retrieved from ProRail luchtfoto [27].

local services. This rolling stock is selected for this thesis for the following purposes:

- This type of train consistently runs 2 to 4 times per hour on the selected case study line and does not alternate with other rolling stock.
- These trains are relatively new and entered service in 2018 [33]. It is therefore thought that these trains use state-of-the-art technology and allow for the most contemporary application of the research.
- These trains are equipped with power sockets to charge the smartphones.

The Longitudinal Level track geometry data in this thesis was acquired from BBMS [25]. The TQI used in this thesis is normalised through min-max normalisation. The TQI of the case study is displayed in 1.4. The standard deviation TQI around kilometer position 76.7 scores as being the highest quality, the peak of the standard deviation around 77.5 displays the lowest quality.

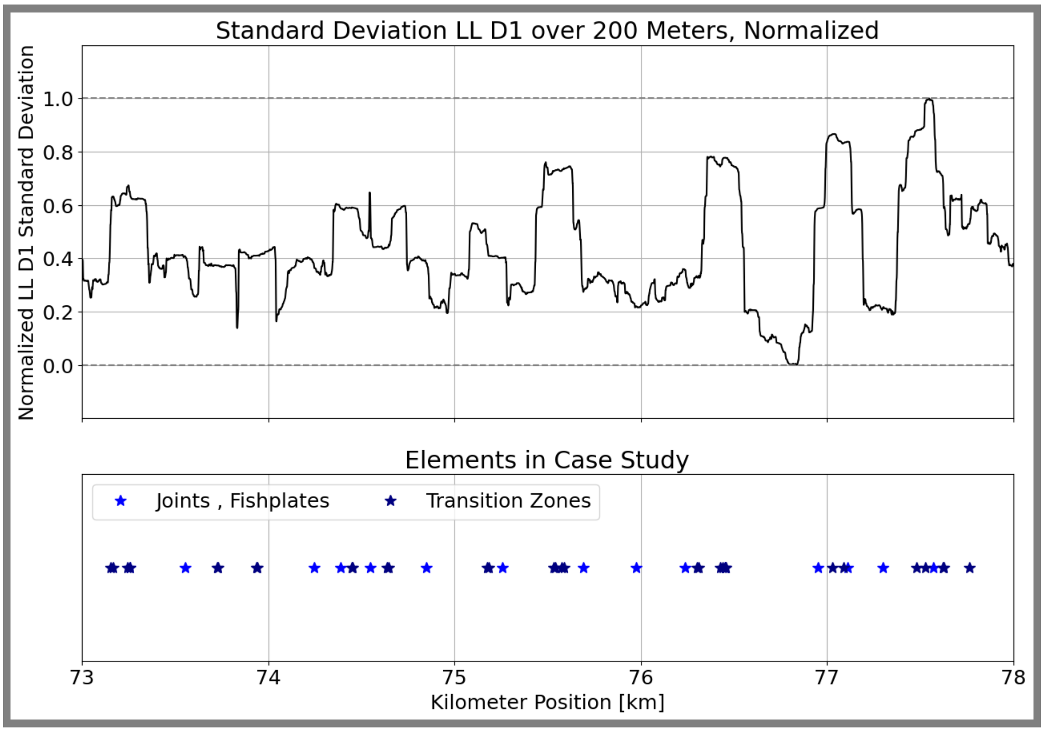


Figure 1.4: Track Quality Index. The standard deviation over 200 meters of the LL D1 is presented normalised over the track segment, with a value of 0 meaning the best TQI score on this segment and a 1 meaning the worst TQI score on this segment. The locations of transition zones and joints are provided for additional context.

2

Literature Review

This section of the report provides insights into the current status of research into monitoring railway infrastructure with mobile phones. The literature review is divided into three distinct segments:

- A literature review on smartphone accelerometer applications for railway infrastructure condition monitoring is presented in Section 2.1. Table 2.1 presents the key sources of literature used in this thesis.
- The results of a survey on mobile crowdsensing knowledge in industry are discussed in Section 2.2. The survey was distributed to European infrastructure managers, to obtain insights in the findings of the industry. The survey is conducted because findings from industry are usually not published or reported in a publicly available manner.
- The conclusions on the identified research gaps and remaining challenges are presented in Section 2.3.

2.1. Smartphone Accelerometers in Railway Condition Monitoring

The concept of (railway) infrastructure monitoring through the use of accelerometers in smartphones is not a novel idea, and has been studied before. This section aims to provide an overview of previous research on the applications of smartphone accelerometers in the field of railway engineering. The section starts by investigating the data quality and sensor characteristics of the accelerometers in Section 2.1.1. The focus of this section lies on the heterogeneity between devices. A brief overview of the application of smartphones for ride comfort monitoring is then provided in Section 2.1.2. A short paragraph on the behaviour of the acceleration signals around railway track elements forms Section 2.1.3. Railway track elements include bridges, transition zones and joints. Track alignment and geometry monitoring through smartphones is addressed next in Section 2.1.4. In Section 2.1.5, research on the operational variables influencing the measured accelerations by smartphones (e.g. speed, different vehicles) are discussed. Previous findings on the effect of the smartphone being present in different positions of the car body is presented in Section 2.1.6. The review ends with Section 2.1.7, a section on how human-caused anomalies are reflected by smartphone accelerometer measurements.

2.1.1. Smartphone Accelerometer Quality and Characteristics

Smartphones are not dedicated measurement devices, and were not designed specifically for railway condition monitoring purposes. Smartphones in previous research have shown differences in sensitivity and noise (e.g. in [2]). This leads to questions regarding the level of heterogeneity, and thus the data quality, between devices. As a result, the accelerometers of smartphones have been compared on multiple occasions to more dedicated or high-end equipment in controlled conditions.

Testing has taken place in the past in laboratory conditions. These tests were usually done to compare the low frequency ranges relevant to ride comfort monitoring. When placed on a cantilever beam in [6], it was displayed that, the magnitudes of the frequency domains of both a conventional sensor and a smartphone complied well for the 5-8 Hz frequency range observable to humans. The figures displayed in the paper related to this test do however display that for higher frequencies (10 -30 Hz) the data does contain observable noise. A laboratory test in [13] using artificial shaking reported a 0 to 10 % relative error range when comparing a smartphone with a professional measurement instrument. The description of the exact experiment and excitation method is however missing in this paper. It is unknown if the excitation frequency range was only limited to the range to the reported range to which humans are most sensitive (2 - 8 Hz [13]). The results of these two studies align with a study on ride quality estimation which used a shaking rig to test an iPhone at 100 Hz versus to a PCB accelerometer [22]. This study reported the measured accelerations to be well-aligned for the frequency ranges of interest (2 - 25 Hz) [22].

A dedicated paper conducting laboratory tests specifically for track irregularity estimations was also identified [19]. This paper focused on the application of smartphone accelerometers for railway irregularity detection in in-service vehicles by placing numerous smartphone models on a shaking rig. The magnitudes of the transfer functions of 6 different smartphone models from 2021 were provided in the frequency domain from 5 Hz up until their maximum sampling frequencies. The sampling frequencies of these smartphones varied per device from 200 to 800 Hz. The paper reported that the devices showed satisfactory results up to 20 Hz, most models showed signs of dampening between 20 and 100 Hz, and show low-pass filter behavior at higher frequencies (above 100 Hz) [19]. Furthermore, this paper concluded that the transfer function and sensor properties can differ substantially per smartphone.

Besides experiments in a lab, in-situ comparisons have been conducted. In a study on ride quality, a higher level of noise and lower level of sensitivity was observed between the smartphones and high-end accelerometer [2]. This conclusion was based on visual inspection of the resulting figures in both time and frequency domain. The signals have been reportedly downsampled to 35 Hz, creating a limited frequency range for comparisons. In [4], lateral and vertical accelerations of 2 smartphone models were compared to a high-precision sensor. The standard deviations over a 5-second window seemed to deliver comparable results for the vertical and lateral accelerations, but still displayed a degree of variance between the devices. The sampling frequency of the devices is not referenced by the paper.

In-Situ comparisons have also been conducted for geometry monitoring purposes. A study on track geometry measurements through smartphones reported that the correlation between smartphone accelerometer measurements and dedicated car body accelerometer equipment showed correlating values up to 90% [36]. This correlation was conducted after a 16 Hz low-pass filter was applied. Another study compared accelerometer measurements obtained by a smartphone to those of a dedicated accelerometric suitcase [5]. This device was capable of measuring up to 200 Hz, and was installed on commercial high-speed trains. The accelerations were filtered using low-pass filters with a cutoff frequency of 10 and 6 Hz for the vertical and lateral accelerations respectively. A statistical analysis of 325 kilometers of data, with a reported vehicle speed of 300 km/h, reported that there were differences between the measured accelerations. These differences did however comply with the tolerances defined in the SNCF Réseau standards [5].

A notable observation found when investigating the figures in [13] and in [4] is that the quality of the smartphone accelerometers compared to dedicated measurement equipment also differs per axis (x, y and z) of the device.

2.1.2. Ride Comfort Monitoring

Due to the smartphones of passengers being in the car body, the vibrations recorded by the smartphones may reflect those experienced by the passengers. Therefore, research has been conducted to the application of smartphones as real-time ride comfort measurement devices. Studies as [2], [6], [13], [22], [23] and [28] all focused on ride comfort monitoring.

The study in [2] developed an app relating vertical vibrations to ride quality indices (Sperling index, RMS) and compared the results to a PCB accelerometer. The paper concluded that lower levels of discomfort showed inconsistencies when compared to the PCB, but higher levels of discomfort showed similarities.

The study in [6] evaluates ride quality over two established industrial standards, the weighted RMS which uses acceleration measurements over a 5 second window, as well as the so called Mean Comfort Standard Method, which uses the 95% percentile value of 60 5-second window RMS weighted accelerations. The paper does not comment on any ground truth of the devices used for the onboard testing but justifies the correctness of the calculated indices based on a shaker test with a different model smartphone.

The figures in the article of [22] show a high degree of overlap between the RMS weighted accelerations obtained from the smartphone measurements and those of the high-end accelerometer. This test was conducted on a light-rail system.

Another study into ride comfort was that of [28]. This study contains a case study investigating through experimental measurements the ride quality of a metro vehicle. The track measured is relatively short, and contains several discontinuities, amongst which transition zones and a fish plate as part of a crossing. The paper itself does not contain any comparison between dedicated sensors and smartphones sensors and purely bases the quality of the observations on those of [2]. Furthermore, the railway system used in the case study is a metro system and not a “heavy rail” system, with trains reaching a maximum speed of 10 m/s.

2.1.3. Behaviour around Elements and Irregularities

Some previous works tried to refer observations in obtained signals by the mobile phones back to elements in the tracks. It has been reported that for low speeds (10 m/s) on lightrail systems, observed spikes in the measured vertical acceleration of mobile phones coincide with elements such as fishplates and transition zones in [28]. This means that both long- and shortwave irregularities may be detectable in the car body. The high magnitude in the vertical acceleration measurements around bridges and crossings was also observed on a heavy rail line in Hungary by [36]. At higher speeds on long distance lines, spikes in (dis)comfort indices such as RMS weighted acceleration were reported to coincide with bridges, switches, culverts and level-crossings in [6]. This is in line with the observed relation between high levels of acceleration-based discomfort indices and the presence of bridges and (deteriorated) switches and crossings using a phone on regional railway lines in [23]. At higher speeds up to 220 km/h, high standard deviations of the measured vertical acceleration signal were reported to generally correspond to irregularities in [24].

2.1.4. Alignment and Geometry Monitoring

Monitoring of the track quality, such as alignment and geometry, has been a topic in a limited number of papers. They are usually relating to cant monitoring, monitoring of the longitudinal level and outlier detection.

Two similar papers have been identified related to the monitoring of alignments, specifically cant and track twist. Both papers made use of dedicated measurement vehicles with smartphones mounted on the floor of this vehicle. The study on heavy rail lines in the Netherlands reported that the smartphones were able to detect when cant starts and stops and the signals from the smartphones were able to report deviations of the cant consistently in relation to each other [30]. A study in Hungary utilized both gyroscope and accelerometer measurements from smartphones and compared these to results acquired from more high-end car body mounted IMU-devices [36]. An observation from this study was that both the two smartphones used for this experiments, as well as individual axes of each phone, showed different levels of correlation to the high-end sensing equipment. The figures in [36] display similar results between cant and curvature calculated by the professional equipment and the smartphones, albeit with small differences persisting. Instances of track twist show missed detections when using smartphones in [36] compared to the measurements of the car body sensors.

The longitudinal level monitoring of railway lines has shown promise in [24], based on the standard deviation of vertical signals, in [34], based on wavelet transformations, and in [20], by integrating the vertical accelerations to displacements on lightrail vehicles.

In [24], a heavy railway line in Portugal (with speeds up to 220 km/h) is studied. A cross-correlation rate between the standard deviation of vertical accelerations of a smartphone and standard deviations of the longitudinal level of up to 0.85 using a sliding window was reported.

In [34] the frequency contents of vertical accelerations of a smartphone are analyzed on regional railway lines with a maximum speed of 85 kilometers per hour. After applying a continuous wavelet transformation, a difference in wavelet amplitude can be seen around a longitudinal level track irregularity in the lower frequency domain (around 1 Hz.) After maintenance works have taken place on the track, no difference in wavelet amplitude can be observed anymore. This paper therefore shows promise that geometrical irregularities can be detected as outliers in the frequency domain of a mobile phone.

In [20], longitudinal geometrical degradation of a tram system was estimated through vertical accelerations from smartphones. The vertical accelerations were passed through an undefined low-pass filter and compared to hand-measured geometry measurements under different speeds [20]. Although the estimations approached the geometry results, a 100% compliance could not be reported by the paper. Repeatability of the measurements at different speeds was assessed based on the DIN EN 13848-2 norm, which was exceeded in some scenarios, but remained within the bounds in others [20]. It is noted that this paper states that the methodology used in it is deemed unsuitable for systems where the vehicle speeds exceeds 70 km/h. The vehicle suspension system is presumed to have a more significant influence on the measured accelerations in those systems [20].

The last category is outlier detection. In [21], it was reported that a railway surface anomaly based on the rotation rate was detected, calculated from measured accelerations by the smartphone. This test was however conducted on a road-rail inspection vehicle instead of an actual train. The likelihood of severe track surface irregularities were identified when the rotation rate exceeded a certain percentile. For finding the location of the anomaly, the GPS-signals of the smartphones are recorded and combined to find a predicated “centroid” location for each of the anomalies. The paper reports the location estimates with multiple phones over multiple runs leads to a predicted anomaly location within a visual sight distance (3-meters) of the actual anomaly location [21]. Applications of smartphones in the health monitoring of lightrail systems has also been investigated. In [15], the amplitude of vertical accelerations of multiple measurements were corrected for their speeds, and converted into a (cumulative) probability of vibration by dividing the vibrations through the total recorded vibrations. Validation of the track health state was done through visual inspection with video recordings. The report concluded that areas with a high cumulative probability of vibrations were “far more degraded” than regions with lower cumulative probabilities of vibrations [15].

2.1.5. Repeatability of Measurements

When monitoring track quality, repeated measurements over the same track should reflect consistency. However, when sourcing data from the smartphones of passengers on in-service passenger trains, the amount of operational variance encountered could influence the repeatability of these measurements. Operational variance is, in this context, variance caused by regular operations on the railway network. Sources of variances included in this literature review are:

- The vehicle speed. If train driving is a manual operation, variations in driving regimes are to be expected per train driver. The same point in the network may be passed at different speeds as a result.
- The use of different vehicles. A train operator may run train services with multiple pieces of rolling stock. Variations in the health state within the vehicle fleet, in particular suspension systems, may lead to different accelerations being recorded.

The observations from [5] and [15] give an insight in the challenges related to how external effects varying per run, such as the vehicle speed, influence the amplitude of the measured accelerations and therefore the consistency of repeated measurements. Difficulties with the repeatability of measurements over the same line have been reported in [5]. This is a paper on the use of using passenger trains for track geometry monitoring on the high-speed rail network of France. This conference paper investigated the repeatability between acceleration measurements on the same track with different train runs on a high-speed line. The acceleration signals showed higher amplitudes in the time domain, which was attributed to the difference in train dynamics at higher speeds and the time synchronisation of the signals during the analysis. The report furthermore reported higher power spectral density levels in the run with a similar, but slightly higher speed [5]. Another report on the monitoring of vibrations on the Melbourne tram network used a linear regression model to quantify a relation between the vehicle speed and measured vertical accelerations [15]. This was done to try and differentiate the vibration-magnifying effect of vehicle speed from that of damage. The accuracy and error of this regression model are not discussed in the paper. High speed magnifying the amplitude of vibrations registered in the car body is also discussed in [23].

A general observation is that, in previous research encountered in the literature review process, there is little reporting on and comparison of repeated measurements over the same track, let alone with different vehicles or car bodies. Exceptions include [5], [15] , [38] and [6], of which only the latter 2 display explicitly the results of measurements in two different car bodies. Both display small variations between the vertical acceleration signals from 2 different car bodies. These differences may also be caused by the use of different smartphones models in the different car bodies. In [38], it is not made clear if the smartphones placed in the different car bodies are the same model, and in [6], the 2 smartphones shown for the 2 different car bodies are of different models. The variance caused by differences between railway vehicles is therefore largely left unexplored.

2.1.6. Research of Position in Car Body

When sourcing data from smartphones of passengers, the smartphones could be anywhere a passenger could be. This raises the question what the effect is of the position of a smartphone within a car body and how previous studies encountered this. A limited number of studies has addressed different positions within vehicles and co-ordinate alignment issues. as passengers can find themselves on any location within the car body.

All of the identified studies on trains have used mobile phones in a fixed position within the vehicle to measure accelerations. Most of the studies mounted the smartphones directly on the floor of the car body, with some using an adhesive or magnets ([4], [5], [22], [24], [28], [38]), others installed the in the drivers cabin [34] or on the window glasses [36]. In most cases, these are rigid surfaces, which allow for more vibrations to be captured from the vehicle movement on the track, as stated in [15]. In [6] experiments are conducted with the smartphone being mounted on softer surfaces (e.g. in a pocket, on a seat) to simulate different signals from passengers in regards to comfort monitoring. Although no in-depth analysis of the signals is given, the combined acceleration of the smartphones are reported to show a similar pattern, with the standard deviations of signals acquired in pockets and on the floor being of similar magnitude. Finally, in [13], a smartphone was placed on a seat and on the floor on two separate measurement runs for comfort calculations. No conclusion can be drawn on the damping conditions of the chair, since the measurements took place on two different runs.

At lower speeds (10 m/s), for an analysis regarding transition zones, no major differences differences were reported in the vertical acceleration signals acquired by smartphones installed at different positions on the floor of a railway vehicle [28]. This conclusion seems to have been drawn on visual inspection, and not through analytical means. Furthermore, the study took place on a vehicle with a relatively short car body. In another paper, on a heavy rail line with speeds up to 120 km/h, four pairs of phones were instrumented along the length in the car body of a measurement vehicle and have shown consistency in the time domain when determining the start and end of cant in a curve in [30]. No in-depth analysis of the different results depending on location within the vehicle is provided.

Finally, the coordinate system of the inertial sensors in smartphones of passengers may not always align with those of the railway vehicle. Methods of aligning the axes of the smartphone accelerometers and the railway vehicle coordinate system are presented in [4] and [38]. The study in [4] makes use of maximum likelihood estimation to retrieve the disalignment between the coordinate systems but does not provide specifications in relation to the used formulae nor does it account for potential disalignments in the z-axis direction. The report of [38] minimizes the covariance between the lateral and longitudinal accelerations during running time after retrieving the angle to the z-axis when the vehicle is at standstill.

2.1.7. Human-Caused Disturbances

A brief note should be made on errors originating from human-caused disturbances. This literature review has not found dedicated research related to this. However, observations have been reported that human interactions cause high-energy spikes visible in the frequency domains, that strongly deviate from the expected signal in [30]. In [6] it is reported that there were observable differences in the acceleration signal between an empty rail car and one filled with passengers. This could perhaps also be attributed to the differences in smartphone models used in this study for the full and empty car.

2.2. Survey on industrial knowledge and developments

This section supplements Section 2.1 with a survey on the industrial experience with mobile crowdsensing for railway infrastructure monitoring. Industrial parties are not synonymous to (academic) research institutes. Because of this, insights obtained and experiments conducted may not have been published or are difficult to access. To further future research into this topic, an overview on experience in the industry may be beneficial for the following reasons, amongst others:

- Demystify the extent to which infrastructure managing parties have developed such concepts and for which specific monitoring purposes.
- Expand or detail the list of key challenges, according to experiences in the field, related to this technology.
- Provide researchers insight on where industrial knowledge on particular topics may be located.
- Illustrate the presence or absence of current demand related to this technology.

A survey was deemed the most effective way to gather information about knowledge and developments in industry on this topic. This way, different perspectives can be retrieved from multiple sources in a relatively short time window. Questions were based on information from the literature review. Infrastructure managers collaborating on WP09 of the Europe's Rail Flagship Project 3: IAM4RAIL were asked to participate on the survey. WP09 of Flagship Project 3 strives to develop "innovative wayside, onboard and crowd-based sensing solutions for the timely extraction of track infrastructure data" [7]. This thesis deems them as experts in the field of industrial knowledge on railway infrastructure asset monitoring. Employees of collaborating partners were asked to fill out an anonymous survey to the best of their knowledge and ability. Questions related to:

- If and to what extent their organisation has researched this topic.
- The specific monitoring purposes their organisation has researched.
- The key challenges their organisation has identified or foresees in the implementation of using a smartphone-based railway health monitoring system.
- If their organisation would be interested in sharing outcomes and observations of their previously conducted research.
- If their organisation would be interested in further research regarding this topic.

The survey itself and responses can be found in Appendix A.

In total, 3 responses were gathered. The organisations that replied were ProRail, SNCF Réseau and Trafikverket, depicted in figure 2.1.

Of the three organisations that responded to the survey, Trafikverket indicated not to have researched the use of smartphones for railway infrastructure condition monitoring. The provided reason as to why this was not investigated was a lack of resources to launch an investigation. ProRail indicated that it has researched the topic in the past in 2018, but is no longer actively researching the topic anymore, citing a lack of promising results. SNCF Réseau is still researching the topic, starting in 2016.

Both ProRail and SNCF Réseau used accelerometers and gyroscopes. The latter sensor is however not present in some of the smartphones used in this thesis. Both organisations investigated the use of smartphones for track alignment or geometry measurements, but ProRail additionally indicated it looked into using it for vehicle condition monitoring. SNCF Réseau also developed a smartphone application called "KELI".

Table 2.1: Table containing main sources of literature used in the thesis. All are related to the use of smartphones for track quality assessment

Ref.	Author	Year	Title	Location Onboard Testing	System	Key Findings Relevant to Thesis
[2]	Azzoug and Kaewunruen	2017	“RideComfort: A Development of Crowdsourcing Smartphones in Measuring Train Ride Quality”	England	Railyard	Smartphones display different levels of noise and sensitivity in the vertical acceleration signal.
[15]	Karimpour and Modripour	2019	“A Novel Method in Light-Rail Condition Monitoring Using Smartphones”	Australia	Tram	The report includes the effect of speed on the recorded vibrations of smartphone accelerometer measurements. It states a relation between the vertical accelerations measured by multiple runs over a track with a smartphone and track degradation based on visual inspection.
[24]	Paixão, Fortunato, and Calçada	2019	“Smartphone’s Sensing Capabilities for On-Board Railway Track Monitoring: Structural Performance and Geometrical Degradation Assessment”	Portugal	High-speed lines	Acceleration measurements are performed from in-service passenger vehicles through mobile phones and compared against the standard deviation longitudinal level of track geometry records.
[28]	Rodriguez et al.	2021	“Smartphones and tablets applications in railways, ride comfort and track quality. Transition zones analysis”	Spain	Commuter line	Reports higher amplitudes in vertical accelerations measured by smartphones around transition zones and short-wave irregularities.
[5]	Dadié et al.	2022	“Track geometry monitoring using smartphones on board commercial trains”	France	High-speed lines	Addresses the challenge in consistency of measured accelerations of smartphones between different measurement runs as a result of slightly different speed profiles.
[19]	Leibner, Stillfried, and Schindler	2022	“Potential of estimating track irregularities from in-service vehicles using smartphones”	N/A	N/A	Provides key insights in the heterogeneic characteristics of the transfer functions of different smartphones, including phenomena such as low-pass filters and resonance frequencies.
[34]	Tsunashima, Honda, and Matsumoto	2023	“Track Condition Monitoring Based on In-Service Train Vibration Data Using Smartphones”	Japan	Regional lines	Time-frequency analysis shows heightened energy levels in the low frequency domain around a longitudinal geometric defect. The levels are not visible on the location after maintenance is conducted.

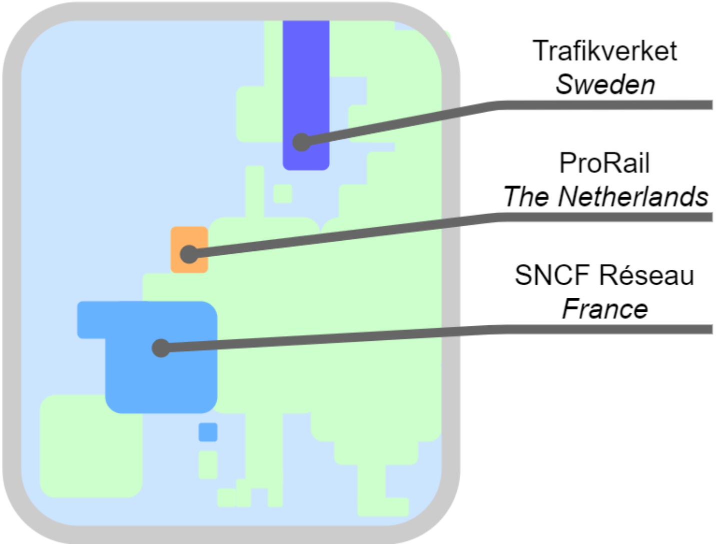


Figure 2.1: Respondents of the survey on a map of mainland Europe.

When asked about the key challenges in the implementation of a measurement system involving the accelerations measured by on-board smartphones, both the Dutch and French response report the following challenges:

- Heterogeneity of vehicle suspension system health states.
- Relating the measured accelerations back to positions in the railway system.
- Differences between different accelerations measurements as a result of different speeds and driving behaviour.

The French response also indicated that the data quality produced by the smartphones is a significant challenge. The Dutch response on the other hand has included that establishing relations between smartphone measurements and railway performance indicators is a challenge. This difference in responses may be related to that the SNCF Réseau has studied the topic longer than ProRail, and may have already found meaningful relations, whereas ProRail indicated it had stopped because of a lack of promising results. The SNCF Réseau may also have more experience with the heterogeneity of the smartphones than the Dutch research, as the investigation time is significantly longer.

Both ProRail and the SNCF Réseau have indicated to be interested in sharing observations of already conducted research involving the use of smartphones as on-board measurement devices for railway condition monitoring. This means that independent researchers, as well as infrastructure managers, could benefit from the knowledge on encountered challenges and identified relations of other infrastructure managers. This could then boost innovation and accelerate breakthroughs on implementation challenges of such a system.

When asked about if the infrastructure managers would be interested in future research and investigations in the field of using smartphones as onboard measurement devices, all respondents replied with “yes”. This illustrates a certain demand for further developments in this technology. The responses for the motivation varied per infrastructure manager. The French response stated that there are still unexplored areas in this research, such as acquiring a reliable position on the tracks, validating data quality over time and exploring new analyses of car body accelerations. The Dutch answer was more sceptical, stating that, although this topic keeps popping up, due to poor positioning and the suspension system, only the cant has shown in the past to be measured properly. It furthermore included that smartphones are only useful for comfort measurements, for which ProRail is not responsible, and that for comfort measurements, gyroscopes embedded in the railway vehicles are the preferred method. Nevertheless, they show interest if there are any new outcomes. Finally, the Swedish response stresses that smartphones can be a cost-effective way to get information of the comfort and train-related issues, in addition to get some information on the railway tracks themselves. The elaborations on this answer are summarised and presented in figure 2.2.

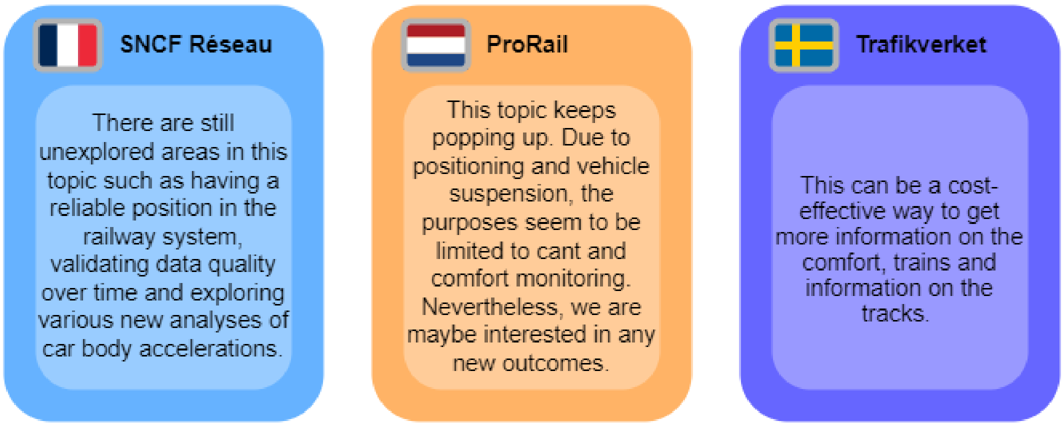


Figure 2.2: Paraphrased or summarised elaborations on why the respondents would be interested in further research and investigations in the field of using smartphones as onboard measurement devices for railway condition monitoring.

2.3. Conclusions on research gaps and challenges

This literature review concludes with the identified research gaps and challenges. The research gaps that this thesis concerns itself with are described and summarised in this section, other research gaps encountered are included in the recommendations for future research in Section 6.4.

First of all, most published research has focused on using smartphones as ride comfort monitoring devices and not for track quality monitoring. Limited research has been done in investigating relations between track geometry parameters and the accelerations measured by smartphones in the car body. Establishment of the relation between the standard deviation of the Longitudinal Level and the standard deviation of the vertical accelerations has already conducted in [24]. This therefore focuses primarily on furthering knowledge on the vertical accelerations measured in the vehicle and its relation to Longitudinal Level track quality.

Detailed analyses in the frequency content of vertical smartphone accelerations and their relation to the track infrastructure is another topic which has not been researched to the fullest. The primary observations as of now being that [34] was able to observe the presence of longitudinal-level irregularities through wavelet transformations and [24] have noted having observed the submultiple of the sleeper spacing excitation frequency in a periodogram. The level of information being able to be obtained from the frequency contents of the smartphone accelerometers is one of the topics to which this thesis seeks to contribute.

Then there is the problem of heterogeneity of the accelerometers embedded in the smartphones. The differences in vertical accelerations observed on board a railway vehicle were documented in [2]. This research was however done using devices from 2011 and 2012, which had already suffered damages and replacements of which the effect on the accelerometers is unknown. Laboratory tests conducted in [19] concluded that the properties of accelerometers and their transfer functions can differ substantially per smartphone. This study made use of more recently released devices, with all device models being first released in 2021 or 2018. As new model smartphones come out each year, the sensor characteristics related to contemporary smartphones need to be quantified continuously. This thesis will therefore investigate a variety contemporary (2023) smartphones, assess their accelerometer characteristics, and verify the observations on heterogeneity in previous works.

Furthermore, this thesis will investigate how this heterogeneity transfers to previously established relations regarding track geometry monitoring. In the correlations of [24] only one type of smartphone was used, a model from 2012. It is unknown if this correlation is as visible in contemporary and different devices. Similarly, the observations by [28], on the presence of high amplitudes in vertical accelerations at (degradation prone) irregularities, do not seem to have been investigated for different smartphone devices.

Another identified challenge is the consistency of repeated measurements over the same track in different runs. In [5], two trains passing the same piece of track with slightly different speeds already result in differences in the time and frequency domain of the acceleration signals. In [15], a relation was established through regression between the vehicle speed and the amplitude of the vertical accelerations recorded by the smartphone, but details of the quality of this regression analysis are lacking in this study. Furthermore, this study was conducted on a light rail system, whereas the system analysed in this thesis is a conventional railway line. The variation caused by variance in the health state of the vehicle fleet may be another unexplored source of uncertainty. Therefore, how to deal with this operational variance remains an open question in the context of mobile crowdsensing. The thesis aims to contribute to understand the effect of speed and different vehicles on the variance of the vertical acceleration signals.

Finally, the effect of different positions of smartphones within the car body has not been studied in-depth in the identified pieces of literature. In most previous research, 1 or more smartphones are simply placed (on the same location) near the bogies. Different positions along the length of the car body are either addressed briefly through visual inspection [28] or deemed outside of the scope of the research [30]. The effect of these different positions along the length of a car body, and its effect in both the time and frequency domain, will be addressed in this thesis.

3

Smartphone Accelerometer Heterogeneity Analysis

Measurements of [2] in 2017 found that different smartphone models will register different accelerations on board of railway vehicles in terms of noise levels, sensitivity and sampling rates. A study in 2023 showed that smartphone accelerometers display strong heterogeneity between different smartphone models when it comes to dynamic sensitivity [19], including the presence of device-specific eigenfrequencies and internal low-pass filters. Although smartphone accelerometers have shown fairly good compliance with dedicated measurement devices in the low frequency domains in [6], [13] and [22], the relative quality amongst different models can differ significantly. Furthermore, information regarding the quality of accelerometers is usually not easily accessible or even available. As a result, the heterogeneity of the main characteristics of smartphone accelerometers used should be analysed through experimental means. The chapter answers the question: In which ways do the sensor characteristics of different contemporary smartphone devices differ?

This chapter includes an assessment of the heterogeneity of a number of smartphone models. Three different smartphone models of different brands were acquired, and some of the characteristics of their accelerometer sensors analysed. Section 3.1 contains information on this set. Section 3.2 includes a static test in which the phones were only subject to gravity. This test analyses the sampling frequencies of the accelerometers, the standard deviation of the measured accelerations and how accurate they could measure gravitational accelerations. An impact hammer test assesses the dynamic sensitivity of the smartphones compared to high-end sensors in Section 3.3. Examples of dynamic sensitivity characteristics are the presence of eigenfrequencies and low-pass filters. Section 3.4 includes tests onboard of a measurement vehicle. This verifies observations of Section 3.3 and gives insights in the relative error between the smartphone accelerometers and dedicated measurement equipment. Finally, Section 3.5 summarises the main conclusions regarding smartphone accelerometer heterogeneity.

3.1. Smartphone Test Set Information

For the execution of this master thesis, 9 smartphones were acquired. The thesis refers to this set of smartphones as the "test set". Three different smartphone models, from 3 different brands, form the test set. The test set thus contains each smartphone model 3 times. Information on the accelerometer specifications within the smartphone is difficult or impossible to retrieve, which makes selecting a set of smartphones containing accelerometers with diverse characteristics challenging. By using 3 different brands, the test set would likely contain devices with different accelerometer characteristics. This resembles the smartphone accelerometer diversity found in real world applications more accurately and makes this study more representative. All smartphones were released in the year 2023, to make the insights in the technology as contemporary as possible. Table 3.1 gives specifications about the devices and their embedded accelerometers.

Table 3.1: Smartphone specifications from test set

Name Model	Brand	Year	Accelerometer Name	Name Vendor
Moto G14	Motorola	2023	Accelerometer Sensor	Sprd Group Ltd.
Nokia C32	Nokia	2023	Accelerometer Sensor	Sprd Group Ltd.
Samsung Galaxy A14	Samsung	2023	mc34x9	MEMSIC

Specifications of the different smartphones. The names of the accelerometers and vendors are retrieved from the Phyphox smartphone application.

3.2. Static Test

In [2], observed different noise levels between different smartphone accelerometers on board of a moving train. This indicates a difference in the precision of smartphone devices. However, [19] presented differences in dynamic sensitivity between smartphones. Therefore, the differences in observed signals may also be attributed to the presence of device-specific resonance frequencies or the presence of internal low-pass filters. A static test in which there is virtually no excitation present can provide insight in the differences in precision or noise of the different devices. Such a test minimizes influences from the dynamic sensitivity to specific frequency ranges. Additionally, this test assesses variance in the sampling frequency as observed in [2] and confirms differences in precision along the different individual axes of the accelerometers established in [13].

3.2.1. Equipment and Experiment Set-up

Three different smartphone models from the test set are mounted on a wooden board using double-sided adhesive tape. This wooden board is placed on a structure resting on a rubber block as depicted in Figure 3.1. Figure 3.2 displays the orientation of the axes of the 3 accelerometers within the smartphone devices. The test was carried out in the Stevin-II Laboratory of the Faculty of Civil Engineering and Geosciences at the Delft University of Technology. During the testing procedure, no vibration-inducing tests were known to be running elsewhere in the laboratory. The structure is therefore presumed ”isolated” from external excitation and only subject to gravity.

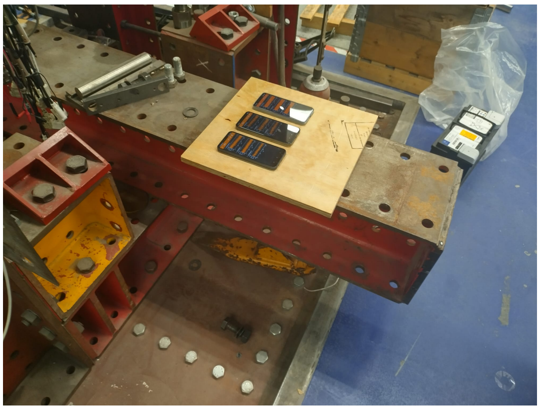


Figure 3.1: Smartphones on the structure on the rubber block.

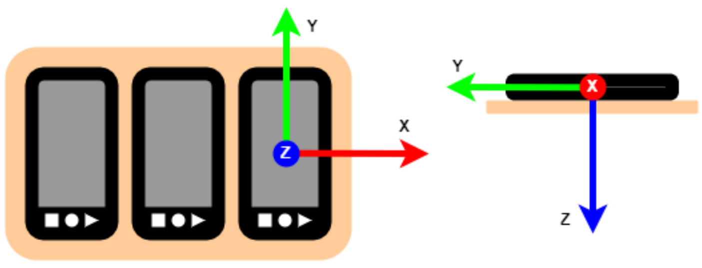


Figure 3.2: Orientation of the axes of the smartphone accelerometers mounted on the board

Extracting data from the sensors in the smartphones is done through the Phyphox app, developed by the RWTH Aachen. This thesis uses this software for acquiring all data from smartphones. This software was chosen because it is both free to use and allows direct built-in exports into the CSV-file format. More information about the Phyphox project can be found in [32].

3.2.2. Methodology

The smartphones collect acceleration data simultaneously for 9 minutes at their respective maximum sampling frequencies. Every minute, the mean and standard deviation of each axis are computed for each smartphone. These means are used to compute the total acceleration the smartphone is measuring through the vector magnitude. This is then be compared to the total expected acceleration the smartphones are subject to (the gravitational acceleration: 9.81 m/s^2). Over the whole 9 minute segment, the mean sampling frequency is computed and the sampling frequency distribution analysed.

3.2.3. Results and Findings

This thesis uses the programming language Python to process and displays data using the Matplotlib package in Python [14]. Figure 3.3 displays the raw acceleration signals recorded by each smartphone, per axis. Figure 3.4 shows the total accelerations every minute, based on mean values per minute. Figure 3.5 displays the standard deviations for the measured accelerations per axis calculated for each 60-second window. Figure 3.6 provides boxplots of the different sampling frequencies over the 9 minute measurement period.

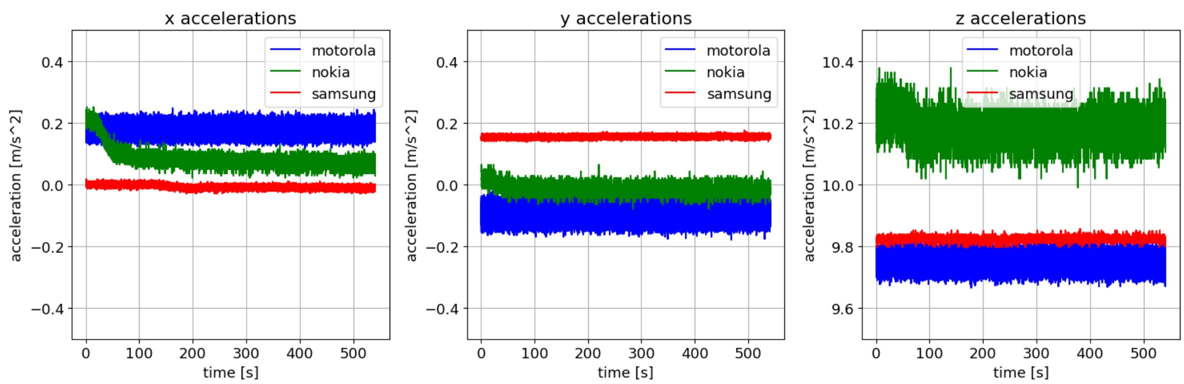


Figure 3.3: Raw accelerations of all three axes for each smartphone

The first finding is that, although the z-axis of the smartphones placed perpendicular to the surface, the mean acceleration measured along other axes was never perfectly equal to 0. For the Nokia and the Samsung, this makes sense, as they have a camera protruding from the back and can not be perfectly placed horizontally. The Motorola does not have this, but still register a mean x-acceleration of around 0.2 m/s^2. This could be attributed to the structure not being perfectly levelled, or the sensor axes of the smartphone not perfectly aligning with the surfaces of the smartphone.

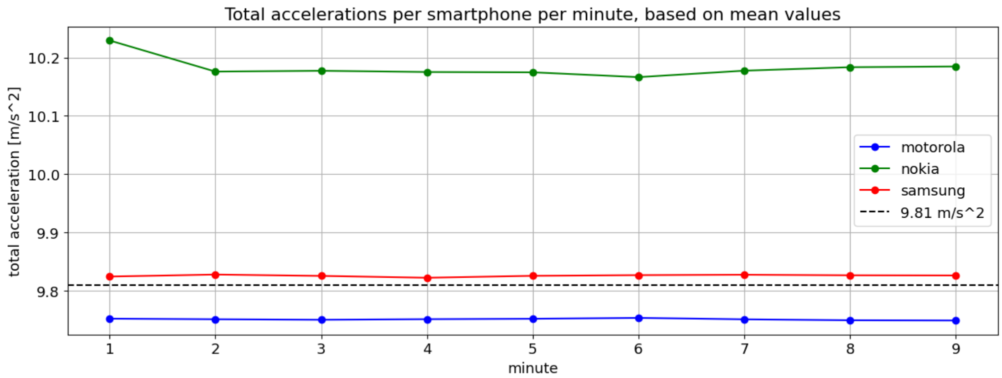


Figure 3.4: Total acceleration per smartphone per minute based on mean values

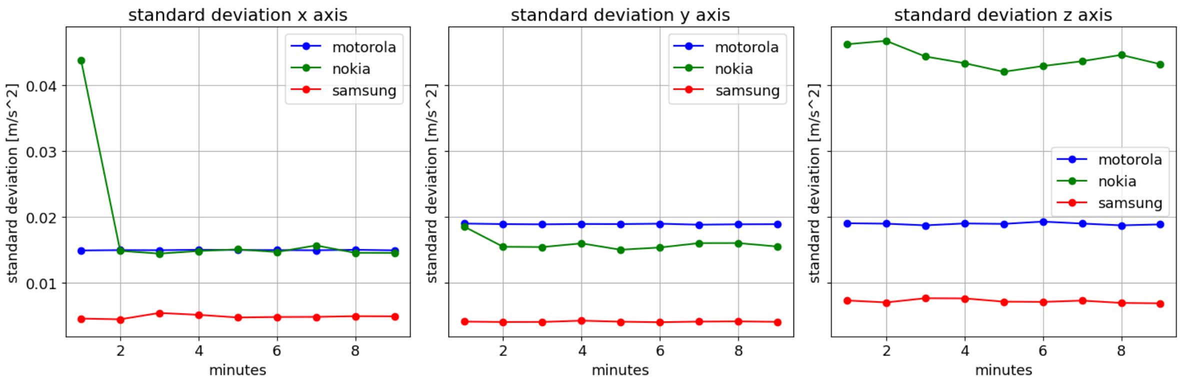


Figure 3.5: Standard deviation per minute, per axis, per smartphone

Based on Figure 3.4, the Samsung has the highest accuracy as it approaches 9.81 m/s^2 the closest of the three sensors. The Nokia on the other hand has the lowest accuracy of the test set, missing the target value consistently by almost 0.2 m/s^2.

Additionally, the Nokia in figure 3.3 shows a decrease in the measured accelerations in all 3 axes in the first 60 seconds of the considered time window, before stabilising around t = 100 seconds. It is unknown what causes these higher measured accelerations at the start of the measurement. This phenomenon has not been encountered in the literature review for this thesis. It is thus unknown if and how this phenomenon has affected the measurements in previous works on smartphone monitoring applications for railways. Detrending may be possible, but at the cost of potentially losing information (e.g. detrending may be unsuitable for cant and twist monitoring such as in [30]).

For the precision, the Samsung shows the lowest standard deviation of all phones in the test set in Figure 3.5, for each axis. The standard deviation around z-axis does seem to be double that of the standard deviation of the x- and y-axis of this phone. The Nokia shows a much stronger standard deviation along the z-axis than for the other 2 axes. The outlier of the Nokia at minute 1 on the x-axis can be related back to the strong downward trend in accelerations observed in Figure 3.3. Finally, the standard deviations of the Motorola along the different axes are within a similar range of one and other.

Figure 3.6 displays that all 3 phones have different sampling frequencies. The Motorola has the highest sampling frequency with a mean of 380.93 Hz, but also has an observable number of outliers beneath the 100 Hz domain, with the minimum observed sampling frequency being 1 Hz. The Nokia and Samsung have less extreme outliers, but at the cost of a much lower maximum sampling frequency at a mean of 195.04 Hz and 200.68 Hz respectively. All smartphones have an interquantile range (IQR) of less than 0.5 Hz.

A point of criticism could be that the rubber block does not fully nullify external vibrations acting on the smartphones. Vibrations from elsewhere in the lab may have propagated through the rubber

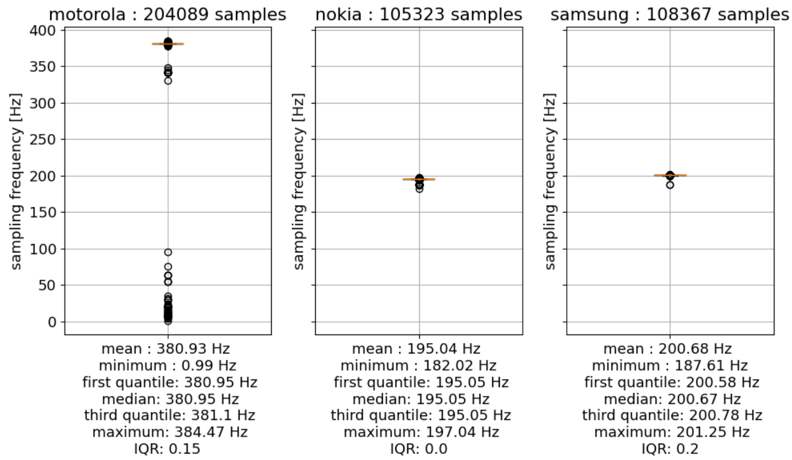


Figure 3.6: Descriptive statistics (boxplots) of the sampling frequencies over the 9 minute period

block and registered by the smartphone accelerometers. This could have resulted in higher standard deviations for one or more of the axes.

3.3. Hammer Test

The most extensive paper found on the assessment of smartphone accelerometers for railway health monitoring is that of Leibner et al. from 2023 [19]. This paper attempts to evaluate the use of smartphone accelerometers for railway track irregularity estimation. In this paper, a number of different smartphones was placed on a shaking rig, together with an industrial grade PCB-accelerometer. Transfer functions were then estimated, up until half the maximum sampling frequency of each model, based on the readings of the PCB as input and the measurements of the smartphones as output. The resulting transfer functions report:

- Visible eigenfrequencies of the phones within the measured frequency.
- Internal low-pass filters above 100 Hz.
- Heterogeneity between devices with the same type of accelerometer.
- Signs of damping in the range between 20 to 100 Hz.

The significant heterogeneity in the transfer functions between the different devices reported in this paper makes it clear that the dynamic sensitivity of the accelerometers for each smartphone should be explored. Furthermore, the presence of internal low-pass filters and eigenfrequencies may limit both the reliability and the amount of features that can be extracted from the frequency domain in assessing the health of the railway infrastructure.

The hammer test seeks to identify the presence of observations as made in [19] for the smartphone models used in this thesis. It differentiates from this previous research by using an impact hammer test on an existing structure instead of using a shaking rig. By using an impact hammer, a known excitation of a broad range of frequencies is applied onto a location on the structure. A measurement device records the response of the structure in the form of accelerations. Through normalising frequency components of the output accelerations by the frequency components of the input force, the dynamic sensitivity of the devices can be tested over a broad range of frequencies.

3.3.1. Equipment and Set-up

The hammer used in this experiment is displayed in figure 3.7. The hammer has the same specifications as the one used in [35]. From this paper, it is cited that the hammer is 5.5 kg, has an embedded PCB (PCB086D5 , measurement range 0-22 kN) to measure the applied force.

For the hammer, a ”soft tip” from rubber is used to excite the structure with the impact loading. The frequency range of interest is relatively low (up to 190 Hz, half the maximum sampling rate Motorola) ,

Figure 3.7: The impact hammer used

as this was the highest sampling rate of the accelerometers in the mobile phones. By using the soft tip, less energy from the input force was wasted to frequencies outside this range of interest, as specified in [11] or [29].

The structure used to conduct the hammer test on was a life-sized model of a railway track in the Stevin-II laboratory of the Delft University of Technology, depicted in Figure 3.8 and Figure 3.9. The structure is deemed suitable because of its high mass. The mass of the structure makes it likely that eigenfrequencies of the structure are encountered within the limited measurement range of the mobile phones.

Figure 3.8: Track structure used in experiment

Figure 3.9: Track structure used in experiment

3.3.2. Methodology

The general experiment follows the following steps:

1. A measurement device (a smartphone model or a dedicated sensor) is placed on the mid-sleeper span on the life-sized track model.
2. The impact loading is then applied manually using a hammer on the driving point (impact location). Figure 3.10 depicts the impact location. The impact loading is spaced approximately 3-5 seconds and applied between 7 to 10 times.
3. Step 1 and 2 are repeated for another measurement device. The order of the tested devices was first the dedicated sensors, second the Motorola, third the Nokia and finally the Samsung.

The following steps form the data processing procedure, with step 1 and 2 applying only for the tests conducted with the high-end sensors:

1. The signals are cut in segments of 1.6 seconds, with the peak of the force occurring around 0.08 seconds. The signals from the mobile phones are upsampled to 10240 Hz, to match the sampling frequency of the high-end sensors and force sensor.

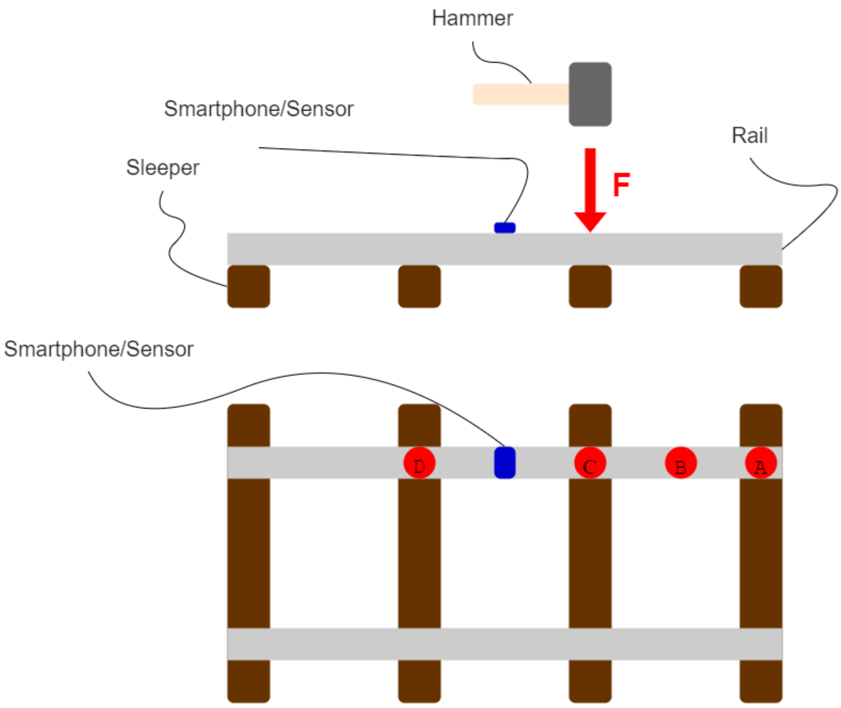


Figure 3.10: Schematic of the impact location. The impact location used in this thesis was location C.

2. The force and acceleration signals are multiplied by a conversion factor to go from volts to respectively Netwons and m/s^2.
3. Each rectangular window is inspected for the presence of double bounces (undesirable, [1]). If these are deemed present, the acceleration signal and force signal of that particular impact are discarded.
4. A rectangular window is then applied around the force, with its boundaries being the boundaries of the force peak. All values in the force signal outside of this window are multiplied by 0, to improve the quality of the force signal artificially. This procedure is similar (albeit, without a smooth transition to 0) to [3]. Some distortion of the force spectrum is thus expected.
5. Both the force signal and the accelerations are subjected to an exponential window.
6. The H1-estimator is then calculated as per [3], using the force as input and the acceleration as output. Noise is expected to be more significant in the output.
7. The resulting H1-estimators are then averaged to reduce the effect of noise.
8. Finally, the individual H1-estimators and their means are plotted.

3.3.3. Results and Findings

Figure 3.11 displays the amplitudes for the H1-estimators.

A resonance peak related to the railway tracks is visible around 37 Hz. It is reflected in the curves of the high-end sensor, the Motorola and the Samsung. The Nokia misses this peak in its FRF-curve.

Another observation of note is that the FRF-curves in the lower frequency domain vary significantly. A reason for this could be that the hammer used in the experiment cannot excite the lower frequencies sufficiently and consistently. Other explanations may be related to the trends observed by the Nokia in Section 3.2 being mistaken for low-frequency components. It is unknown why the amplitude of the high-end sensors in the 0-10 Hz domain is so much lower compared all other curves.

Similar observations are made as those encountered in the shaking rig test by [19].

- Eigenfrequencies related to the device, or its embedded accelerometers, are identified as peaks

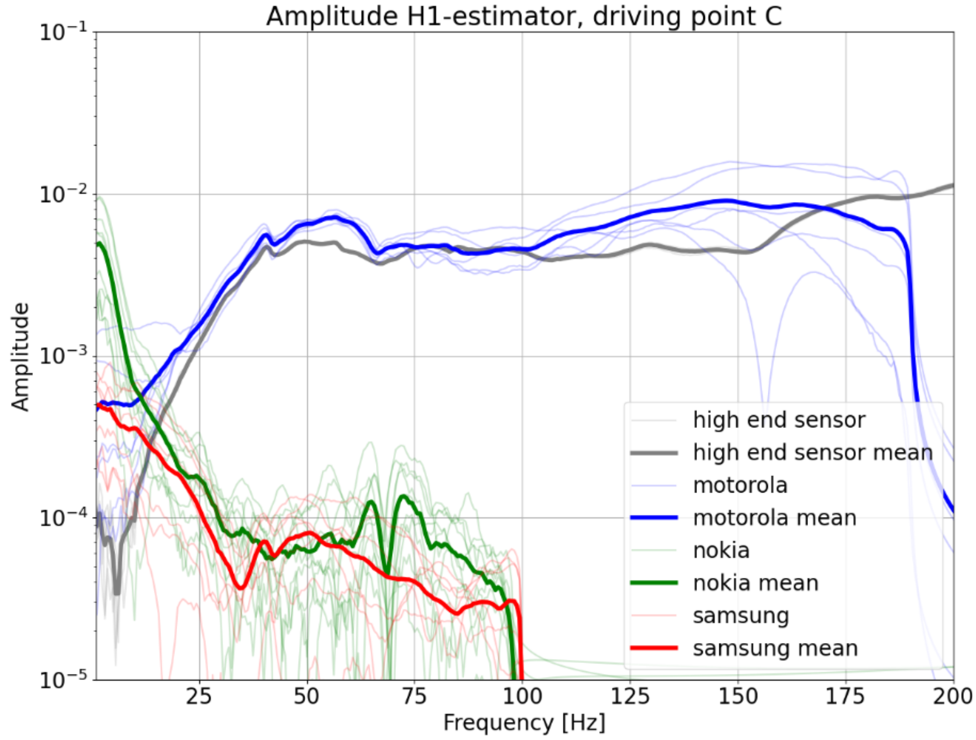


Figure 3.11: The amplitudes of the H1-estimators for the different measurement devices. The thin, semi-transparent lines represent the individual FRF-curves, whilst the thicker lines represent their means. The high-end sensors are represented by a grey line, the Motorola by blue, the Nokia in green and the Samsung in red.

or crests not being visible in the FRF-curve of the high-end sensors. The Nokia has two of these clear peaks indicating device-specific eigenfrequencies around 60 to 70 Hz. The Samsung shows an unexplained upward trend in FRF-amplitude from 80 Hz onwards, but it is unknown if this is caused by some device-specific resonance, the response function or noise in the measurements.

- Low-pass filter behaviour as encountered in [19] is observed in the FRF-curves of the Nokia and the Samsung, which both show a steep decrease from 15 Hz onwards in FRF-amplitudes as the frequency increases in relation to the one from the high-end sensor. However, in [19] for models from 2021, these low-pass filter behaviours are observed starting at higher frequencies. This leads to the conclusion that two of the cutoff frequencies of contemporary (2023), low-budget smartphones used in the test set are much lower than those of the set tested in 2021 in [19].

Some key reflective points include:

- The people applying the impact loading were not experienced hammerers. This may have resulted in more double bounces having to be filtered out in the post-processing. Additionally, there may have been difficulties in hitting the driving point with the exact same orientation and location, which is deemed undesirable (e.g. in [1]).
- The hammering was done in one afternoon. It is likely that due to the physical toll that applying the loading takes on the hammerers, hitting the exact same driving point may have become more difficult as the afternoon progresses. Variance in the impact location is undesirable, as stipulated in [1].
- The system times may have not perfectly aligned. For a small time window (1.6 seconds), this may have had consequences for the computation of the Frequency Response Functions and may have had varying influence per device.

3.4. In-Situ Test

An in-situ test is conducted to assess the heterogeneity of the measurement devices. The test evaluates the vertical accelerometers embedded in the smartphones in operational conditions on a measurement vehicle. This vehicle is the CTO train, which is a carriage used for experiments and measurements by the Delft University of Technology.

The primary aim of the in-situ test is to obtain insights into the relative error of the accelerometers in smartphones under onboard vibration conditions in comparison to dedicated measurement equipment. The experiment can confirm or expand observations regarding the dynamic sensitivity of the smartphones achieved in Section 3.3. Moreover, some of the advantages of testing in the CTO train include the controlled conditions for measurements, without disturbances from passengers and increased control of the placement location of the phones. This is in contrast to the case study experiments of Chapter 4 and 5, where the effect of variability in rolling stock conditions and disturbances from passengers are present.

3.4.1. Equipment and Set-up

For this experiment, a wooden board, with 3 different smartphones from the test set and an Inertial Measurement Unit, was placed on the floor of the CTO measurement vehicle. The devices were mounted on the wooden board with double sided tape. The z-axis of the devices was assumed to be perpendicular to the surface of the wooden board. The other 2 axes of each device were aligned with the coordinate system of the train, with the y-axes of the smartphones measuring the longitudinal accelerations of the car-body, and the x-axes of the smartphones measuring the lateral accelerations of the car-body. Figure 3.12 and Figure 3.13 show the set-up and a schematic of the devices, respectively.

Figure 3.12: The wooden board with the measurement devices

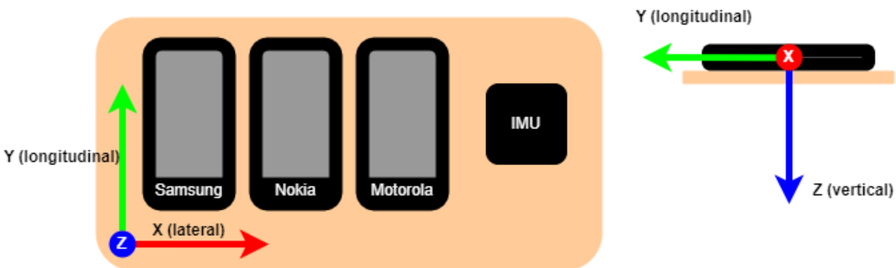


Figure 3.13: Schematic of the wooden board with the measurement devices

The model of the IMU is a PhidgetSpatial Precision 3/3/3 High Resolution 1044_0. The IMU has a sampling frequency of 250 Hz, and measures both angular and axial accelerations. The signals from the IMU are the considered close to the ”ground truth” of accelerations present in the car-body up until

250 Hz.

A first trial of measurements was conducted on the 5th of March, 2024. However little to no data was collected due to a variety of reasons:

- The data collection from the IMU did not function, which resulted in almost no validation data being collected.
- The smartphones often crashed while writing excel-files of the measurements. This likely had to do with the files being too large, due to long measurement times.

On the 23rd of April 2024, the measurements were repeated. To avoid the previously mentioned problems from occurring again, the following additional measures were taken:

- More frequent checks that data from the IMU was collected.
- Measurement periods of the mobile phones were limited to 10 minutes maximum, instead of continuous measurements over the journey.
- Measurements by the mobile phones were written to .csv-files instead of .xlsx-files. Writing to .csv-files did not cause the device to crash a single time, whereas the writing to.xlsx-files frequently crashed the device.

3.4.2. Methodology

The methodology and data processing consists out of the following steps:

1. The smartphones and IMU-device are set to record data at their maximum sampling rates. The data is then aligned into a 9 minute segment based on their system time. The system times seemed to match on second level, but in-depth analyses on misalignments in the system times have not been conducted. Possible differences in system times are considered negligible compared to the total signal duration.
2. The acceleration along the z-axis for each device is resampled to 180 Hz. This allows for an easier comparison when computing the Power Spectral Density estimates.
3. All vertical accelerations are divided into discrete windows of 10 seconds, with 50% overlap. The mean vertical acceleration is removed, to avoid the 0 Hz frequency or small changes in the trends leaking into surrounding (low) frequencies. A Hanning window is applied to further reduce the effect of spectral leakage. The windowed signals are then transformed into the frequency domain using the Discrete Fourier Transformation (through Fast Fourier Transformation) as specified by [39].
4. For each window, an estimate of the Power Spectral Density is made. The Power Spectral Densities of the windowed vertical accelerations are then averaged per device resulting in a spectral estimate in accordance to Welch's Method [39]. Through averaging, this Welch-periodogram mitigates the variance. The Welch-periodogram for each device are plotted in the same figure. This thesis uses the SciPy package in python for the computation of Power Spectral Densities, periodograms and spectrograms [37].

3.4.3. Results and Findings

Figure 3.14 and Figure 3.15 display the resulting Welch-periodograms and the raw vertical accelerations (minus their mean) respectively.

The first observation that can be drawn from figure 3.14 is that the Motorola reflects the vertical accelerations registered by the IMU device quite well, albeit at a higher magnitude from 10 Hz onwards.

Another observation is that of the internal low-pass filters of established in Section 3.3. The Nokia and Samsung clearly show a strong damping of higher frequency vibrations from around 8 Hz onwards compared to the IMU device and the Motorola. The Motorola does not seem to show any structural damping of higher frequencies compared to the IMU device, but instead indicates much higher energy levels than the IMU-device in most of the frequency domain above 10 Hz. This could be related to higher response function of the Motorola in this range, as well as differences in the damping that the casings of the Motorola and IMU possess.

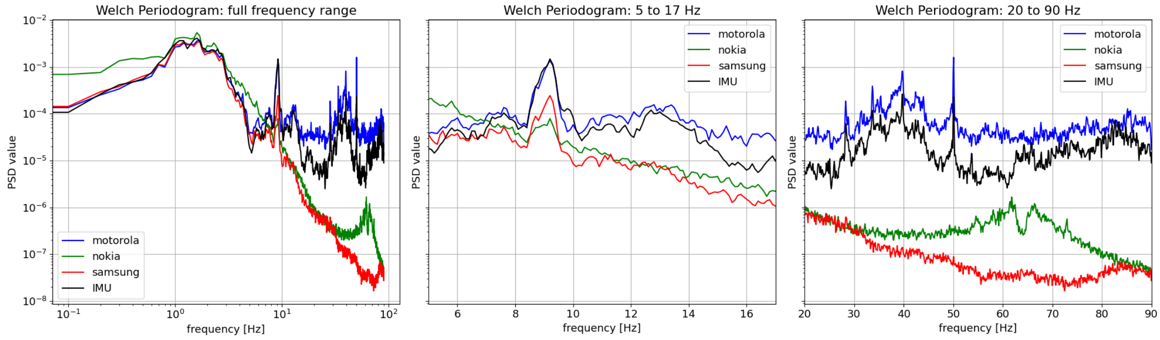


Figure 3.14: Welch-Periodogram of all the measurement devices for different frequency ranges

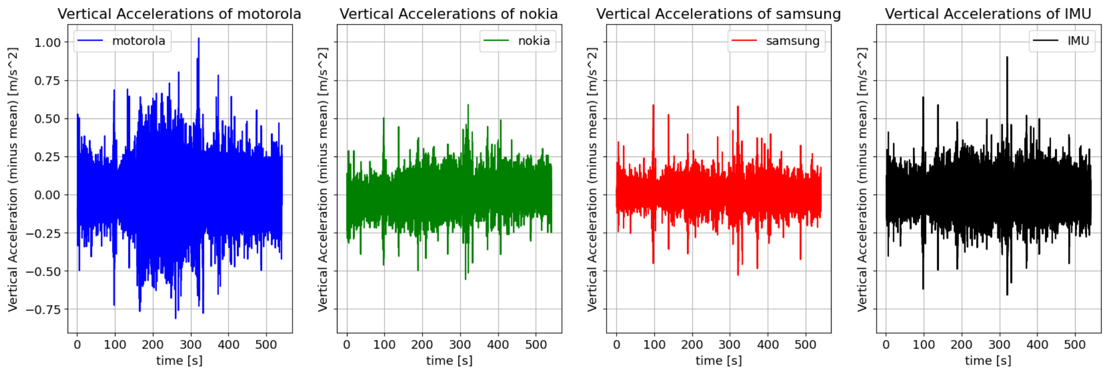


Figure 3.15: Vertical accelerations per measurement device. A clear trend is again visible in the Nokia.

Then there are the peaks observed in Figure 3.14. The peak registered by the IMU around 9 Hz is clearly visible for all 3 smartphones, although the Nokia shows only a minor increase in PSD on this frequency relative to surrounding values. A wide crest in the 30-45 Hz domain is visible in the Motorola and IMU device. Resonance peaks established in Section 3.3 for the Nokia are once again visible in figure 3.14, with clear peaks between 60 Hz and 70 Hz. Additionally, the Samsung shows an upwards crest in PSD values in frequencies from 75 Hz onwards. It is unknown if this is due to a device-specific resonance frequency, as the Motorola and IMU both show a local increase in PSD value. A very sharp peak is also observed in both the Motorola and the IMU at 50 Hz, albeit with different energy contents. A general observation is that peaks visible in the Motorola and IMU can be better observed in the Samsung than in the Nokia. The Nokia barely reflects the peaks and crests of the IMU at all at higher frequencies.

In the lower frequency ranges, the PSD values do not fully match, with the Nokia having an almost 2 times higher value than the Samsung and Motorola around 10^{-1} Hz. This may have something to do with the Nokia displaying a downward trend in figure 3.3 for the first 100 seconds of the device measuring accelerations. This trend may have been translated to low frequency components of the Fourier Transform.

The Samsung displays a something resembling sinusoidal "rippling" pattern in the 30 to 80 Hz range, which seems to resemble the results displayed in [19] for the Nokia G10 between 60 and 100 Hz.

Finally some reflections and comments on the experiment:

- Increasing the amount of windows may have lead to a smoother periodogram, with even less variance or noise present.
- Although axes of the measurement devices were made to align as well as possible with the axes of the vehicle and each other, misalignment of the axes is likely to occur. The Nokia and Samsung have protruding cameras on their back and it is therefore impossible to place them perfectly horizontally. Lateral or longitudinal accelerations may have been mistaken for vertical ones and

vice versa.

- Small misalignments in the system times may have lead to differences in the vibrations present in each window between the different devices.
- The mounting conditions (amount of double sided tape) may differ slightly per device. Therefore, the amount of damping between the car-body and the measurement device may be different.

3.5. Conclusions on smartphone accelerometer heterogeneity

The main conclusion is that smartphone heterogeneity persists for smartphones of the year 2023. The frequency ranges that can be accurately measured by the individual smartphones are limited by factors such as heterogeneity in sampling frequencies and dynamic sensitivities. Low-pass filter behaviour is encountered in both the Nokia and Samsung, with cut-off frequencies being present at much lower frequencies than displayed for a set of smartphones from 2021 [19]. Furthermore, the Nokia displays clear device-specific eigenfrequencies within the range of its Nyquist rate (around 60 - 70 Hz). Some sensor characteristics, such as the standard deviation, were also found to vary per axis. Other factors, such as the presence of non-stationary trends, may influence the frequency content of the signal and require special attention.

4
Smartphone Signal Analysis

The literature review shows few studies discussing the differences in measured signals by different smartphone devices. Based on the conclusions of chapter 3, it is believed however that the heterogeneity in devices will have significant impacts on the signals measured onboard railway vehicles. The question most prevalent in this section is therefore: In which ways do different recorded acceleration signals from smartphones on in-service passenger trains differ? A strongly related question is how this heterogeneity is reflected in the repeatability of measurements, one of the key challenges encountered in the literature.

This thesis analyses the signals recorded by three different smartphone models through a case study. First the data acquisition process is explained in Section 4.1. Then the processing steps are briefly touched upon in Section 4.2. Processing includes positioning (Section 4.2.1), cutting and filtering (Section 4.2.2 and additional steps (Section 4.2.3). In section 4.3, some key observations regarding the (frequency content of) the vertical accelerations are described. In this section, the global behaviour of the signals are analysed, including element detection. The chapter then proceeds with some challenges related to the repeatability of measurements in section 4.4, specifically with regards to varying vehicle speeds and positioning within the car body. Finally, the chapter provides an outline of the main conclusions in section 4.5. Figure 4.1 displays an overview of the structure of the chapter.

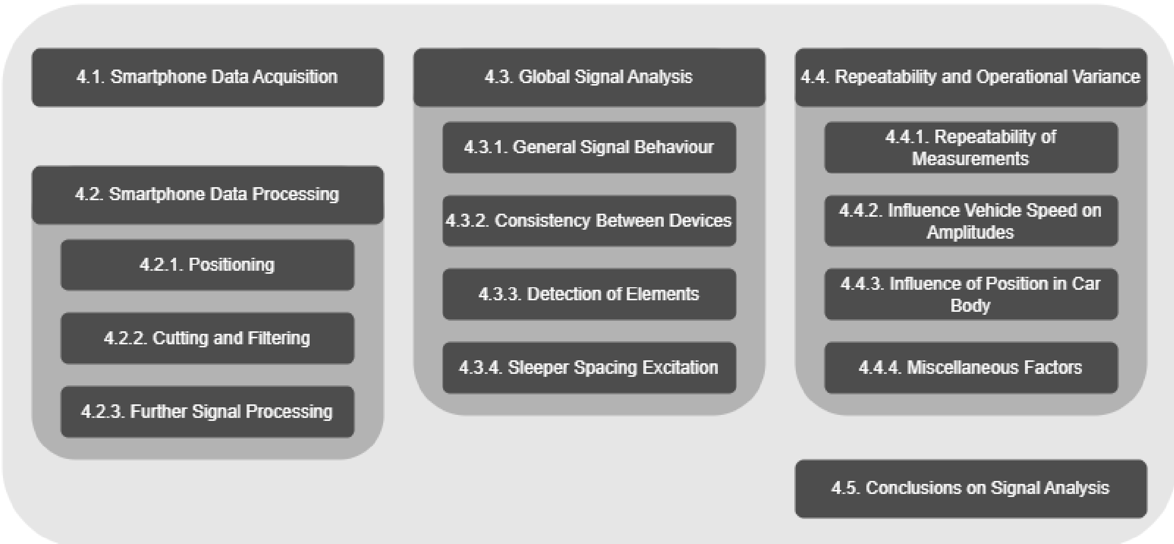


Figure 4.1: Outline of chapter 4, split into sections and subsections.

4.1. Smartphone Data Acquisition

Data was acquired with 5 different measurement runs, spread over 2 days. Similar to the measurements on the CTO, 3 wooden boards were prepared, containing 3 different smartphone models from the test set each. The smartphones were fastened to the board through double sided adhesive tape. Figure 4.2 provides a schematic overview of the orientation of the mobile phones on the wooden boards. These boards were placed on different locations in the car body. All boards were placed on the floor, under a seat. Board 1 and 2 were placed on both the left and right side of the car body, near the bogies, board 3 was placed near the center of the car body on the left side. The exact location of the boards could vary per measurement run, as a result of availability of seats or crowding in the train. is found in Figure 4.3 displays a schematic overview of the car body and the target seats for the measurement boards.

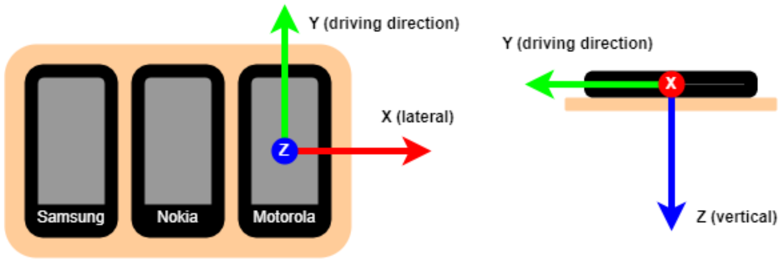


Figure 4.2: Schematic overview of the measurement boards, in relation to driving direction.

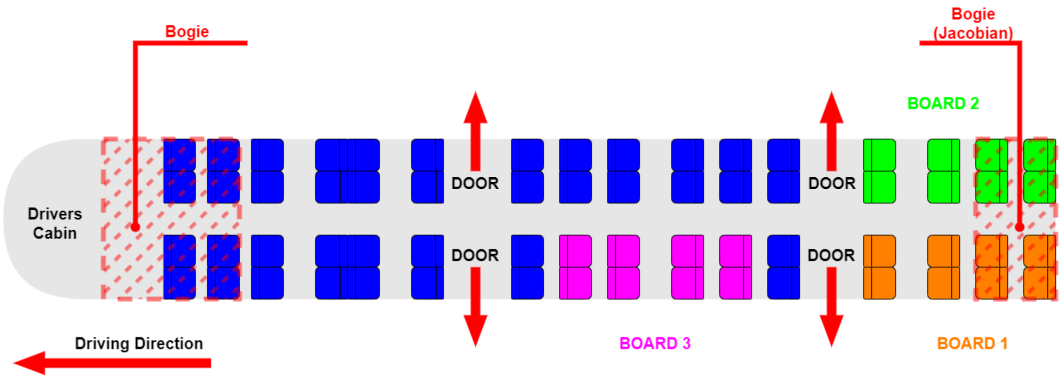


Figure 4.3: Location within car body of the measurement boards on a schematic overview of the car body. In Measurement run A, only Board 1 was instrumented. The bogies and target seats are indicated.

4.2. Smartphone Data Processing

Data processing constitutes all processes after data acquisition before the signals can be analysed. It consists of assigning the dataset to a position in Section 4.2.1, cutting and filtering the dataset in Section 4.2.2 and finally transforming the dataset into the frequency domain in Section 4.2.3.

4.2.1. Positioning

The purpose of the smartphones is to monitor the state of the tracks. Therefore the acquired acceleration signals should be related back to specific track locations. Relating measurements back to positions on the railway system has been reported as a key challenge of the smartphone technology in the survey results of Section 2.2. For the data collected on-board the in-service vehicles, it was thought that the GPS-location acquired by the smartphones could be used to approximate the position. The primary considerations behind this were:

- a dedicated positioning system equipment is difficult to bring on board, or transport to, the in-service passenger trains.
- setting up dedicated equipment may require time, which is limited due to the train schedule.
- the smartphones are there anyway, no additional equipment is necessary this way.

- previous research demonstrated that the GPS was able to be received on-board passenger trains up to 150 km/h [6].

Although assessing the GPS sensors of the smartphones is not within the scope of this thesis, some insights in the uncertainties involved in terms of positioning are desirable. To this end, the smartphones used on the CTO measurement vehicle in Section 3.4 were also set to record GPS data every second. The GPS-data recorded by these smartphones would then be compared to more advanced methods of positioning present on the measurement vehicle (GPS, axle circulation counts).

On both CTO measurement campaigns, there was difficulty in receiving a GPS signal with the phones mounted on the wooden boards on the floor. The phones would measure accelerations and GPS-data for 10 minutes. Usually, but not always, the Samsung smartphones would pick up a GPS signal first, after a period of approximately 5 minutes. The Nokia would shortly after this also pick up a GPS signal. The Motorola phones used in this set-up would never record any GPS-data. This would leave a relatively short 4 minutes per measurement period in which there was a GPS-signal recorded for 2 out of the 3 smartphone models.

An attempt was made to improve the reception of the GPS sensors by placing the phones with double sided adhesive on a windowsill at the front of the measurement car (displayed in Figure 4.4). The phones were programmed to record 1200 seconds of both accelerometer and GPS data. This time, the Motorola picked up a GPS signal within 10 seconds of starting the measurements until the end of the measurement period, whilst the other two models did not pick up a GPS signal over the entire 1200 second measurement period. It is noted that the Motorola was located the closest of the three phones to a small hatch to the outside of the carriage.

The lack of a simultaneous recorded GPS signal by the three phones, and inconsistency in reception between measurements, would have made a comparison with a dedicated system mounted on the CTO challenging, labour-intensive and would likely provide only limited insights. Therefore, it was decided to discontinue the comparison with dedicated positioning equipment on board the CTO and instead assess the relative differences of the GPS signals recorded by the phone on the in-service trains. GPS signals were able to be received on in-service trains in [6] , [5] and [30] for instance. This however, also unexpectedly proved unsuccessful, as none of the phones in the test set were able to receive a GPS signal on the floor of the car body of the in-service trains used in this thesis. Thus, no dedicated analysis on the uncertainty of the positioning based on the GPS sensors in the smartphones is present in this thesis.

Figure 4.4: Smartphones on the windowsill

Challenges in receiving GPS signals in a dedicated measurement vehicle were also recorded in [30], from a previous study in the Netherlands. In [30] , this is attributed to the measurement train having "narrow windows and the complete metal enclosure", which are similar conditions to the CTO used in the thesis. However, this paper also notes that the GPS position was available on-board the passenger trains [30], which is not the case with the data collection on the floor of the passenger trains in this thesis. The difference in these observations could perhaps be attributed to the following possibilities:

- Modern (2023) smartphones may use worse GPS-sensors than smartphones used in [30] , published in 2017.
- The smartphones used in this thesis are relatively cheap models, and may have lower quality GPS receivers embedded in them.
- The GPS reception may have been better in the NS rolling stock used in [30] than the Sprinter Nieuwe Generatie trains used in the thesis.

Instead of using the smartphones of the test set, an additional phone (an iPhone 13 Pro Max) was used to monitor the GPS inside the vehicle. This phone had a consistent GPS-signal over all measurement runs, and was placed on the floor or windowsill near the phones of board 1. This GPS location of this smartphone were orthogonally projected onto the track to obtain a kilometer position. Through the central difference method, a vehicle speed was estimated for each of these positions. The resulting speed profile for measurement run A is displayed in figure 4.5.

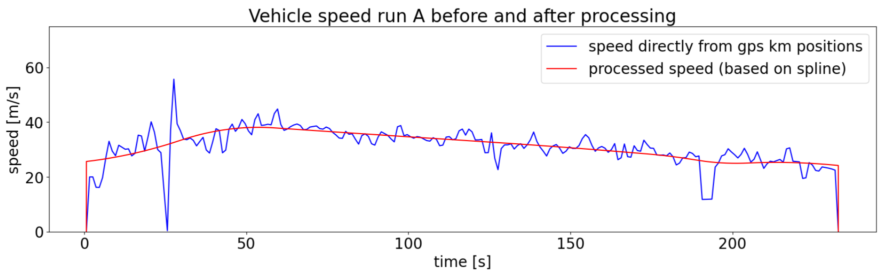


Figure 4.5: Speed profile based on GPS recordings of the iPhone for measurement run A. In blue: the speed profile based on track kilometer positions of the iPhone. In red: the speed profile after the track kilometer positions after a univariate spline was applied.

An encountered problem while using this method was that the speed profile was unfeasible. The maximum allowable driving speed on the line was exceeded (39 m/s), as well as driving accelerations above 1.3 m/s^2 (maximum acceleration SNG according to [33]) were present. To solve this issue, a univariate spline was applied on the projected kilometer positions. This method provided a more realistic speed curve. Although the uncertainties and errors of using this method were not investigated in-depth, traditional railway vehicle speed profile behaviours, like accelerating, cruising and coasting, were now visible. Figure 4.5 displays the results of this method for run A. This method was applied for all other measurement runs for positioning and speed.

4.2.2. Cutting and Filtering

The signals were cut to only contain the area of interest (the track section containing track kilometer position 73 and 78 km). All signals are aligned based on the system times of the measurement devices. One of the Nokias in the test set showed a signal continuously 1 or 2 seconds ahead of the others. showing that this method is not suitable for local analyses without additional manual signal alignment first. The timestamps of devices being different was also reported in [38].

Filtering of signals would constitute the removal of clear outliers or otherwise undeniably faulty measurements. Causes of these could be manual errors or movements induced by handling the equipment. No filtering was required for this measurement campaign as no such obvious outliers were present.

4.2.3. Further Signal Processing

Further processing on the vertical acceleration signals was then conducted. All signals were resampled to 180 Hz, to simplify visualisation and analysis. Additionally, the smartphone signals measured in measurement run A were then further analysed with two additional methods.

- A spectrogram was produced by calculating the Power Spectral Densities over 1-second windows of a signal with 0 overlap. This spectrogram allows quick insights in the frequency contents of the vertical acceleration over the entire frequency domain up until 90 Hz, with a spectral resolution of 1 Hz.
- A continuous wavelet transformation (CWT), similar to a study with smartphones in [34] was applied. The wavelet type was the Morlet wavelet, and the applied scaled ranged from 0.1 Hz to 5 Hz, with steps of 0.1. The Continuous Wavelet Transformation acts as a microscope for the lower frequency domain. In [34], high wavelet coefficients around 1 Hz were shown to indicate the presence of longitudinal-level irregularities. This thesis uses the PyWavelets python package for computing the wavelets [18].

4.3. Global Signal Analysis

To assess the effect of heterogeneous measurement devices, observations of previous academic works are verified and compared in both the time and frequency domain. For this section, the signals acquired in measurement run A are analysed.

4.3.1. General Signal Behaviour

Figure 4.6 depicts the vertical accelerations of measurement run A and their periodograms.

The Motorola shows much higher absolute accelerations than the other two phones in Figure 4.6. The plots of the Samsung and Nokia signals show a large degree of similarity. Peaks are for the most part observable at the same timestamps for all three signals, although the peaks are more pronounced in the time domain of the Samsung and Nokia than the Motorola.

In terms of frequency content, the periodograms of all three smartphones show a similar peak around 2 Hz and similar values up until 5 Hz. After this however, the low-pass filter behaviour of the Nokia and Samsung starts to show. The crest around 10 Hz visible in the periodogram of the Motorola is a lot weaker for the Samsung and barely visible for the Nokia. The crests around 40, 60 and 90 Hz are only visible in the periodogram of the Motorola. The Nokia shows its established eigenfrequencies around 70 Hz when plotted on logarithmic scale.

4.3.2. Consistency between devices

To understand the difference in frequency content per device, the mean periodogram was obtained for each model by averaging all periodograms for that model in measurement runs B, C , D and E. The mean periodograms for all devices over measurement runs B, C , D and E and their differences to the total mean periodogram can be found in Figure 4.7. The following observations are made:

- The Nokia shows a deviating pattern in the lowest frequency bins (10^{-2} Hz), which may be attributed to the trends uncovered in chapter 3.
- The mean periodograms for all smartphones are the closest between 1 and 3 Hz, indicating that this frequency band is the most consistent for the test set.

To zoom in on the peaks in the 0 - 5 Hz domain, a Continuous Wavelet Transformation was made for the smartphones on board 1 for run B. The CWT results show a large degree of similarity and are presented in Figure 4.8.

4.3.3. Detection of Elements

In [28], vertical accelerations signals show significantly higher amplitudes around discontinuities such as transition zones and fishplates. However, this paper did not provide any information on the dynamic sensitivity of the devices used. To assess whether or not one is able to observe irregularities with all smartphones, the joints and transition zones of the case study are plotted in Figure 4.9. The figure also displays absolute vertical accelerations. Although most transition zones correspond to peaks in the vertical acceleration, joints and fishplates appear at times much more pronounced in the signal of the Motorola. This indicates that smartphones without low-pass filter behaviour can identify joints and fishplates better.

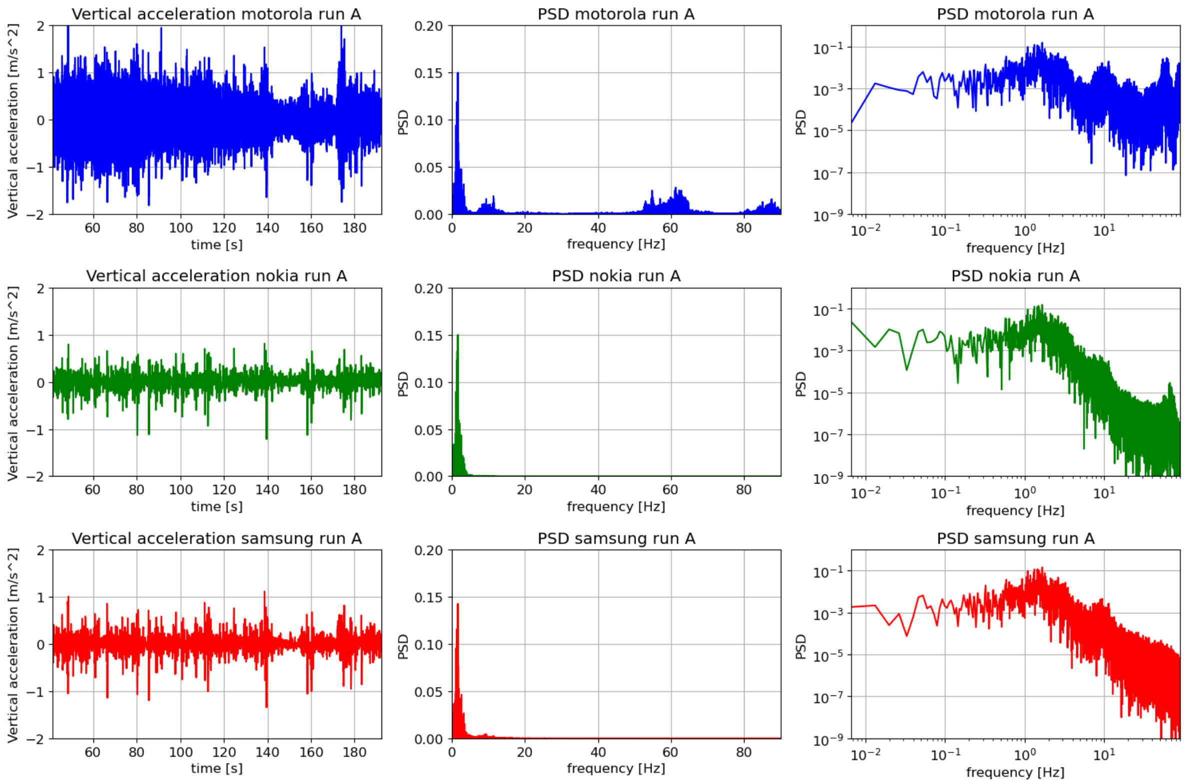


Figure 4.6: Vertical accelerations in time and frequency domain of all smartphones. The vertical accelerations are detrended by removing their mean over the entire length. The periodograms on the right are plotted on a logarithmic scale.

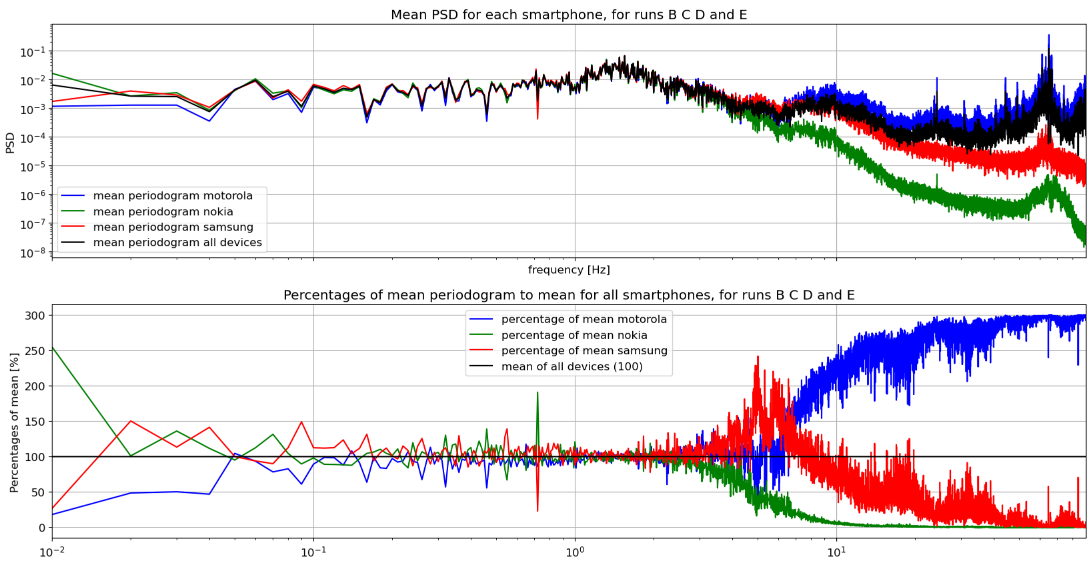


Figure 4.7: (Top) Mean periodograms for all devices over measurement runs B, C , D and E. (Bottom) Percentage of the total mean periodogram for each mean periodogram of the smartphones.

4.3.4. Sleeper Spacing Excitation

In [24], the frequency content of the vertical accelerations recorded by a smartphone displayed a sharp peak around 25.4 Hz. The paper related this peak back to a submultiple of the sleeper spacing excitation frequency. However, in the figures provided in that study, it is also depicted that the speed of the vehicle is not consistent, with accelerations in the longitudinal direction hinting at the presence of a varying speed curve, rather than a constant speed. This leaves some uncertainty whether or not

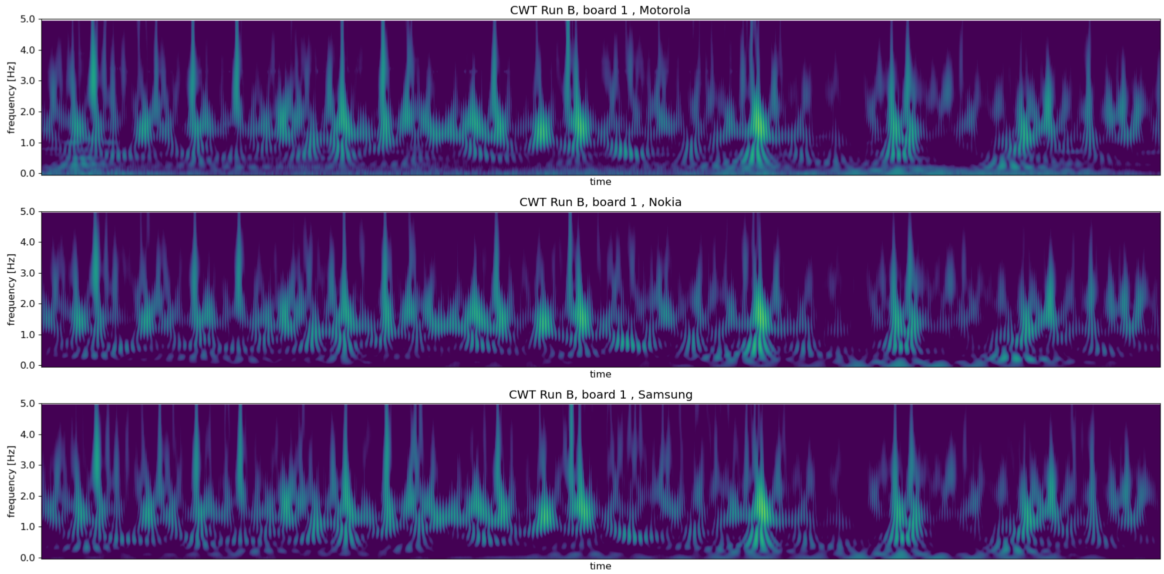


Figure 4.8: CWT of the vertical accelerations of the smartphones on board 1 for run B.

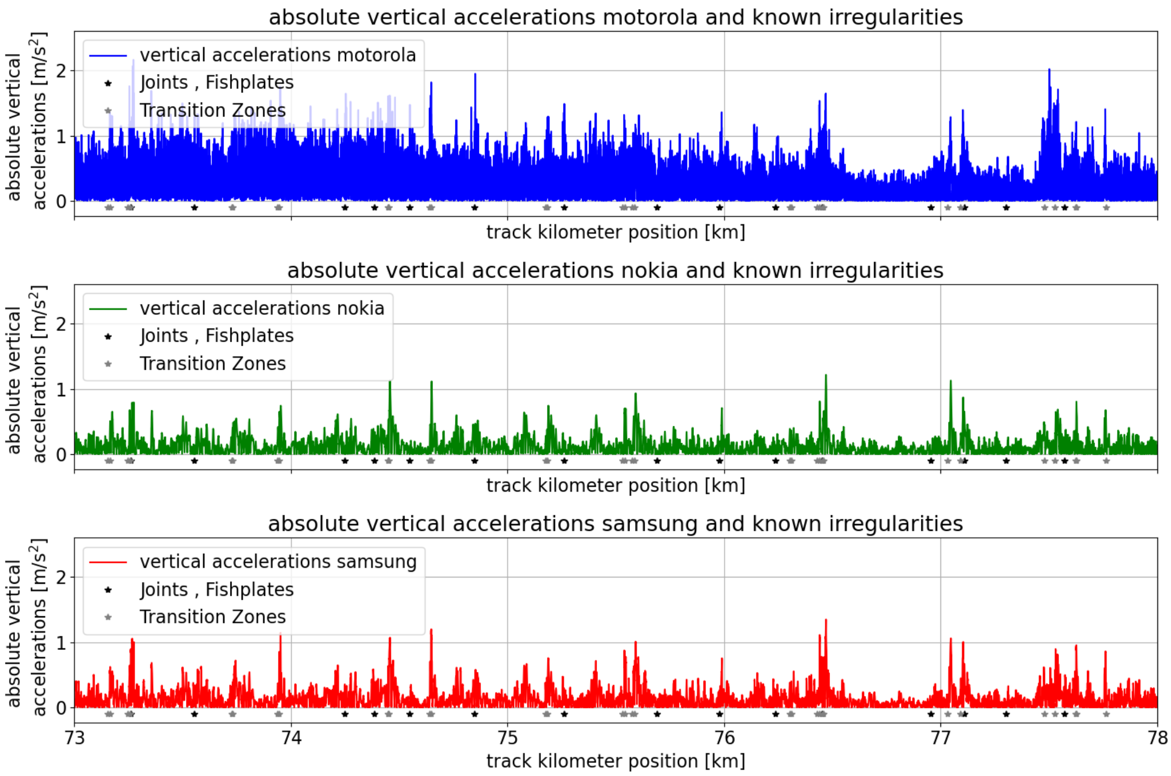


Figure 4.9: Absolute vertical accelerations versus the kilometer position for each device in the test set. Data is taken from measurement run A. All infrastructure elements (joints, transition zones) are plotted.

the observable peak is indeed the result of the relation between vehicle speed and sleeper spacing distance, or if this peak is perhaps caused by device-based eigenfrequencies observed in [19] and in Chapter 3 of this thesis.

This section aims to find if a (submultiple of) the sleeper spacing excitation is observable in the frequency content of the vertical accelerations measured by the test set. Furthermore, through the use of a spectrogram, the frequency contents at different speeds can be analysed, to verify the observation that such peaks are indeed the result of a relation between the vehicle speed and the sleeper spacing.

The spectrogram of the Motorola contains a curve with high-energies between 50 and 60 Hz. When dividing the approximated speed by a sleeper spacing of 0.6 meters, this resulting curve matches the curve in the spectrogram quite well. Other curves of high energy contents in lower frequencies may be attributed to harmonics, the most notable one being an appearant 5-sleeper spacing excitation frequency around 10-12 Hz. Figure 4.10 provides this spectrogram.

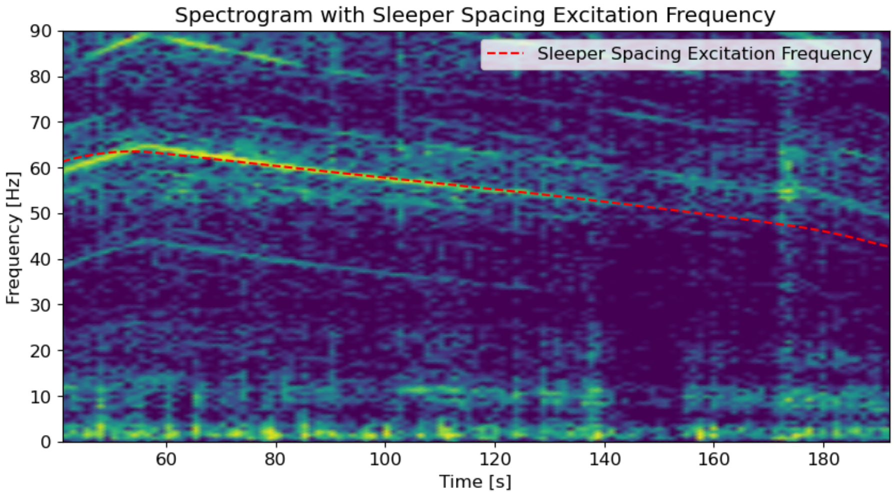


Figure 4.10: Spectrogram of Motorola in run A, with sleeper spacing frequencies based on the speed and sleeper spacing indicated with lines.

The vast majority of the track is conventional ballasted track. The distances in the case study not containing sleepers is very short (1 or 2 bridges and a level crossing) and therefore, no comparison between the presumed sleeper spacing excitation at these locations and on the rest of the track was carried out.

The main conclusion of this section is that information regarding vehicle speed is retrievable from vertical accelerations, using the relation between observed peaks in frequency content and the sleeper spacing distance. In 2 out of the 3 phones in the test set, a submultiple of the sleeper spacing excitation (seemingly corresponding to 5 sleepers) is visible in the frequency content of the smartphones. Through observations in the spectrogram of the Motorola, it is established that not only a submultiple of the sleeper spacing is visible as in [24], but also the actual sleeper spacing excitation. The reason why the sleeper spacing excitation frequency was not visible in [24], can be attributed to that research using a sampling frequency of 100 Hz. This sampling frequency is simply too low to observe the sleeper spacing excitation of 101.85 Hz corresponding to 220 km/h. Factors limiting these observations are therefore both the sampling rate of the smartphones, as well as the presence of device-specific dynamic sensitivity or low-pass filter behaviour.

4.4. Repeatability and Operational Variance

Indicators based on signals involving track geometry must be repeatable, regardless of a varying speed profile or position in the vehicle. 2 measurements taken on the same day should reflect a certain degree of similarity. This section will assess consistency of the recorded frequency content along measurement runs and in between (position of) devices.

4.4.1. Repeatability of Measurements

The repeatability or consistency between different measurement runs has been cited as being an existing challenge in the use of smartphones in [5]. This paper noted that differences in the periodograms of two different measurement runs, as a result of slightly varying operational speeds. This periodogram has been repeated for the case study, which indeed shows varying frequency content per measurement run. Figure 4.11 gives the speed profiles. Figure 4.12 provides the resulting periodograms for measurement runs B to E for board 1. The frequency content over the line between 0 and 5 Hz looks similar across all devices and across all runs in Figure 4.12 . In the periodogram for 5 - 15 Hz, differences are slightly more notable, especially for run D in the Samsung. Finally, the frequency band 15 - 90 Hz shows significant variances for the Motorola. Notably measurement run D shows clear PSD spikes around 70 and 65 Hz and a crest of PSD values from 80-90 Hz. Combined with the observations for the 5-15 Hz domain, these higher PSD values could potentially be caused by slightly different positions of the board in the vehicle or by variations in the vehicle suspension system (e.g. the suspension system of the car body in run D may not sufficiently damp higher frequency components).

Figure 4.11: Speed curves of the different runs.

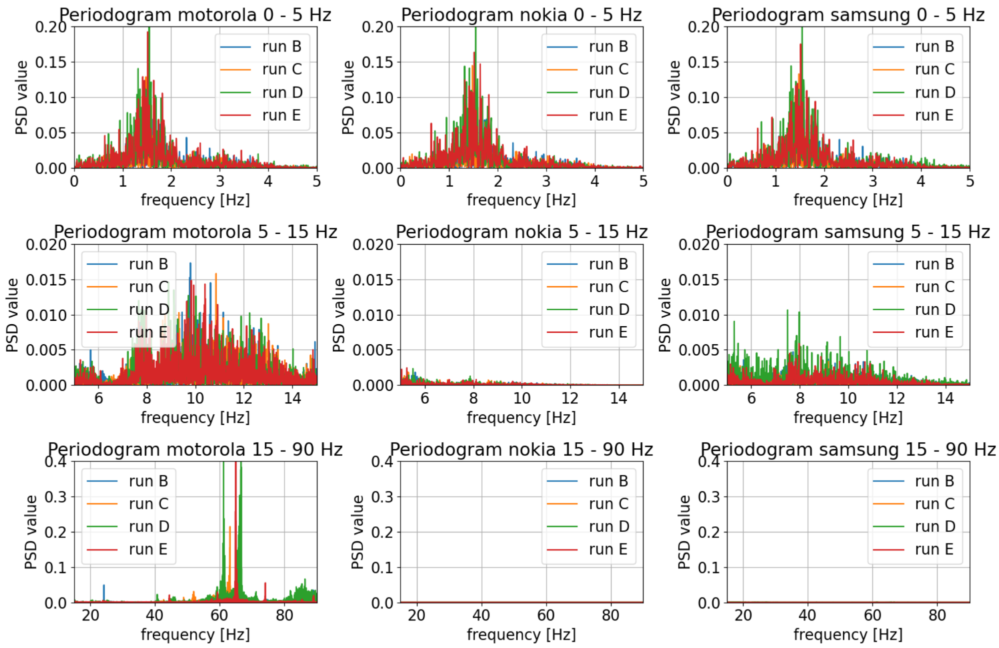


Figure 4.12: Periodograms for board 1 for each of the different runs.

Local analysis is conducted by comparing signals of the smartphones smartphone between different measurement runs around the peaks in the time domain of joints and transition zones. These locations were selected because of the poor positioning in the case study: the peaks found around these elements allow for relatively simple manual alignment. The alignment target was a local crest or sag curve. Figure 4.13 and Figure 4.14 show the vertical accelerations around a joint and a transition zone. The approximated vehicle speed did not show much variance throughout runs B to E. This gives insights in how the signals vary when the joint or transition zone is passed at a similar speed. The height of the peaks show some level of variance, but appear somewhat consistent in height. This variance could be related to slight differences in the vehicles or vehicle health states. A more varying pattern is observed around both J7 and B7 for the Motorola, with measurement run D seemingly showing high frequency components with high energy levels. It is unknown what the cause of this is. The high frequency components appear to affect the repeatability between measurements and seem to increase the absolute amplitudes of the measured accelerations significantly compared to the Samsung and Nokia.

Figure 4.15 and Figure 4.16 display similar curves for culvert C1 and bridge B10 respectively. The range of vehicle speeds in these locations varies more, and thus, some information regarding the consistency of recorded accelerations under different vehicle speeds can be extracted. Again, it is observed that the acceleration peaks are quite comparable in height, especially for the Nokia and the Samsung. The high-frequency acceleration components of the Motorola make a visual comparison again quite difficult, but the lower frequency sinusoidal shapes are clearly recognisable and comparable under the different speeds. Measurement run D again shows significant levels of noise compared to (for example) measurement run E.

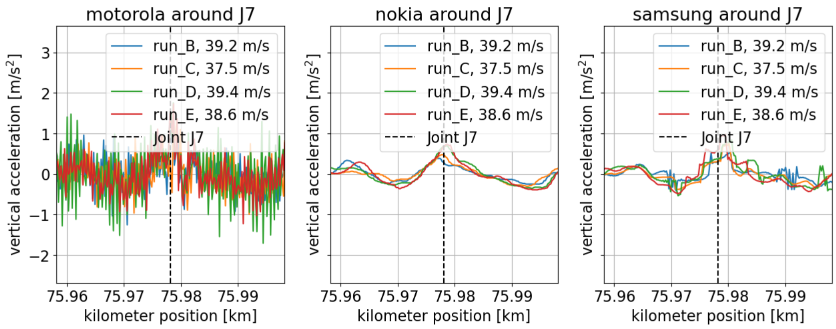


Figure 4.13: Vertical accelerations of smartphones of board 1 on different measurement runs insulated joint J7.

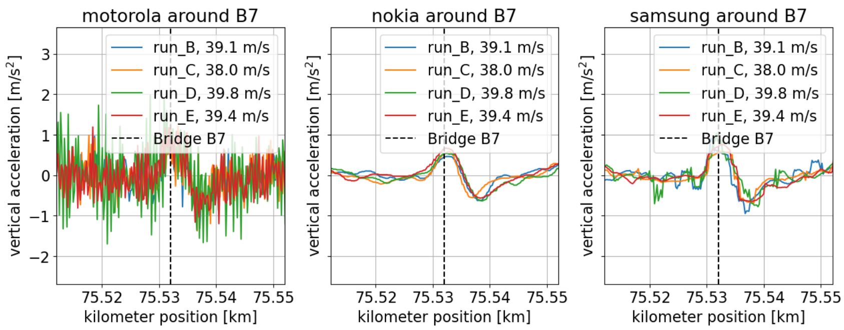


Figure 4.14: Vertical accelerations of smartphones of board 1 on different measurement runs around bridge B7.

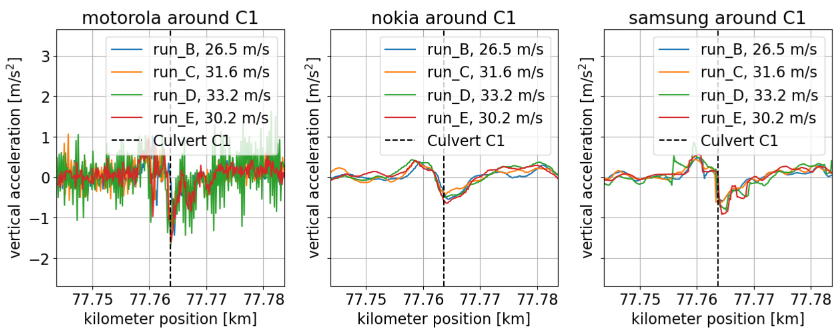


Figure 4.15: Vertical accelerations of smartphones of board 1 on different measurement runs around culvert C1.

4.4.2. Influence of Vehicle Speed on Amplitudes

The spectrogram in Section 4.3.4 showed that the frequency contents of a signal change with different speeds. The amplitude of the measured vibrations is also affected by different speeds. The magnifying effects of speed on the amplitudes of vibrations has been explicitly mentioned by [23]. Other research on comfort evaluations seem to show drastically lower values for their indices around apparent stops, such as in [6]. In [15] a regression model between the measured vertical acceleration and the vehicle speed was developed. However, this regression model seems to have been done for one specific

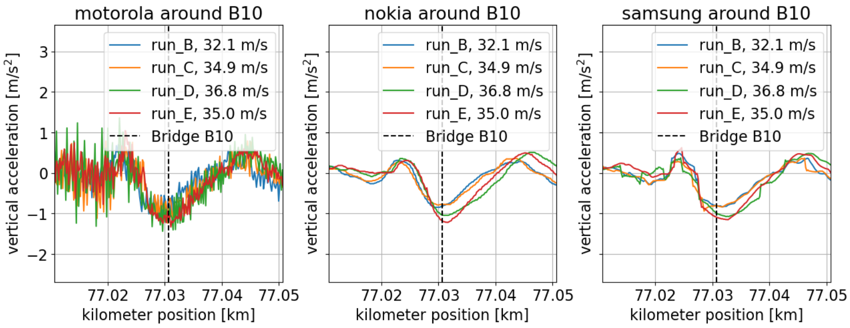


Figure 4.16: Vertical accelerations of smartphones of board 1 on different measurement runs around bridge B10.

device, and no indication of the quality of the regression model is provided. The differences in dynamic sensitivities per device make it likely that the amplitude scaling of the measured accelerations is different for each device.

To this end, the absolute vertical acceleration of each device (minus the mean vertical acceleration of that device) are plotted against the vehicle speed at the recorded acceleration value. The vehicle speed curve and accelerations of run A are plotted in Figure 4.17. The results are visible in Figure 4.18, with the Pearson correlation coefficients between the different smartphones in Figure 4.19.

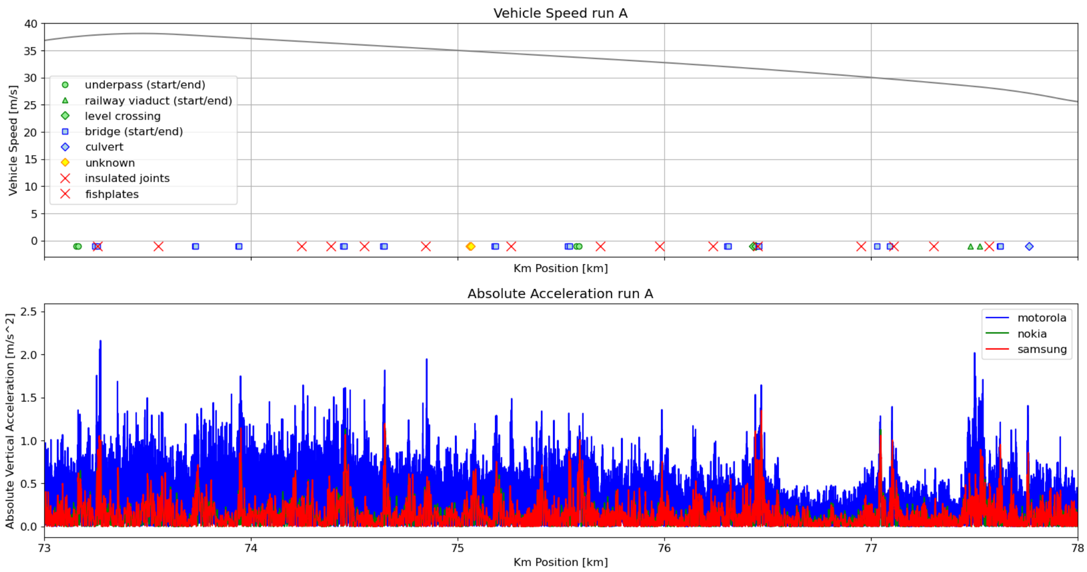


Figure 4.17: Speed profile run A, with the absolute vertical accelerations (minus the mean acceleration for the run) per phone.

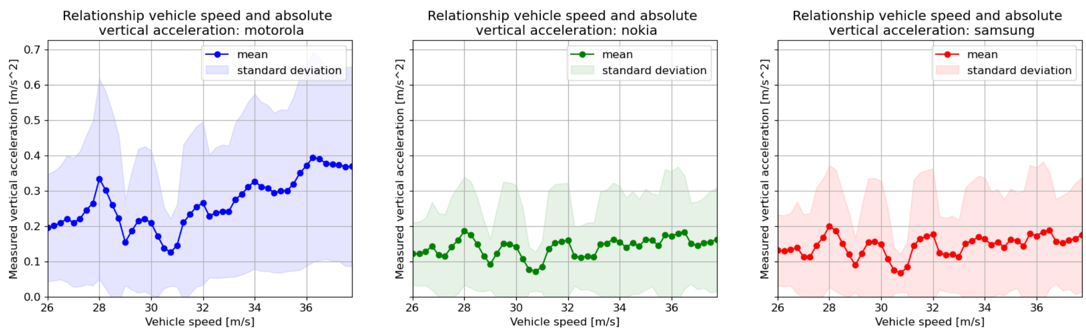


Figure 4.18: Vehicle speed versus absolute vertical acceleration per smartphone. The means are calculated by dividing the datapoints up into bins of size 0.25 m/s

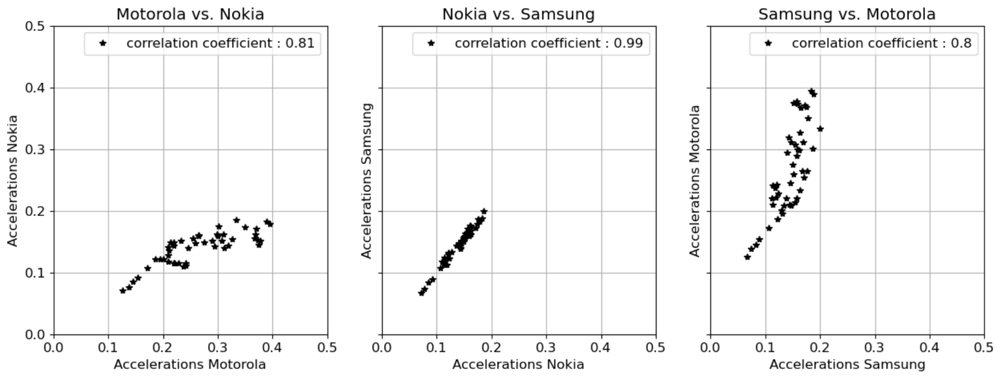


Figure 4.19: Correlation coefficients of the means found in Figure 4.18 between the different mobile phones.

All devices show somewhat of an upward trend. Based on visual inspection in Figure 4.18, the Samsung and Nokia behave very similarly, with a correlation coefficient of 0.99 depicted in Figure 4.19. This is likely attributed to them both possessing low-pass filter behaviour in their dynamic sensitivities. The Motorola reports a correlation coefficient of 0.81 and 0.8 for the Nokia and Samsung respectively, with figures resembling exponential behaviour in Figure 4.19. The means depicted in Figure 4.18 are also nearly twice as high as the other two phones at the same speeds. These differences are likely the result of vertical acceleration components with frequencies above the cut-off frequencies of the Motorola and the Samsung. An example of these frequency components are those to the sleeper spacing excitation found in Section 4.3.4.

The results in Figure 4.18 are clearly distorted by high amplitudes around transition zones as observed in [28]. As can be seen in 4.17, no speed is maintained for a longer period of time, and then the high amplitudes found around irregularities report a higher mean vertical acceleration than would be found on open track without irregularities on that speed. An example of this is the jump at 28 m/s in Figure 4.18, likely distorted by the large absolute vibration around the railway viaduct seen in Figure 4.17. Much more data with different vehicle speeds is required to confidently make conclusions on the magnifying behaviour per device.

4.4.3. Influence of Position in Car Body

Chapter 2 concludes that the effect of different positions of smartphones within the car body has not reported on in previous works. In the context of crowdsensing, the position of the smartphone in the car body is likely unknown, or difficult to retrieve retroactively. The consistency between the smartphone accelerations within the same vehicle may influence the repeatability of measurements, as smartphones could be hypothetically in every position within the car body. Therefore, it is pivotal to obtain insights in how signals from 2 different positions in the car body vary.

The mean periodograms of run B, C , D and E were obtained separately per model for smartphones near the bogies (board 1 and 2) and the smartphones at the center of the car body (board 3). Figure 4.20 displays the results. Some observations:

- The mean periodogram for all smartphone models placed near the bogies show a higher PSD value for frequencies between 1 and 2 Hz than their counterparts placed near the center of the car body. This may be related to the pitch of the car body.
- For all smartphone models, the mean periodograms of the smartphones near the bogies and those of the smartphones near the car body center show a certain amount of coherence for frequencies below 1 Hz and the frequency band between 2 and 3 Hz.
- The peak around 60 Hz visible in the Motorola and Samsung (likely related to the sleeper spacing excitation) is reflected much weaker in the periodograms of the smartphones at the center than those in the car body.

Additionally, the impact on the amplitudes in the time domain were analysed for one of the transition zones. Bridge B7 was selected, as the acceleration peaks are quite visible and because the speeds of two of the measurement runs (B and E) were relatively similar around this transition zone. The results are plotted in 4.21. A clear observation in this figure is that, for all smartphone models, the smartphones placed near the center of the car body display 2 peaks in the vertical acceleration rather than 1. The peaks visible for smartphones at the center of the car body furthermore seem to be lower in amplitude than those placed near the bogies. Finally, the sags following the peaks appear to be lower in amplitude as well for the Nokia and Samsung on board 3.

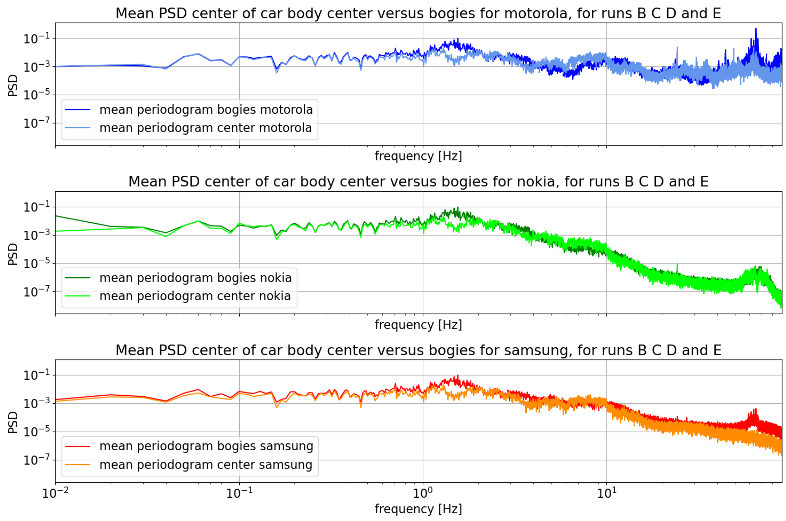


Figure 4.20: Mean periodograms of smartphones in the center of the car body and on the bogies, for all devices over measurement runs B, C , D and E.

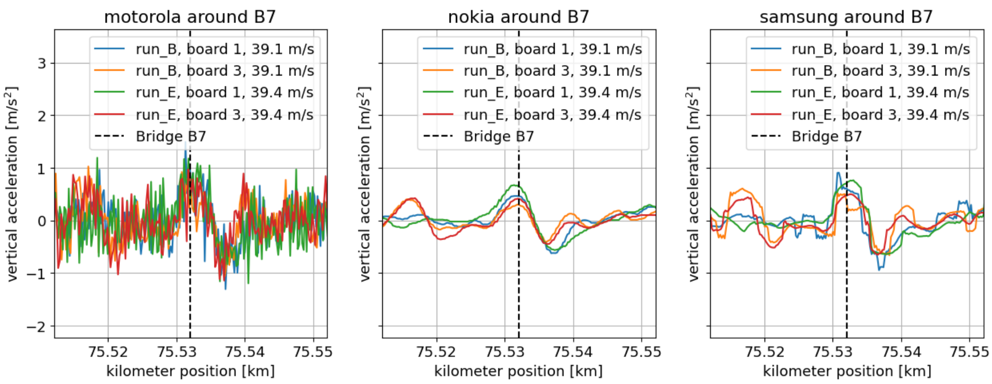


Figure 4.21: Vertical accelerations around bridge B7. Signals are aligned manually around the peak visible around B7.

The periodograms for the smartphones for measurement run E were also plotted seperately for easier analysis in Figure 4.22. In this figure, the peak registered around 1.5 Hz for both board 1 and 2 (smartphones placed near the bogies) is not visible for board 3. This peak being smaller may be the cause for the peaks in Figure 4.21 being of a lower amplitude. Furthermore, the peaks registered by the Motorola in the 15 - 90 Hz domain vary significantly between the ones on the bogie and near the center of the car body. The peak registered for board 2 around 65 Hz is nearly 10 times higher for board 2 than for board 3. This peak is likely related to the sleeper spacing excitation (65 / 0.6 = 39 m/s, a speed present in run E visible in Figure 4.11).

Finally, Figure 4.23 displays the the Continuous Wavelet Transformation for the 0-5 Hz domain. This is done to verify the observations in Figure 4.20 and Figure 4.22. It is indeed visible in this figure that the clear spikes in the scaleogram for board 1 around 1.5 Hz are missing from the scaleogram for board 3. The rest of the scaleogram shows a degree of similarity.

The findings from Section 4.4.3 highlight that smartphones record different signals at different positions in the car body. Although this creates variance in consistency in retrieving information on static

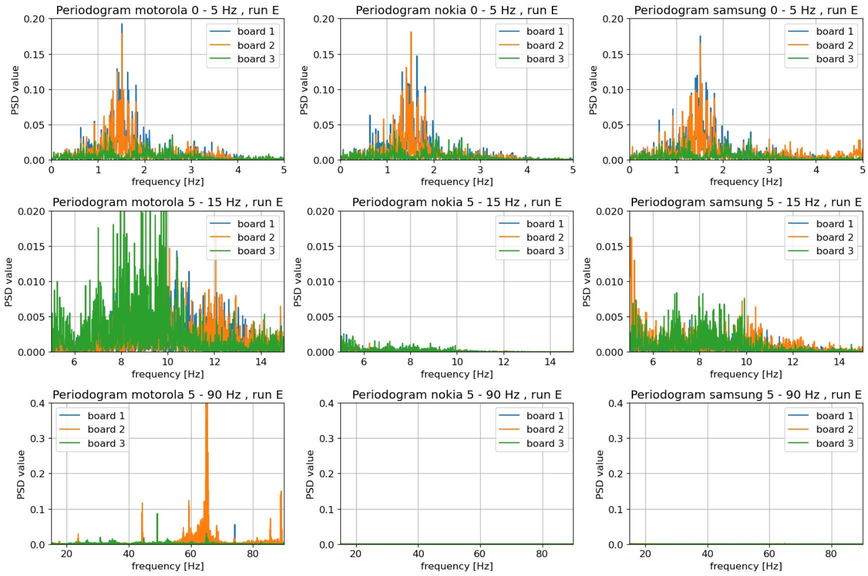


Figure 4.22: Periodograms for the different smartphones, for different boards in run E.

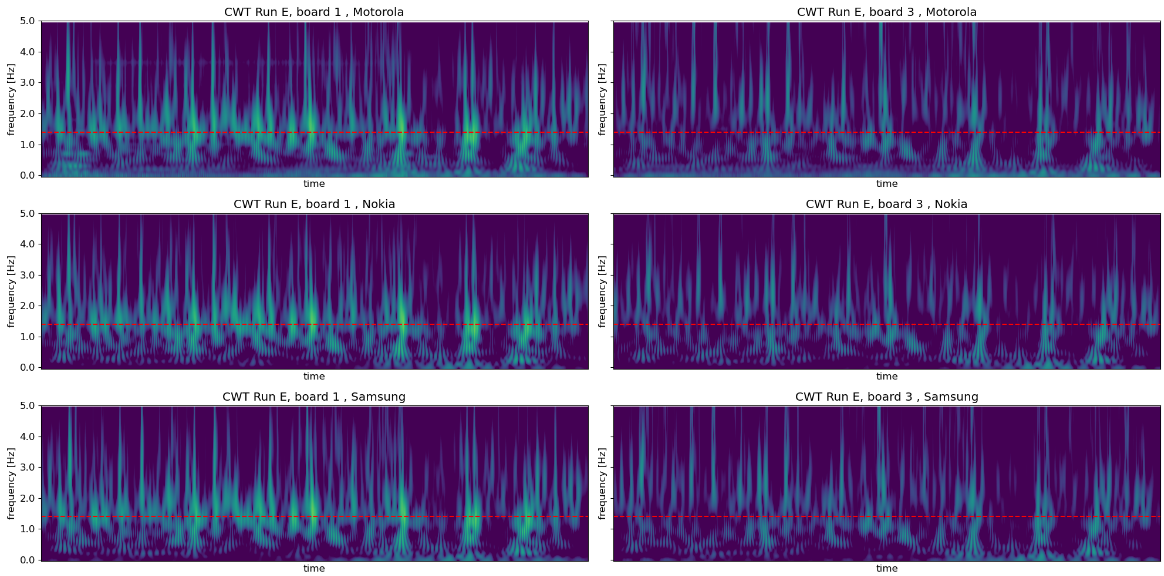


Figure 4.23: CWT for run E, board 1 and 3. The red dotted line is present to make identifying the missing frequency components more easy for the reader.

measurements, such as track geometry, these differences provide insights in the dynamic response of the car body. An interesting contrast is drawn to other dynamic measurement technologies technologies such as the Axle Box Accelerations discussed in [23]. In this set-up, accelerometers are mounted on the axle boxes of a vehicle. The accelerometers on the axle box measure vibrations from the train-track interaction without these vibrations first passing between the additional suspension systems present between the axle box and the car body. The vibrations are therefore not filtered by the extra suspension layer to which the smartphones in the car body are subject to. On the other hand, these sensors are only instrumented in one position, and do not capture the accelerations, vibrations and movements of the car body. There is thus a degree of complementarity between these measurement systems.

4.4.4. Miscellaneous Factors

Besides the challenges in repeatability mentioned above, other factors may create anomalies or outliers that could potentially distort the repeatability of the measurements.

Firstly, during the measurements, it occasionally happened that a train on the other track crossed the SNG-train the measurements were conducted in. More often than not, the passing of this train and its corresponding kinematic envelope seemed to induce movement (shaking) of the car body. It is unknown if this had any effect on the recorded vertical accelerations.

Finally, human interactions (or human-caused vibrations) can represent anomalies that may affect the repeatability of measurements negatively. Although no clear human-caused anomalies were encountered in the data processing of the case study, measurements on the CTO campaign managed to capture one. A human-caused outlier similar as found in [30], was encountered in this thesis whilst producing a spectrogram for the Motorola, which had been touched during the measurements. Figure 4.24 depicts this anomaly in the spectrogram. It contains a high level of energy in all frequencies, not visible in the spectrograms of other devices and rarely encountered at other instances in the same spectrograms. This confirms the observation of [30] that these outliers may be clearly identified.

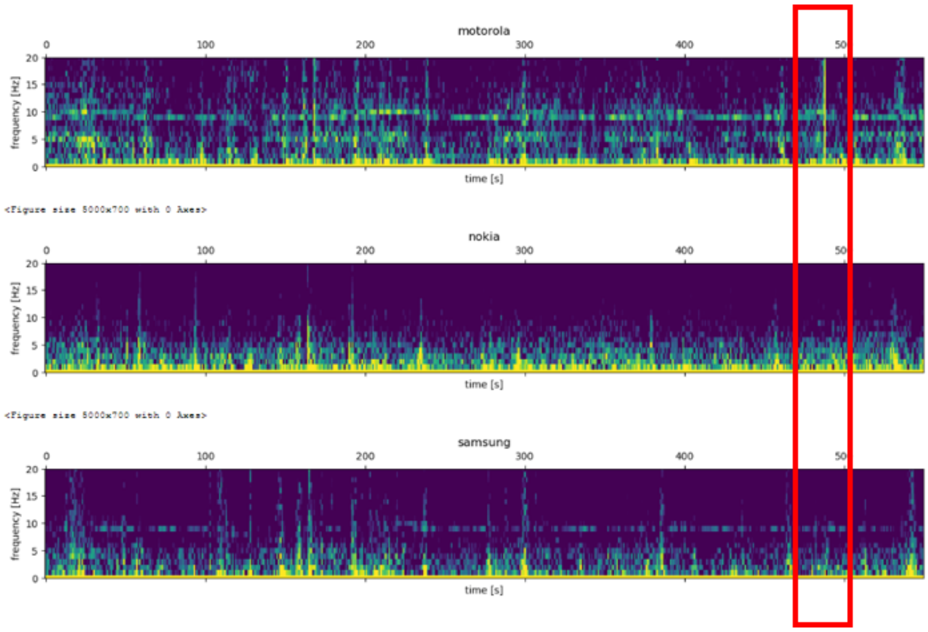


Figure 4.24: Spectrograms of the measurements on the CTO. The human-caused outlier is observable around time = 480 seconds as a bright yellow line, indicating high energy content in all frequencies.

4.5. Conclusions on Signal Analysis

Through a case study, this chapter provides insight into the variables and uncertainties involved in obtaining and using smartphone accelerometer signals from in-service passenger trains.

To compare different signals, measurements in the time domain have to be assessed a position on the tracks. Positioning issues through GPS persist, and is not advisable. Alternative sources of information based on the vertical acceleration signals are able to be retrieved in the case study. Examples of this are high acceleration peaks at known elements (joints). Information on vehicle speed (sleeper spacing excitation frequency) can be retrieved from spectrograms. This observation displays that the frequency content of the vertical acceleration signal changes as a result of varying vehicle speeds.

On repeatability, this study presents that variations in the peaks of measured vertical accelerations exist around transition zones. However, the Motorola also showed a certain degree of variance as a result of the presence or absence high frequency (>15 Hz) components. It is uncertain what causes these variations. The different smartphone models have shown an increase in absolute measured vertical accelerations as speed increases. Due to the acceleration peaks around transition zones and joints, it is difficult to establish clear relationships between speed and amplitudes. Different accelerometers observe different behaviour in the magnification of the amplitudes, depending on the sensor characteristics. Much more data is required to establish clear relations between vehicle speed and the amplification of vertical accelerations. Finally, The location within the car body where the smartphone is placed matters for both the frequency content and the amplitudes of the vertical accelerations.

5

Track Quality Assessment

Utilising the signals of smartphones of trains to extract information on the health state of the railway system has been done in the past, but an often overlooked aspect has been the limitations posed by using different mobile phones and the repeatability of such measurements.

This chapter focus on the question as to what extent can (repeated) on-board smartphone accelerometer measurements reflect differences in track quality. The relationship reported in [24], between the standard deviation of the Longitudinal Level and measured vertical accelerations by a smartphone, is analysed for our test set of smartphones on our case study. This is done in Section 5.1. This is followed by a more extensive analysis on the repeatability of monitoring the Track Quality Index, introduced in Section 1.2, in Section 5.2. Section 5.3 analyses the variance observed due to the position of the smartphones in the vehicle. The track quality assessment is expanded with an additional device (iPhone) in Section 5.4. Finally, Section 5.5 summarises the observations of this chapter.

5.1. Application of Standard Deviation Correlation

In [24], a strong correlation was reported between the vertical acceleration signals of a smartphone on a high-speed passenger train and the standard deviation of the combined LL D1 and LL D2 parameter. This section repeats the measurements done in [24] for the Delft-Schiedam case study, to see how this relationship behaves with different models of smartphones. Similarly to [24], the smartphones closest to the bogies are analysed in this section.

For the case study, the combined standard deviation of the LL D1 and LL D2 over 200 meters does not reflect the patterns of the standard deviations of the vertical accelerations well. Therefore, this report continues the analysis for the use of smartphones for the monitoring of the Track Quality Index introduced in Section 1.2, rather than also including the information on the LL D2. Possible causes for this poor relation may be due to the following reasons:

- The study conducted in [24] does not specify the dynamic sensitivities of the device used for the measurements. The presence of low-pass filter behaviour found in the Nokia and Samsung of the test set may also be present in the smartphone used in that study.
- The study in [24] is done on high speed railway lines, with speeds up to 250 km/h. It is possible that the suspension system of the vehicles are more effective in damping higher frequencies components than the local SNG trains in the case study.

The standard deviations of the LL D1 over 200 meters and the standard deviations of the vertical accelerations of the mobile phones of board 1 for run B are plotted in Figure 5.1. An observation from 5.1 is that the Samsung generally reports higher values for the standard deviation than the Nokia. This can be attributed to the frequency components around 10 Hz as found in Section 4.3, which are absent in the Nokia.

As the speed decreases, the standard deviations of the vertical accelerations of the Motorola start

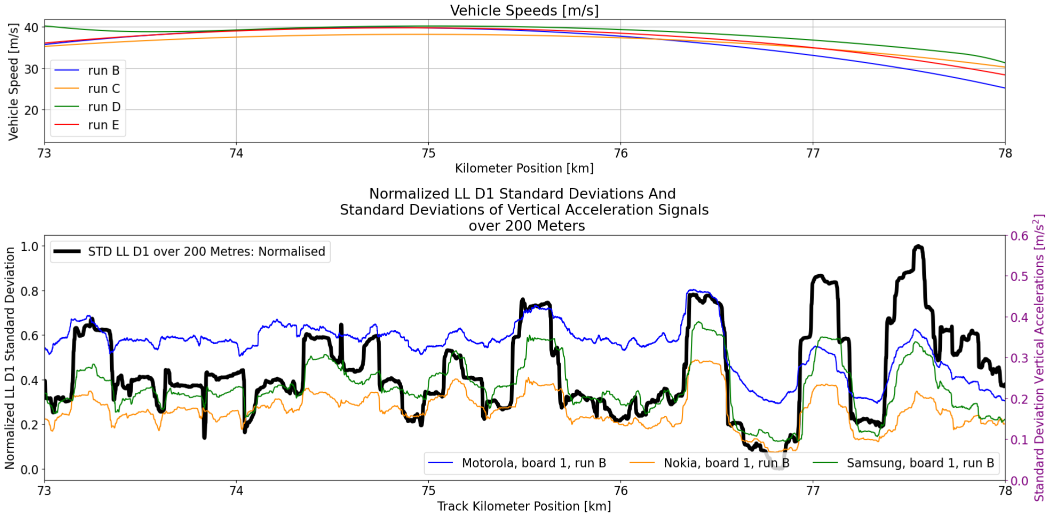


Figure 5.1: Standard deviations of the track geometry parameters versus the vertical accelerations of the mobile phones for the smartphones on board 1. The top plot displays the vehicle speed of the various runs.

to resemble the track geometry data. Another observation is the Samsung and Nokia showing decreasing peak values for their standard deviations for the peaks around kilometer position 76.5 , 77.2 and 77.5, although the Track Quality Index reports climbing peak values over these 3 peaks. This can be attributed to the speed of the vehicle decreasing between these kilometer positions, reducing the amplitude of the vertical accelerations as seen in Section 4.4.2. The notable frequency component absent in [24], but encountered in the Motorola of our test set, is the frequency component related to the sleeper spacing. It is likely that this frequency component distorts the relation found by Paixão in [24] for the Motorola in our test set. This frequency component was more visible in Figure 4.10 for measurement run A up until kilometer position 76. After kilometer position 76, the Motorola reflects the relationship between the standard deviations better as seen in Figure 5.1.

Small deviations in the exact locations of the peaks between the smartphones and the track geometry can be attributed to the poor positioning and small differences in the clock times of the smartphones. The geometry measurements were done roughly 2 months before the smartphone measurements.

5.2. Repeatability of LL D1 Assessment

Repeated measurements on the same day should reflect a similar health state. To this end, Figure 5.2 displays the results of measurement run B to E for board 1. The data is low-pass filtered to 10 Hz, to eliminate the distorting effects of higher frequencies observed in Figure 5.2 and to create a more "fair" comparison between the different devices. Key observations are:

- Higher vehicle speeds tend to produce higher standard deviations, seen previously in Section 4.4.2.
- In measurement runs B and C, board 1 was placed further away from the bogies than in measurement runs D and E, due to crowdedness in the vehicle. A general observation is that the standard deviations of the former are lower than those of the latter, particularly visible for the Nokia and Samsung. This indicates that the positioning within the vehicle can drastically change the recorded standard deviation.
- Slight disalignments in the kilometer position between the peaks of different measurement runs and track geometry are visible. This is likely caused by errors induced by the approximation used for the positioning in this thesis.

5.3. Effect of Position in Vehicle on LL D1

A comparison is made between the results from the smartphones of board 1 and 3, for measurement runs B and E. This is done to assess the differences in results for smartphones situated near the center

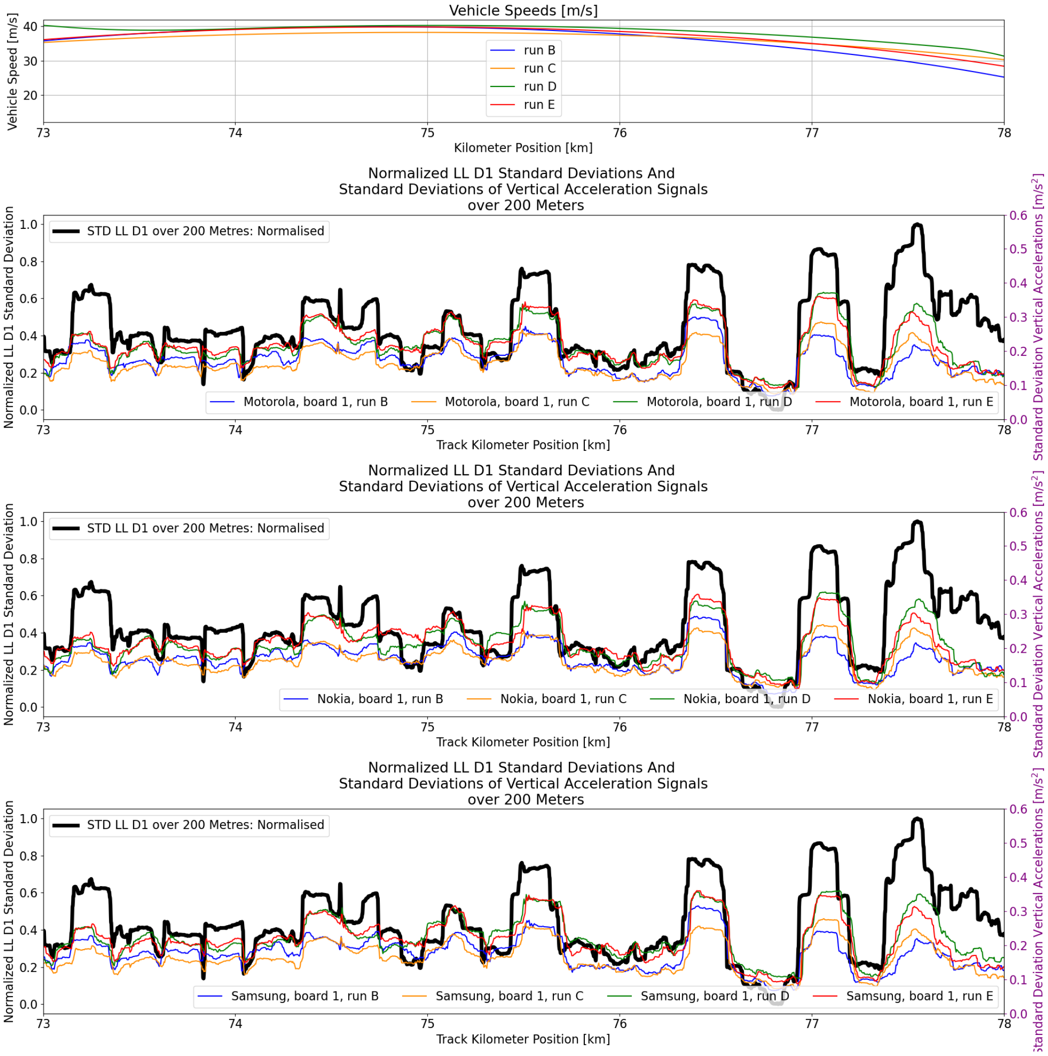


Figure 5.2: Standard deviations of the track geometry parameters versus the vertical accelerations of the mobile phones for the smartphones on board 1. The top plot displays the vehicle speed of the various runs. The vertical acceleration filters have been low-pass filtered for 5 Hz.

of the car body, and those located closer to the bogies. Figure 5.3 displays the results. Some key observations based on this plot:

- The smartphones near the bogies generally show higher standard deviations of their vertical accelerations than those placed near the center of the car body. Exceptions are observed between kilometer position 77.6 and 78, for the Motorola (run B and E) , the Nokia (run B) and the Samsung (run B and E).
- At lower speeds, the difference between the standard deviations of the smartphones near the bogies seem to approach those of the smartphones near the center of the car body. This is best visible for the Nokia and Samsung in Figure 5.3 from kilometer position 77.5 onwards.
- Sharp peaks and dips in LL D1 standard deviations over 200 meters are more easily identifiable for the smartphones near the bogies than for those in the car body. Examples of these are observed for the Nokia and Samsung around kilometer position 73.8, 74.5 and 75.5.
- The timestamp differences between the Nokia on board 1 and the Nokia on board 3 are clearly visible in Figure 5.3. Alignment of (processed) measurement results based on the system times alone introduces errors and may not be suitable for condition monitoring purposes. A way to mitigate this may be to align the vertical acceleration signals based on peaks values around the known irregularities visible in the time domain in Section 4.3.3.

- As previously mentioned, board 1 on measurement run B was placed further away from the bogies than in measurement run E. The standard deviations of board 1 in run B tend to display levels more closely related to the smartphones at the center of the car body in runs B and E than those of board 1 of run E. Slight deviations of positions within the car body may therefore result in significant variation in the measured accelerations.

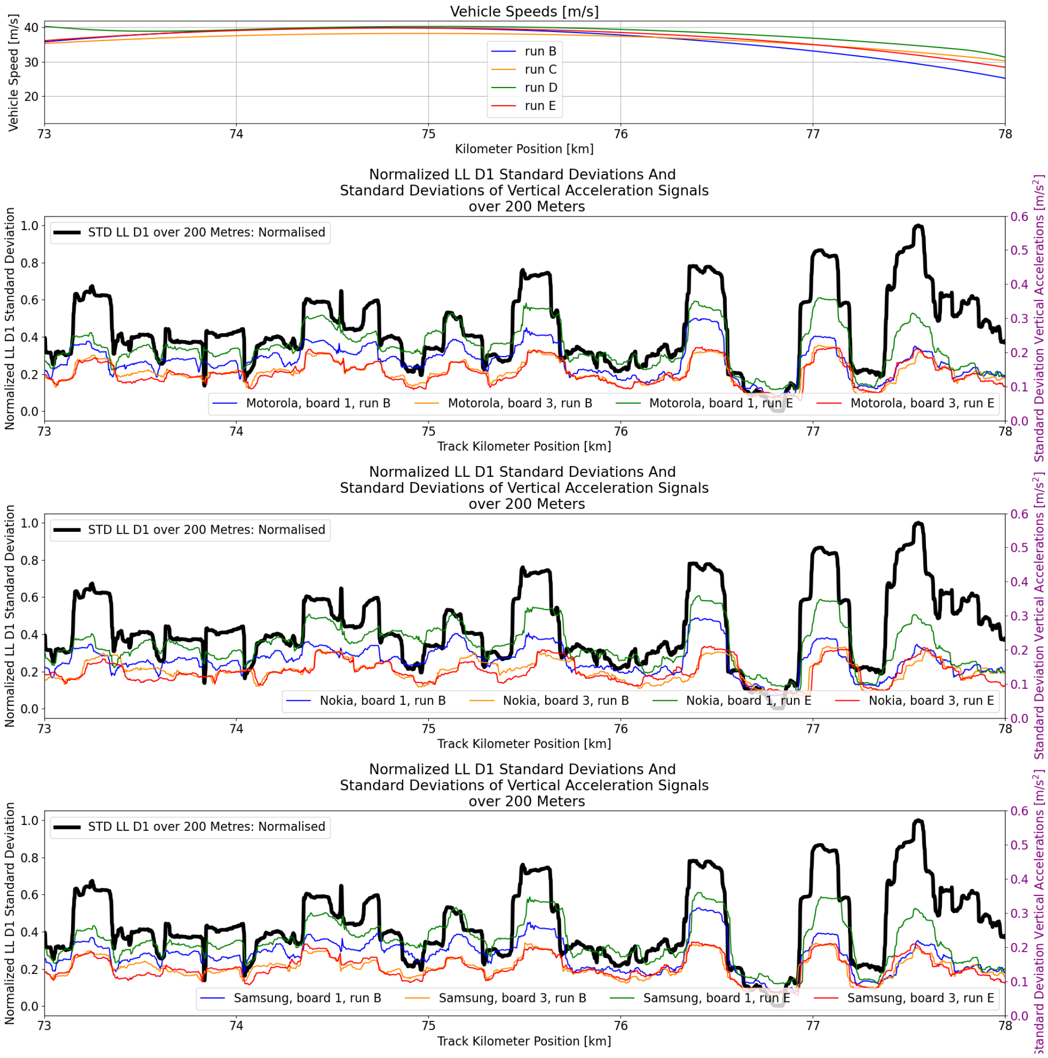


Figure 5.3: Standard deviations of the track geometry parameters versus the vertical accelerations of the mobile phones for the smartphones on board 1 and 3. The top plot displays the vehicle speed of the various runs. Depicted are the results for runs B and E.

5.4. Inclusion of an iPhone Device

The experimental results presented so far in this thesis were performed on a set of mobile phones of different brands with an Android operating system. In Chapter 3, different tests showed a significant variance between different smartphone accelerometer characteristics. Thus, to better quantify these variances, one additional brand of phone is analysed. This is the Apple iPhone, which uses an iOS operating system. As mentioned in previous chapters, the GPS-signals of the iPhone 13 Pro Max were used for positioning. In this chapter, the inclusion of health state assessment with an iPhone device is presented and compared to the results of the Motorola.

The iPhone was placed on a windowsill or the floor near board 1 for all measurement runs to capture positioning. During run E, the iPhone was near board 1, and during run B on a windowsill. Figure 5.4 and Figure 5.5 show the vertical acceleration signal of the iPhone and Motorola (board 1) during runs B and E respectively, along with the periodograms between 0-90 Hz and 0-5 Hz. The sampling frequency of the iPhone is around 100 Hz, resulting in no frequency components displayed in the periodogram above 50 Hz when compared to the Motorola. When downsampled to 10 Hz, the signals in run B show a strong resemblance in the frequency domain, whereas in run E, the Motorola shows a significantly higher peak around 1.5 Hz when compared to the iPhone.

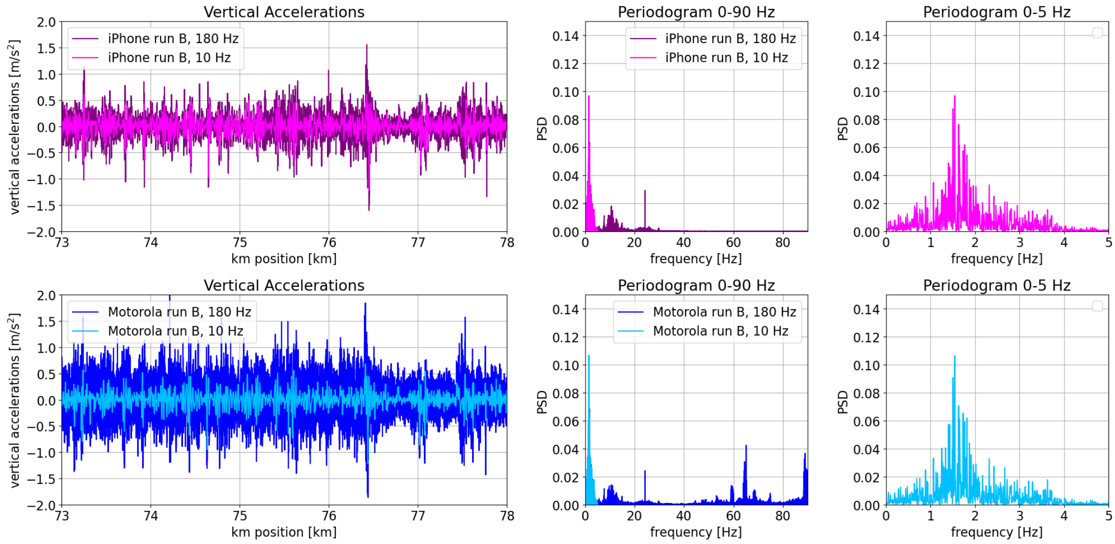


Figure 5.4: Vertical signals of the iPhone and the Motorola for run B. The maximum sampling frequency of the iPhone was 50 Hz, hence the lack of frequency content in the periodograms past 50 Hz for this device.

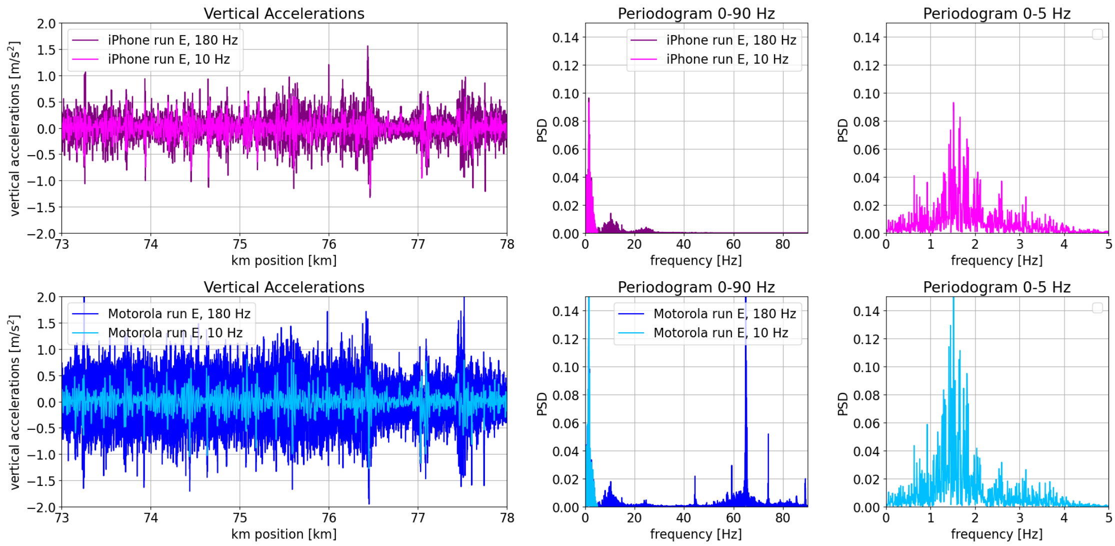


Figure 5.5: Vertical signals of the iPhone and the Motorola for run E. The maximum sampling frequency of the iPhone was 50 Hz, hence the lack of frequency content in the periodograms past 50 Hz for this device.

Figure 5.6 shows the standard deviations of the iPhone, together with the signals from the Nokia, Samsung and Motorola on board 1. All signals have been downsampled to 10 Hz for a fair comparison, and to eliminate the relation-distorting effects of high frequency components. It is observed that the iPhone resembles the patterns visible for the other smartphones on board 1. In run E, board 1 was placed in the car body on the floor on top of the bogie, whilst the iPhone was placed on a windowsill slightly further away. It is clear that the vertical accelerations recorded by the iPhone were lower than the ones of board 1 recorded on the floor of the car body. This finding confirms that different phones show a certain degree of variance, while the signal pattern shows similarities.

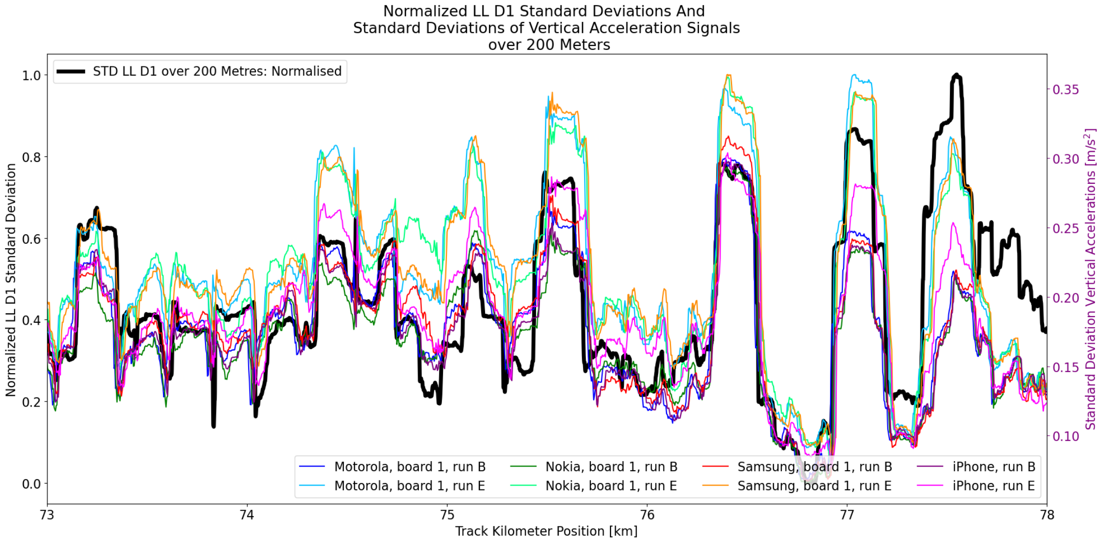


Figure 5.6: Standard deviations of the normalized track geometry and the standard deviations of the vertical acceleration signals of the smartphones. This figure includes the iPhone measurements.

5.5. Conclusions on Track Quality Monitoring with Smartphones

This section covers the main conclusions of Chapter 5. The standard deviations of the phones with the low-pass filter behaviour reflect the differences in Track Quality Index without much further processing, indicating that even smartphones with low cutoff frequencies are therefore able to reflect the track quality in this case study. High frequency components distort the relation between the vertical accelerations and the Track Quality Index and thus low-pass filtering the acceleration signals is suggested.

The relation is furthermore subject to a large degree of variance. Variance in standard deviation levels are encountered between different smartphone models, even after low-pass filtering. Furthermore, higher vehicle speed magnifies the vertical accelerations. Clear relations have to be established between the amplification of the standard deviations of the vertical acceleration and the vehicle speed to strenghten the repeatability. Finally, small deviations in the position within the car body were found to influence the magnitude of the accelerations significantly for this case study.

6 Conclusion and Recommendations

This report aims to answer to what extent smartphone accelerometer measurements on board of in-service passenger trains can be used to monitor railway track quality? This research question is answered through four chapters. Section 6.1 draws the main conclusions based on the conducted research. This is followed by a possible methodology on how a more developed monitoring system using smartphones could look like in Section 6.2. Section 6.3 covers the possible future societal and ethical threats and opportunities of the technology. The final section of this chapter, Section 6.4, provides a final list of recommendations, based on findings in the research.

6.1. Conclusions

The conclusions are formed by answering the main research question of this thesis: ”to what extent smartphone accelerometer measurements on board of in-service passenger trains can be used to monitor railway track quality?” The question is answered through four chapters, each associated with a research question stated in chapter 1.

Research Question 1, What research regarding on-board ride and track quality measurement techniques (especially smartphones) have already been conducted and what experience is already present in the industry? Key pieces of literature regarding smartphone-based railway infrastructure monitoring methods are identified to find current research gaps. The literature review is extended with a survey, distributed among European infrastructure managers, to also obtain insights in (unpublished) experience present in the industry. The review reveals limited studies in the use of smartphones for track quality or condition monitoring, particularly on the topic of repeatability of measurements subject to operational variability in in-service conditions. Furthermore, smartphone accelerometers display differences in sensor characteristics in previous research. The review finds that the effect of different positions of a smartphone within the vehicle was usually left out of the scope of earlier work, or not covered in-depth.

Research Question 2, In which ways do the sensor characteristics of different contemporary devices differ? To assess the heterogeneity of the smartphones encountered in real world applications, three phone models from 2023 are purchased for this research and they are subjected to three tests: a static test, a hammer test, and an in-situ test. The overall conclusion of on smartphone accelerometer heterogeneity is that the sensor characteristics of contemporary smartphones can vary significantly. The different sampling frequencies, presence of eigenfrequencies, low-pass filters, non-stationary trends and noise levels limit the frequency ranges that can be measured accurately per device.

Research Question 3, In which ways do different recorded acceleration signals from smartphones on in-service passenger trains differ? To see how the vertical acceleration signals of the different devices would differ, the thesis makes use of a case study. Smartphones are installed on different in-service passenger trains passing the same railway tracks. Information on the positioning is retrievable by vertical acceleration peaks around known elements such as joints. Vehicle speed (sleeper spacing excitation) can be extracted from the vertical acceleration signals through a spectrogram. For repeatability: the study finds that acceleration peaks around transition zones and joints may vary per measurement run, even when passed at similar speeds. Higher frequency components (above 15 Hz) are found to create high levels of variance between each measurement runs in general, likely relating to vehicle conditions or speeds. Higher vehicle speeds report magnifying effects on the vertical accelerations measured by the mobile phones. Accelerations measured by a smartphone near the bogies are found to be generally higher in amplitude than those near the car body center. Much more data is required to establish clear relations between these variance-inducing factors.

Research Question 4, To what extent can (repeated) on-board smartphone accelerometer measurements reflect differences in track quality? The standard deviations of the low-pass filtered vertical accelerations of all smartphone signals show a degree of correlation to the selected track quality index, albeit with a large degree of variation. Variation of the TQI is observed with repeated measurements. Speed is found to amplify the standard deviations, and this thesis recommends finding some regression model to correct for this. Furthermore, the position of the vehicles is found to influence the amplitude of the accelerations significantly as well. More data is necessary to fully understand the effect of this variance on the repeatability of measuring TQI's.

It thus shows promise that track quality can be reflected through smartphone measurements on passenger trains, but major challenges remain. The parameters to be monitored are largely restricted by the sensor characteristics of modern smartphones, varying per smartphone model. Track quality indices that can be monitored by low frequency accelerations, such as the standard deviation of the LL D1 over 200 meters, may therefore be able to be monitored by a broader range of smartphones, albeit with variation in measurements per device. Operational variability, notably the vehicle speed, location in the car body and variation in vehicle (suspension) health states, require large amounts of data to be understood, and pose challenges for selecting robust features for railway track quality. The combination of variance in measurement devices and operational variance onboard in-service passenger trains may form boundary conditions to what track quality information can be monitored accurately and reliably.

6.2. Outlook on Developed Measurement System

Based on the observations in this thesis, a following potential framework is proposed in Figure 6.1 for the near continuous monitoring of the Track Quality Index through mobile crowdsensing. This framework consists of 5 steps:

- **Step 1, Geometry Measurements**: Track geometry measurements are required to form a baseline of the Longitudinal Level quality. These measurements take place on a low frequency (1-4 times per year, as per current practice).
- **Step 2, Data Acquisition**: Between the geometry measurements, acceleration data is acquired from the smartphones of the passengers onboard in-service trains. Besides accelerations, positioning data such as GPS or a train-bound positioning system should also be collected, to relate accelerations back to locations on the railway line and approximate the vehicle speed. If possible, the location of the smartphones within the car body should be registered as well, to account for the strong variability encountered in the signals of Chapter 4.
- **Step 3, Data Processing**: If required, positioning information can be retrieved from peaks in the vertical accelerations related to joints, and vehicle speeds from the sleeper-spacing excitation. In this step, outliers can be removed caused by human interaction and low-pass filtering of the data takes place. This should then be followed by the computation of the standard deviations of the vertical accelerations over a spatial window. Furthermore, the standard deviations of the accelerations should be scaled by a factor related to the vehicle speed, which can for example be obtained through a regression model.
- **Step 4, Data Aggregation**: The data processing is followed by data aggregation. Smartphone data over a single run or over a single day are combined, to take into account variance in the vehicle suspension systems and differences in the position within the car body. Trends of this aggregated data can be analysed over time through time series analysis, to retrieve information on the relative degradation of the Track Quality Index compared to the geometry measurements conducted by the dedicated measurement vehicle. Through analysing these trends, conclusions on

track geometry alignment can be drawn on a near continuous basis. Deviations can be monitored over time and maintenance can be planned accordingly.

- **Step 5, Quality Control**: Periodically, the data quality of contemporary smartphones should be tested as done in Chapter 3 of this thesis. This is to assess if the frequency ranges from which features are extracted contain low-pass filter behaviour or eigenfrequencies, which were also encountered at unexpectedly low frequencies in some of the smartphones in this thesis. This way, the infrastructure manager can maintain some insights and control over the quality of the data.

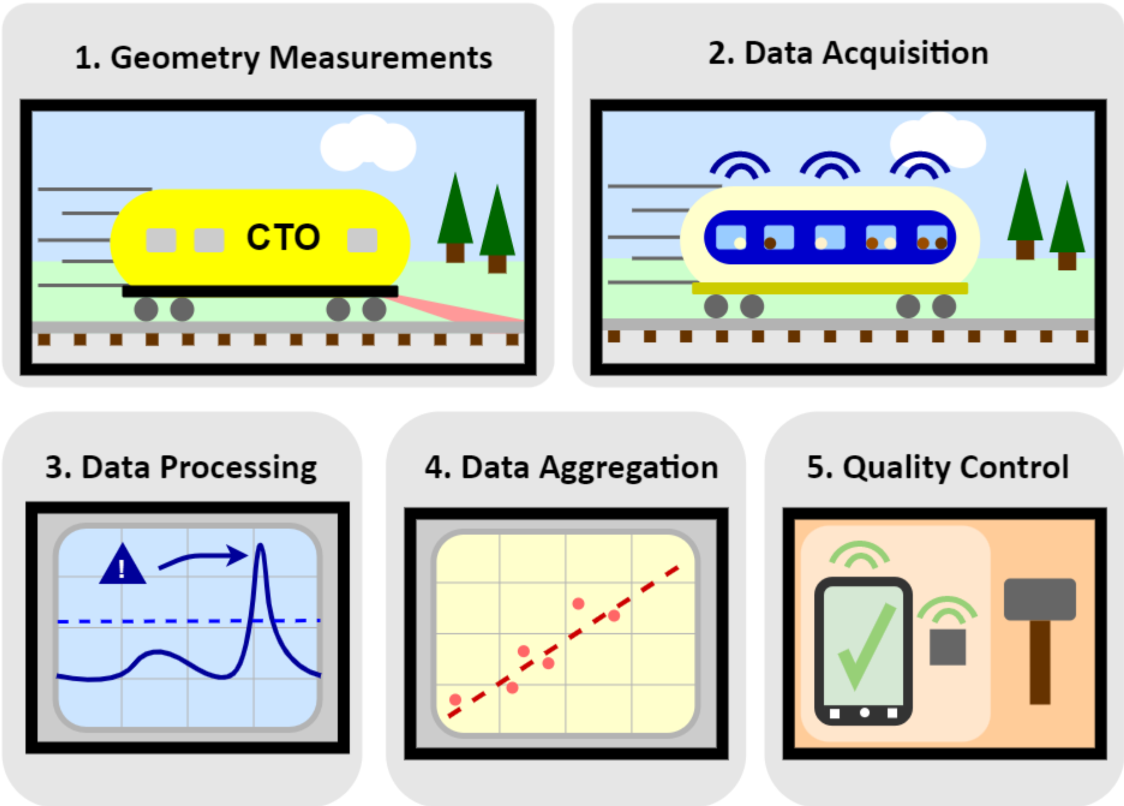


Figure 6.1: The steps of a possible monitoring framework for the Track Quality Index, based on observations in this thesis.

6.3. Ethical and Societal Impact

Although the technology researched in this thesis is by far not yet applicable for implementation, a brief outlook is provided on the possible societal impacts of a further developed monitoring system using the technology. Some of the ethical aspects and impacts are also discussed here. These impacts are addressed through their relation to a list of stakeholders, visible in Figure 6.2. It should be noted that the focus of this thesis was not the societal impact for a monitoring system. This section is here to provide an overview of some of the possible future opportunities and threats in the context of societal impact, as identified by the author, which are to be verified and expanded on in future research.

The first stakeholders are the infrastructure managers. A system using smartphones provides data about the railway system without additional unavailability of the infrastructure and at a low cost. The cost aspect has also been addressed in the Swedish response to the survey in Section 2.2. The affordability of this technology can be interesting from an equity point of view. Countries or organisations which lack the resources for dedicated measurement equipment could use further developed variants of this technology to monitor the alignment of their railway lines. An opportunity may lie in to identify and involve organisations that are in such a position, and develop this concept further with them through international cooperation. The same goes for regional lines, which may not be as profitable for infrastructure managers and operators as mainlines and may therefore not be the top priority to monitor

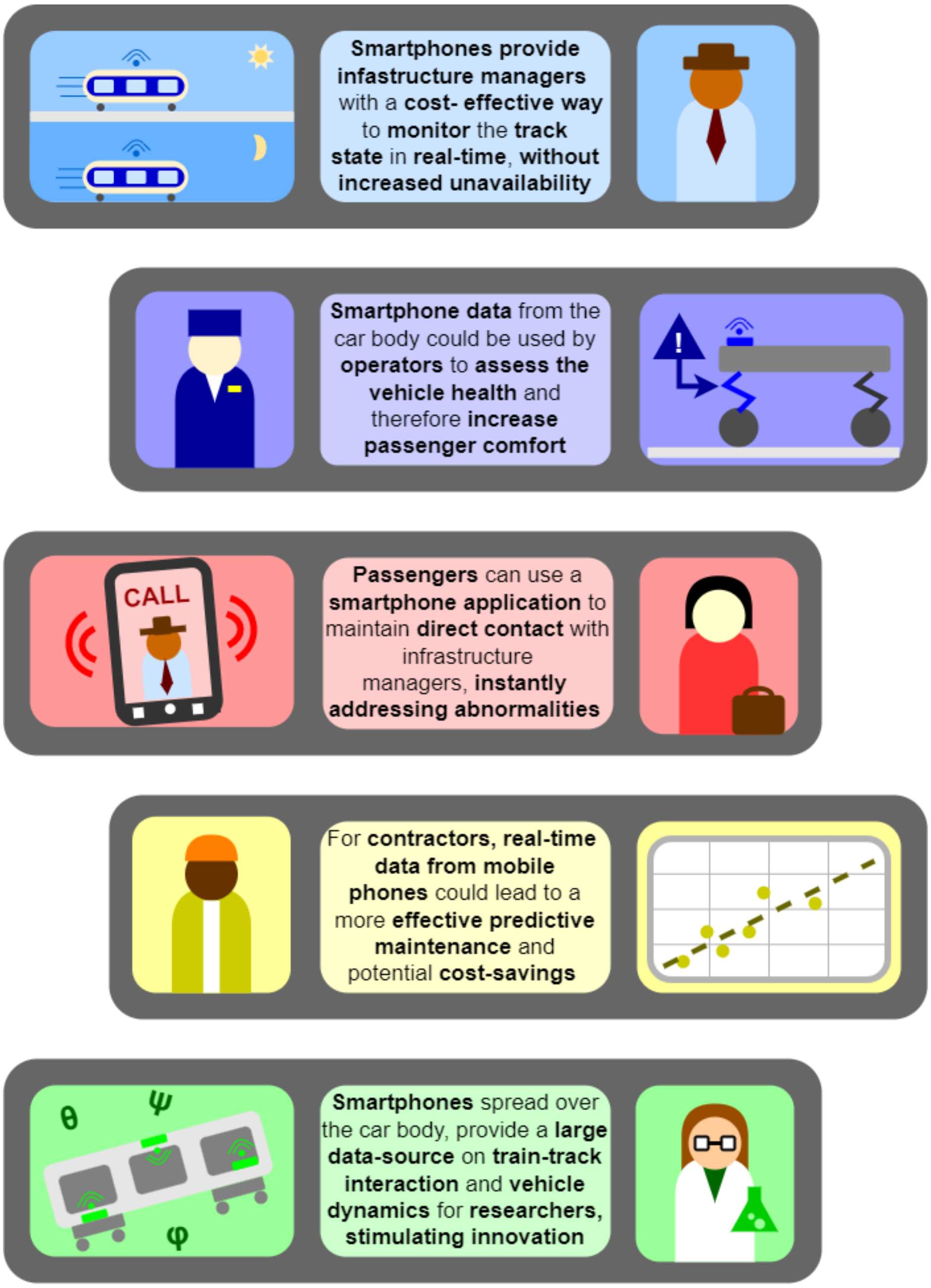


Figure 6.2: Outlook on possible impacts on, or involvement of, a selection of stakeholders when continuing the development of the concept of railway infrastructure monitoring through smartphones.

frequently. But these lines still form transportation arteries for the local communities. By implementing mobile crowdsensing technologies, the threshold and investment costs for additional monitoring of these lines go down, the detection of early stage defects goes up and therefore the availability and comfort of the regional line may experience a positive effect.

The second stakeholders involved are the railway operators, running trains on the network and transporting goods. Chapter 4 reports differences in accelerations recorded around transition zones between different runs. This may be related to vehicle characteristics, such as the suspension health states. Furthermore, Section 2.2 reports heterogeneity of vehicle suspension system health states as a key challenge for this technology. Combining the measured accelerations with data on the vehicles, possibilities for railway vehicle fleet monitoring can be explored and integrated in a railway infrastructure monitoring system using the smartphones. It is thus advised to include railway operators in further development of such a system, both to mitigate a key challenge and to add value to the use of smartphones for condition monitoring.

A smartphone app could be developed for passengers to download on their devices and gather data for the infrastructure managers. Not only could such an app deliver data to the infrastructure manager for the assets, but functions can be added for passengers to directly interact with, and report observations to the infrastructure managers. This would theoretically extend the sensing through mobile phone sensors with sensing through human senses.

This research has contributed to the use of crowd-sensing for condition monitoring purposes. Although the technology developed in this thesis is by far not suitable yet for crowd-sensing deployment, one needs to be cautious not to violate the rights of individual passengers when obtaining data. This thesis stipulates the need of passengers to be informed if their sensor data from their smartphones is used for monitoring purposes, and measures should be taken by infrastructure managers to avoid collecting any personal data.

Another opportunity lies in involving contractors in future research, to better understand for what (predictive) maintenance purposes they would desire a monitoring system with a short measurement interval possible with mobile phones. Repeating a survey similar in Section 2.2 for contractors may provide additional monitoring purposes and help identify key challenges for future research. Furthermore, more information on the assets may strengthen decision making processes for the contractors, which in turn may lead to cost-savings.

A final stakeholder to be mentioned in this section are research institutes. Research institutes may be interested in acquiring data from smartphone accelerometers to increase the academic understanding of vehicle dynamics. Section 4.4.3 displays that different measurement positions reflect differences in the (frequency content of) signals. Measuring accelerations on multiple locations in the car body could provide information on movements in all six directions. As passengers' smartphones can be positioned anywhere in the car body, this could form an extensive data-source for these purposes.

6.4. Recommendations for Future Research

The last section of this thesis contains recommendations for further research, based on observations, simplifications and conclusions in this thesis.

The first set of recommendations consist of (minor) research gaps encountered in the literature review in Chapter 2, and include the following:

- Most (if not all) published research has been done with the same type of rolling stock. Comparing results between smartphone measurements on different types of rolling stock are an open gap in research. Future research could repeat a similar case study as the one conducted in this thesis, but run on 2 different types of passenger rolling stock.
- The vast majority of studies mount the smartphone on a rigid surface. Comparing the accelerations smartphones under different mounting conditions has not yet been done extensively. Comfort measurements as done in [6] reported that the compressibility of the seat may create larger variation in the measured accelerations. An idea for future research could be to repeat the measurements conducted in this thesis, but with additional wooden boards on top of the seats, to compare the time and frequency domain of the signals under rigid and damped mounting conditions.
- Limited observations regarding the effect of human interactions with mobile phones or the effect of changing the orientation of the smartphone are currently available.

. The second set of recommendations are some points of reflection on the measurement methods used in Chapter 3 and 4:

- The thesis assumes that the accelerometers of the same smartphone model would exhibit the exact same sensor characteristics. It therefore uses 3 random different models, for each test in Chapter 3. In a follow-up study, the smartphone accelerometers used should be assessed individually, rather than per smartphone model.

- Better sensor alignment with the vehicle is advised for future research, to avoid the contamination of the vertical acceleration signal with lateral or longitudinal vibrations. More advanced alignment is deemed too advanced for the purposes of this thesis. Examples of alignment methods were presented in [4] and [38].

The third group of recommendations is related to the relatively small scale testing of previous works. A common trend encountered in the literature review is that the concept of assessing railway infrastructure condition through mobile phones is often tested on a relatively small scale, with a handful of devices or no repeated measurements. This stands in stark contrast with a potential asset of this technology: data having many different sources and being recorded frequently. The heterogeneity of sources and the conditions under which data is recorded affect the vertical acceleration signals, and are to be researched further. The small set-ups and pilot studies also fail to address the large amount of operational variances, which require sufficient data to be overcome and understood. These causes affect the repeatability of the measurements, and are pivotal to understand to retrieve robust information regarding the state of the tracks based on mobile phone measurements. This thesis could not gather enough data to fully understand these relations, due to lack of time. This thesis therefore strongly recommends a much more extensive monitoring campaign, to address the effect of vehicle speed, positioning within the vehicle and the effect of differences in the vehicle health state on the measured accelerations.

- The magnifying effect of speed on the measured accelerations observed in Chapter 4 may be understood better by applying a regression model based on a larger amount of data and can be conducted in a similar manner for the trams in [15].
- An analysis using a large amount of data can be used to understand the variance of different positions within the car body. The different amplitudes in vibrations by having smartphones further away from the bogies, as observed in Chapter 4 pose a challenge from a repeatability perspective. This thesis recommends to place a smartphone under every seat during a large measurement campaign to conclude if and how this difference in amplitudes can be mitigated through using a large number of smartphones (e.g. averaging, statistical methods).
- Smartphone measurements taken from the car body in Chapter 4 display a degree of variance per measurement run, even if the vehicle ran at similar speeds. This variance can possibly be related to the state of the vehicle, or the health of the vehicle's (secondary) suspension system. This thesis therefore recommends to compare the results of a larger measurement campaign not only with track geometry, but also with the health indicators of vehicles. This would shift the relevance of a system from only track monitoring, relevant to infrastructure managers, to also include (real-time) vehicle fleet monitoring, relevant to railway operators. Additionally, difference in the health state of vehicles was reported to be a key challenge in the survey results of Section 2.2 by 2 of the infrastructure managers involved. An increase in the understanding of the relation between signal variance and vehicle health state could prove to be beneficial in creating robust indicators reflecting the state of the tracks.

Another set of recommendations is related to positioning and synchronisation issues encountered in Chapter 4 and Chapter 5, as well as being cited as a key implementation challenge mentioned by SNCF Réseau and ProRail in the survey of Section 2.2. Positioning on the tracks is key for relating back vibrations to track defects. GPS signals are not always available on board passenger trains. Alternative methods of retrieving an accurate position of the smartphones on the track should be investigated. An example could be to use the impacts around known irregularities (joints, fishplates) as primers, although this thesis shows that not all smartphones are able to register these irregularities as peaks. A related issue to the positioning is the system time misalignment between devices. The misalignment in system times make for a challenge in synchronising measurements within the same run over the same piece of track. Quick ways to do this on board the passenger trains should be investigated for developing the technology further. A way to do this is through the use of an induced impact or a known impact location (such as a joint or fishplate) similar to the positioning problem.

Then there is the combination of measurements for decision making purposes The effect of integrating measurements by multiple smartphones for track condition monitoring purposes has also not been studied, or at most to a very limited extent. The use of multiple measurement devices and runs to detect outliers in measured vibrations has been a topic of research in [15] and [21]. A possible future research gap included is therefore to see if and how using the measurements of multiple smartphones in the same car body may give more details on track geometry degradation present.

The challenges related to the heterogeneity between smartphone characteristics discussed in Chapter 3 are also a topic for future research. Different smartphone models are able to monitor different frequency ranges accurately, which may constitute problems when combining the measurements of different measurement devices. This thesis strongly recommends to further investigate methods of integrating acceleration signals measured by different types of devices.

Repeating measurements over a longer time period to analyse the trends and accuracy of data over a time window is also a logical next step, to see if trends in track quality levels are statistically significant before the next geometry measurement is conducted. To this end, this report strongly advises to repeat measurements on a high frequency over a period between 2 conventional track geometry measurements (e.g. 3-6 months). With this dataset, the statistical significance of trends observed in the Track Quality Index can be tested, to see if the variance in measurements can be distinguished from degradation in the geometry of the railway system happening over time.

A recommendation should be made regarding the data quality of the smartphones used in this thesis when comparing the results to previous works. In Chapter 3, this thesis encounters cut-off frequencies that were notably lower than displayed in previous works, especially when compared to a study with models from 2021 [19]. This could have multiple reasons, such as the smartphone models used in this thesis being relatively cheap models when compared to the ones in [19], but another reason could be that contemporary phones are simply equipped with sensors capable of measuring a more limited range of frequencies accurately. This observation does highlight a potential threat when using smartphone sensors, in that the infrastructure-related parties have little influence on the quality of the sensors of (future) smartphones. Therefore, this thesis recommends to also involve smartphone manufacturers for future developments on railway structural health monitoring through smartphone sensors. This way, the direction the industry is moving can be better understood and insights in boundaries posed by the smartphone sensors obtained. Furthermore, information on the sensor characteristics might be retrieved more efficiently this way, rather than through empirical testing procedures present in previous published works and this thesis.

This thesis limits itself to relating the vertical accelerations to a Track Quality Index for the LL D1 parameter. No in-depth analysis is present which frequency ranges are required to optimise the correlation of this relationship. Future research may further improve this correlation by investigating which frequencies components are responsible for this relation and which create undesired noise.

An obvious recommendation for future research is to investigate the relationship between vertical accelerations and other railway assessment systems or KPI's. Another Track Quality Index specified in the norms is counting the number of isolated defects over a certain length exceeding a certain preset limit [16], and incorporating this TQI may make the quality overview of the tracks more complete. Examples of future research could also be to correlate or compare the results of Axle-Box Acceleration measurements and InSAR data with smartphone signals. Furthermore, lateral accelerations are currently largely left out of scope in current research. Therefore, this thesis advises to investigate the relationship between lateral accelerations and other track geometry parameters, or combining lateral accelerations with vertical accelerations. When combining measurements of different smartphone axes, this thesis would like to stress the observation in Section 3.2 that different accelerometer axes within the same device may have different sensor characteristics.

Finally, the survey results in section 2.2 illustrated a demand amongst infrastructure managers for further developments and investigations into this topic. This report therefore encourages future researchers to keep developing the concept of railway infrastructure monitoring through smartphone sensors and attempt to overcome the key challenges identified in previous works and in this master thesis. Furthermore, both ProRail and the SNCF Réseau have indicated to be interested in sharing observations of already conducted research involving the use of smartphones as on-board measurement devices for railway condition monitoring. Data and observation may therefore be made available for future researchers, which can in turn accelerate innovations and breakthroughs in overcoming the challenges related to the implementation of such a system. This thesis furthermore proposes the formation of a European body of experts, to share conclusions and observations in this field thus far and is in charge of keeping knowledge on this topic both findable and easily accessible for future research, in accordance with the FAIR-principles described in [40]. This assures that future researches have the state-of-the-art knowledge regarding this topic more directly at hand, and avoids obsolete repetitions of research of individual railway organisations and researchers.

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A

Appendix A : Survey Infrastructure Managers

This section contains the questions and answers for the Infrastructure Manager survey discussed in section 2.2 of the thesis. Responding organisations are marked by the initials of their respective country: NL for The Netherlands (ProRail), FR for France (SNCF Réseau) and SW for Sweden (Trafikverket).

1. Has your organisation researched the possibility of using smartphones as onboard measurement devices for railway conditions monitoring?

- Yes : NL , FR
- No : SW
- Unknown

2. Why did your organisation not investigate the possibility of using smartphones an onboard measurement devices for railway condition monitoring?

- Lack of promising results from previous research by other parties
- The implementation challenges of such a system were deemed too complex
- Lack of resources (money, time, manpower) to launch investigation: SW
- Other

3. Is your organisation still actively researching the possibility of using smartphones as onboard measurement devices for railway infrastructure condition monitoring?

- Yes: FR
- No: NL

4. Why did your organisation stop investigating the possibility of using smartphones as onboard measurement devices for railway condition monitoring?

- Lack of promising results from investigation: NL
- The implementation challenges of such a system were deemed too complex
- Lack of resources (money, time, manpower) to continue investigation
- Unknown
- Other

5. In which years did research into the topic take place within your organisation?

- FR: 2016 - now
- NL: 2018

6. What sensors in the smartphone did your organisation investigate in the context of onboard railway condition monitoring?

- Accelerometers: NL , FR
- Gyroscopes: NL , FR
- Microphones
- Other

7. For what railway system condition monitoring purposes did your organisation investigate the use of smartphones?

- Ride comfort evaluation
- Track alignment or track geometry monitoring: NL , FR
- Vehicle condition monitoring: NL
- Other

8. Did your organisation develop a smartphone application ("app") for railway condition monitoring purposes?

- Yes : FR
- No : NL
- Unknown

9. What is (or was) the name of this application?

- FR: KELI

10. What challenge(s) would you deem most significant in the implementation of a measurement system involving the accelerations measured by on-board smartphones?

- Acquiring data from smartphones
- The data quality produced by the smartphones: FR
- Heterogeneity of different smartphone models
- Establishing relations between smartphone measurements and railway performance indicators: NL
- Dealing with noises in signal due to passenger movement
- Heterogeneity of vehicle suspension system health states: FR , NL
- Relating the measured accelerations back to positions in the railway system: FR , NL
- Differences between different accelerations measurements as a result of different speeds and driving behaviour: FR , NL
- Other

11. Would your organisation be interested in sharing observations of already conducted research involving the use of smartphones as on-board measurement devices for railway condition monitoring?

- Yes : NL , FR
- No

12. Would your organisation be interested in further research and investigations in the field of using smartphones as on-board measurement devices for railway condition monitoring?

- Yes : NL , FR , SW
- No

12. Please elaborate briefly why your organisation would be interested in further research and investigations in the field of using smartphones as on-board measurement devices for railway condition monitoring.

- FR: There are still unexplored area in this topic such as having a reliable position in the railway system, validating data quality over time and exploring various new analyses of car body accelerations.
- NL: I would not perform research in this topic, but maybe interested if there are any outcomes. Over the course of several years this topic keeps popping up. Due to localisation problems, GPS inaccuracies and the suspension of the car: the cant is the only signal which can be properly measured. Smartphones are only useful for passenger comfort measurements and ProRail is not responsible for those. Passenger comfort is more cheaply measured with onboard accelerarometers/gyroscopes fixed in the train already.
- SW: This can be a cheap way to get more information of the comfort and other issues on the trains. Also to be able to have information of the track is interesting.