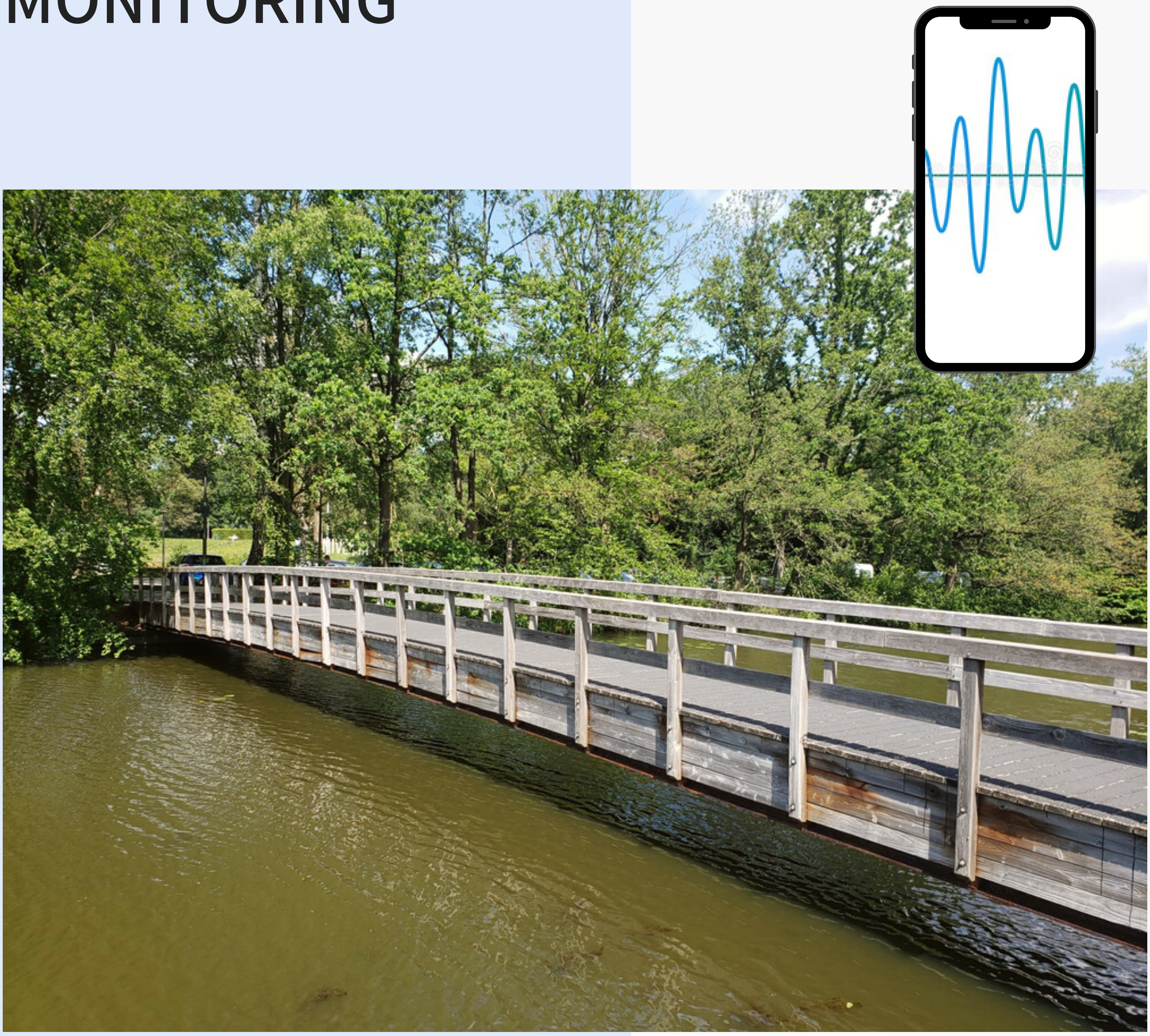
SMARTPHONE-BASED VIBRATION ANALYSIS FOR BRIDGE HEALTH MONITORING

JULY 2022



BSC-Thesis CE

Avnon, R.
(Reuven, Student B-CE)
S2360349

UNIVERSITY OF TWENTE.

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Smartphone-Based Vibration Analysis for Bridge Health Monitoring

Author

Name:	Reuven Avnon
Student Number:	S2360349
Title:	BSc-CE Student at University of Twente, Netherlands
Email Address:	r.avnon@student.utwente.nl

Internal Supervisors

Name:	Dr. Rolands Kromanis
Title:	Assistant Professor at University of Twente, Netherlands
Email Address:	r.kromanis@utwente.nl
Name:	Maria Xofi
Title:	PHD Candidate at University of Twente, Netherlands
Email Address:	m.xofi@utwente.nl

External Supervisor

Name:	Prof. Eloi Figueiredo
Title:	Full Professor at Lusófona University, Portugal
Email Address:	eloi.figueiredo@ulusofona.pt

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Preface

This thesis is written as part of the third year of the bachelor program of Civil Engineering at University of Twente (UT). It is commissioned by Dr. Rolands Kromanis (UT) with collaboration with Prof. Eloi Figueiredo from Lusófona University, Portugal.

As part of the research in the Structural Health Monitoring (SHM) at the UT, Dr. Rolands Kromanis has been leading the research team: SHM for smart infrastructure. Their research focuses on bridge health monitoring using sensors such as accelerometers, load cells, temperature, and vision-based systems. To further explore infrastructure monitoring options, the feasibility of using smartphones for SHM is investigated in this research.

I would like to thank Prof. Eloi Figueiredo and Maria Xofi for their excellent guidance and support during this process. A special thanks to Dr. Rolands who invested valuable time to supervise me on a regular basis. Rolands always pushed the standards higher and challenged me. I liked the way he also gave me freedom to do things in my own way.

To my colleagues at the UT who were there to share ideas and opinions. My parents and family deserve a particular note of thanks for being there for me throughout my studies.

Enjoy the reading, Rubi.

Abstract

The relation between bridge dynamic responses to load is the essence of vibration analysis. Bridge dynamic properties could serve as a reference for its "healthy" condition. An observed change in bridge response could be a sign of degradation or even damage. Currently, researchers usually use fixed sensor networks for monitoring purposes. These sensor networks consist of expensive sensors which require complex installation and high maintenance requirements. The management and aggregation of data from such networks is a challenging task. Alternatively, smartphones, which are equipped with networks, sensors, and storage capacity, might be useful for vibration testing, reducing cost and the need for expert installation. The outspread of smartphones has shaped the opportunity to utilize crowdsourcing for structural monitoring purposes. Crowdsourcing networks are widely desirable for their potential to generate Bigdata, cost-effectively and collectively. A network in which smartphones serve as mobile sensors, sharing structural vibration and location data to a cloud server. This BSc thesis presents innovative applications of smartphones to measure dynamic bridge responses and practical information for SHM. Three questions were investigated: (i) methods for extracting natural frequencies from smartphone measurements, (ii) achievable frequency accuracy, and (iii) ways for using gyroscope and GPS data for bridge monitoring. The smartphone measures acceleration, gyroscope, and GPS data while carried in the pocket, demonstrating crowdsourcing. The bridge is excited by walking over it and performing heel drops on its mid-span. One method enables the extraction of the bridge's eigenfrequencies from the walking measurements. It involves splitting the acceleration data into measurements on the bridge, and reference walking before and after the bridge, computing the Fast Fourier Transformation (FFT) for each data set individually, subtracting the outputs, and manually inspecting the resulting Power Spectral Density (PSD) difference graphs. The smartphone's gyroscope captures the walking frequency and gait cycles. Dominant frequencies computed with gyroscope data could be eliminated as bridge response candidates. GPS measurements were insufficiently precise to detect exact location and assist in pairing frequencies with their mode shapes. Natural frequencies estimated from smartphone measurements appear to be comparable to vision-based systems frequency measurements. However, smartphone measurements seem to assist in computing more modal frequencies than cameras by providing 3D spatial data. The vibration analysis suggests that smartphones can measure bridge dynamic responses while placed inside a pocket. Natural frequencies can be computed by removing the

walking frequency and adjusting the power spectral scale. Averaging small data sets from the crowd could serve as a database to monitor our infrastructure without installing and maintaining complex fixed sensor networks.

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1. Introduction

Bridge dynamic responses to different loads provide an insight into its structural condition. Deviations from expected bridge vibration reactions could be a sign of fatigue or even damage (Giurgiutiu, 2014; Vardanega et al., 2022; Sony et al, 2019; Hughes et al., 2021). Nowadays, complex fixed sensor systems are usually installed to gather Bigdata for monitoring purposes (Matarazzo et al. 2017). A system that consists of an many sensors is costly and complicated to install. Other challenges with operating such systems are the high maintenance requirements and the management and coordination of such scattered data (Feng et al., 2015; Zhao et al. 2017; Matarazzo et al. 2017; Feldbusch, 2017). As an alternative, a mobile sensing system with low setup costs could ease the extraction of data. Modern smartphones that are equipped with accelerometers, gyroscopes, and GPS sensors can be effectively used for bridge structural assessment. Due to the competitive nature of the market, the variety and accuracy of these sensors tend to improve significantly with each new smartphone model.

The widespread availability of smartphones has created the opportunity for a new source of vibration data for SHM, crowdsourcing. Crowdsourcing is a collaborative problem-solving technique that involves the community and volunteers, resulting in mutual gains (Estelles-Arolas and Gonzalez-Ladron-de-Guevara, 2012). In this context, a crowdsourcing network offers a platform in which smartphones operate as mobile sensors, sending structural vibration data and GPS position data to a cloud server (Ozer et al., 2015). Long-term vibration measurements and the ultimately discovered structural vibration characteristics will generate a baseline database for the structure. This baseline can be used as a reference for structural health monitoring and damage identification (Dackermann, 2020; Jimin & Zhi-Fang, 2001; Abdo, 2014). Engaging the public enables effective and affordable bridge monitoring in the urban environment.

This research aims to (i) investigate smartphone applications for collecting acceleration, gyroscope, and GPS data and (ii) translate this data into meaningful parameters for SHM. An attempt to estimate the footbridge's dynamic properties such as natural frequencies with a smartphone is carried out. The author collects data while he crosses the footbridge with his smartphone in his pocket, demonstrating crowdsourcing. After the data is collected, measurements are transferred to a computer for further analysis. Acceleration and the gyroscope data are analyzed with the Fast Fourier Transformation (FFT) to compute the most dominant frequencies.

Measurements collected on the bridge are compared with reference walking datasets to isolate bridge responses. Furthermore, GPS measures the location of the author during the measurements. The findings of the analysis are compared with previous and parallel studies which utilize a vision-based system (camera system) to measure bridge dynamic responses.

1.1 Crowdsourcing

The phrase crowdsourcing relates to a range of activities in various situations. Crowdsourcing's adaptability allows it to be implemented in different fields (Estellés-Arolas & González-Ladrón-de-Guevara, 2012). A diagnostic of crowdsourcing's features is performed to understand how it might be employed in SHM.

Schenk and Guittard (2011) point out that crowdsourcing is a combination of the words crowd and outsourcing. Thus, defines crowdsourcing as outsourcing to the public. Brabham (2008) claims that as a problem-solving paradigm, crowdsourcing was one of the elements that replaced traditional, static, individual techniques with a revolutionary, online, distributed one. Estelles-Arolas and Gonzalez-Ladron-de-Guevara (2012) developed a consistent definition of crowdsourcing, based on a literature review of 32 distinct definitions. They define crowdsourcing as an online participation activity that relies on the voluntary contributions of individuals or groups for mutual benefit.

In a perfect Structural Health Monitoring world, engineers would like to have access to large sets of data that enables them to monitor infrastructure smartly and remotely. Moreover, they would like to gather this data simply and cost-effectively. Therefore, utilizing crowdsourcing as a smart structural monitoring option is becoming widely desirable among engineers. In this context, crowdsourcing represents the online participatory process for which passersby provide sensing data to the monitoring system using their smartphones (Figure 1). The crowd voluntarily contributes data with the mutual aim to monitor the infrastructure that they use daily. It is an opportunity to capitalize on a recurring circumstance in which the crowd crosses the infrastructure with their devices on them.

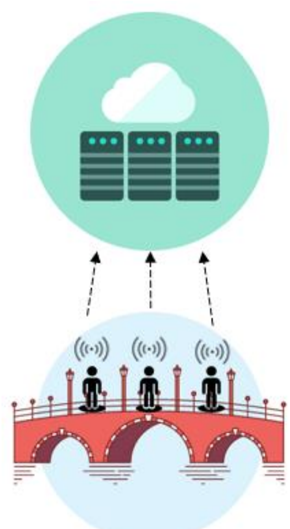


Figure 1 - Illustration of crowdsourcing in SHM

1.2 Research Aim and Objectives

As mentioned earlier, engineers aspire to utilize crowdsourcing and smartphone devices for SHM as they are motivated to gather large sets of data comfortably and cost-effectively. Therefore, this research aims to investigate smartphone applications for gathering bridge dynamic response for SHM. Four objectives are formulated, following this research aim: (i) collect acceleration, gyroscope, and GPS measurements from a footbridge, using a smartphone device, (ii) investigate ways to extract natural frequencies from the smartphone data, (iii) Identify and compare natural frequencies with reference frequencies, and (iv) explore how gyroscope and GPS data extracted by a smartphone could be useful for bridge structural monitoring.

1.3 Scope of the study

This chapter lay a foundation for this thesis. To summarize, the widespread availability of smartphones creates a great motivation to establish a low-cost wireless citizen sensor network and generate big data for SHM. Applications of smartphones to extract dynamic properties from footbridges are investigated. Chapter 2 is a literature review. It sets a base knowledge about SHM, Modal Analysis, and smartphone applications in bridge SHM. Gaps in using smartphones to monitor bridges are identified in this chapter. In chapter 3, a three-step methodology is presented. The methods corresponding to data gathering, analysis, and comparison are explained in detail. A case study of the UT campus bridge is shown in chapter 4. Measurements are analyzed and compared to reference points. In chapter 5, the results from the study case are discussed, and recommendations and drawn. Chapter 6 concludes the thesis by outlining the key findings, the discussion, and the study limitations.

2. Literature Review

This chapter provides the point of departure for this thesis. It establishes familiarity with existing knowledge in SHM and modal analysis. Also, the latest smartphone applications for bridge monitoring are presented. A concluding section summarizes the potential and gaps in using smartphones for bridge vibration analysis.

2.1 Structural Health Monitoring

The rising age of our current infrastructure raises concerns about the expense of maintenance and repairs. Structural health monitoring (SHM) may help with this by substituting scheduled maintenance with condition-based one. Indeed, saving resources on unnecessary maintenance while also preventing unexpected maintenance (Giurgiutiu, 2014). Vardanega et al. (2022) claim that SHM's principal goal is to identify damage or degradation. Data may be utilized to cost-effectively optimize maintenance activities. However, this is insufficient to cover the complete range of SHM's possible applications. SHM should provide practical information to assist decisions making regarding our infrastructure. Structural Health Monitoring, by Sony et al (2019), is an effective diagnostic method for detecting problems and preventing disasters in structures. Data capture, system identification, condition assessment, and decision-making/maintenance are the four components of the SHM.

According to Sohn et al. (2004), the SHM problem is primarily one of statistical pattern detection. This paradigm consists of four steps: (i) operational evaluation, (ii) data acquisition, fusion, and cleaning, (iii) feature extraction and information condensation, and (iv) statistical model development for feature discrimination. Operational evaluation sets the motivation for an SHM system. Usually, it concerns safety or economic reasons. Damage and damage critical states are defined. The environmental and operational conditions and their impact on data extraction are studied. In the data acquisition step, the tools (sensors), their location, the amount, and the sampling frequency are decided. The data is then smartly aggregated and refined. Feature extraction discovers damage-sensitive qualities obtained from observed system responses. The most prevalent characteristics utilized for damage identification are linear modal properties: natural frequencies, mode shapes, or properties derived from mode shapes such as flexibility coefficients. A statistical model analyses these characteristics intending to detect damages, their location, severity, and the structure remaining life (Hughes et al., 2021) (Sohn et al., 2004).

Humans have traditionally been engaged with visual inspectors in SHM, usually with the assistance of tools such as meters and levels. For a while, these low-tech tactics have been effective. However, in light of recent improvements in sensors, communication, and signal processing technologies, it is feasible to monitor structural attributes and behavior with sufficient clarity to assess damage levels and anticipate future structural health cycles (Huston, 2019). Nowadays, data is usually retrieved utilizing sophisticated sensor systems (Matarazzo et al., 2017). The next sensing generation of SHM according to Sony et al (2019) are cameras, UAVs, mobile sensors, and smartphones.

2.2 Modal Analysis

The application of modal analysis (vibration analysis) for damage detection is based on changes in structural response to load due to damage. It opens the potential of detecting damage based on differences in structural responses before and after damage. Damage detection expresses the link between structural damage and modal parameter changes. When a structure is in perfect dynamical health, a 'fingerprint' or 'baseline' of its modal parameters is collected. When these values change in the future, it is possible to evaluate the structural damage that caused the changes (Dackermann, 2020; Jimin & Zhi-Fang, 2001; Abdo, 2014). Structural dynamic responses should be nearly constant, even when the structure is excited by different loadings conditions. These responses are affected by structural characteristics such as size, material, et cetera. Modal parameters including frequency, mode shape, and damping are usually used for vibration based SHM (Yang et al., 2021).

2.2.1 Frequency & Natural Frequency

Frequency (f) measured with Hertz (Hz) represents how often something happens while the period (T) refers to how long it takes for something to happen (in seconds). The frequency and the period are the inverses of one another. An example is given in Figure 2; 2Hz frequency completes a full cycle (period) after 0.5sec and 2 cycles per second. Likewise, a frequency of 5Hz has a period of 0.2sec and 5 periods are completed within 1sec. The resulting signal for the summation of 2Hz and 5Hz is also shown. A harmonic signal or wave has a frequency that is an integral multiple of the fundamental frequency. It can also refer to the ratio of the frequency of such a signal. For example, the harmonic series of 2Hz frequency is: second harmonic 4Hz, third harmonic 6Hz, fourth 8Hz, and so on.

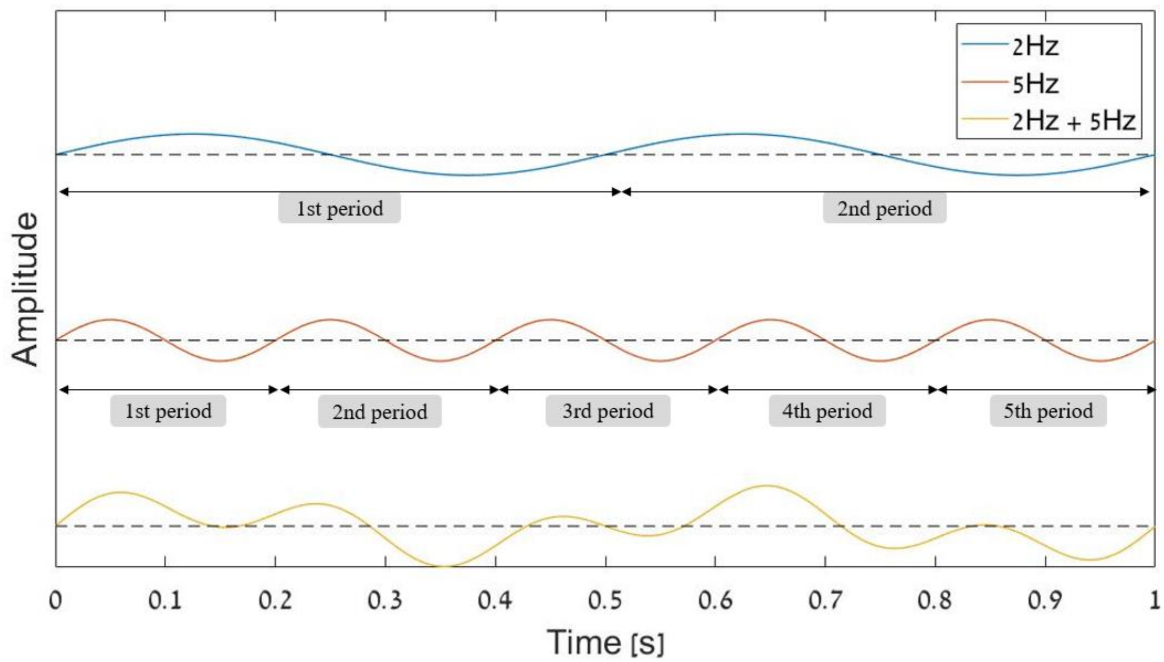


Figure 2 - Frequency illustration

Natural frequency, fundamental frequency, eigenfrequency, modal frequency are synonyms that describes the tendency at which a system oscillates without any driving or damping force. The two factors that influence natural frequency is the system's mass and stiffness. The system in this study refers to the footbridge. The existence of damage or degradation in a structure (or system) produces shifts in the structure's fundamental frequencies (Salawu, 1997). When observed natural frequencies are significantly lower than predicted, stiffness loss is evidence, and vice versa. A change of 5% in eigenfrequency can be enough to detect damage. However, a significant frequency change alone does not infer damage, as ambient conditions can influence vibration response (Salawu, 1997).

2.2.2 Mode of Shape

Mode shapes are the initial displacements of a system that cause it to oscillate harmonically. If a system has multiple natural frequencies, each one of them has a corresponding mode of vibration (Hashimoto et al., 2020). Bending and torsion modes of vibration are presented in Figure 3 as examples. Other common modes are combinations of modes (asymmetric modes), and higher degree modes. Changes in modal properties might not be the same for each mode of shape. This is depending on the location, the severity, and the nature of the damage. Matching natural frequencies to their mode of vibrations could assist in analyzing the damage remotely (Salawu, 1997).

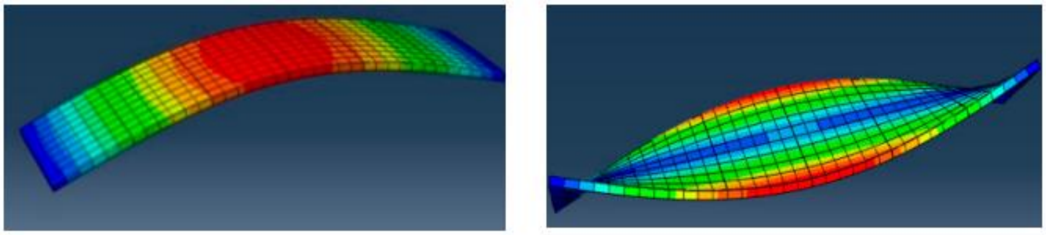


Figure 3 - Modes of Shape example: (left) Bending mode, (right) Torsion mode (Hashimoto et al., 2020)

2.2.3 Damping

All oscillators, in the end, stop in practice. Their amplitudes decrease due to resistive forces, such as friction or air resistance, acting in the opposite direction of oscillator motion. Damping is the lowering of oscillation energy and amplitude caused by resistive forces on the oscillating system. Damping is applied until the oscillator reaches equilibrium. The frequency of damped oscillations does not vary as the amplitude falls. For example: after jumping on a flexible structure such as a footbridge, its vibration decays steadily until it eventually stops. The way a system or a structure is damping can be monitored over time. There are three types of damping: light damping, critical damping, and heavy damping (Figure 4). Light-damping is when oscillations gradually disappear over time, like in the example. Critical damping is when a system reaches equilibrium in the shortest possible time, without any oscillations. A system does not oscillate in heavy damping as well, but it returns to zero after a long time. (King, 2009).

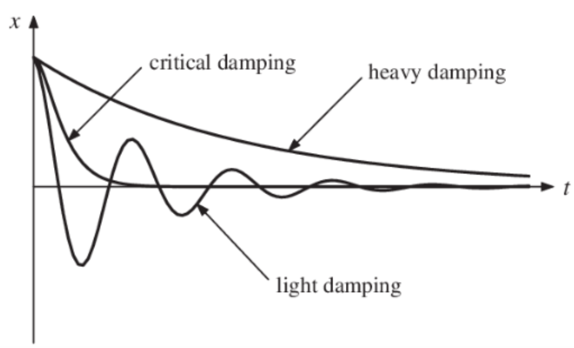


Figure 4 - The motions of a damped system (King, 2009)

2.3 Smartphone Applications in Bridge SHM

The main studies that tried to use smartphone as a structural monitoring tool are presented in this section. This background review illustrates the great potential of using smartphone-based system for SHM as well as the development opportunities.

Ozer et al (2015), made two first steps towards a citizen sensor network. First, the feasibility of employing smartphone accelerometers to detect structural vibration under normal and high loads was investigated. Smartphone accelerometer performance was evaluated based on a series of tests where measurements were compared to conventional sensor ones. The tests were performed on Civil Engineering structures such as bridges and yielded satisfactory results. In their next step, a Multilayered Computer Platform App that called "*Citizen Sensors for SHM*" that allows users to monitor structural vibration using their smartphones, upload the data to an internet server, and have the data instantly processed into a database, was developed. 135 student volunteers assessed the App, by uploading their collected data from the structure. With this experiment, it was possible to evaluate the modal parameters by the submitted data.

Feldbusch et al. (2017) was using a self-developed program named "iDynamics". Their research explores and explains the possibilities of mobile devices for vibration analysis, system identification, and structural monitoring. It displays the differences between professional accelerometers and smartphone sensors, as well as the vibration measurement and assessment capabilities of "iDynamics". Vibration measurements with professional equipment and software were used to validate the application.

Zhao et al. (2017) presented a mobile application for a group of cellphones to collect vibration and geospatial data for the SHM at the same time. They took use of a low-cost testing technique in the iPhone 4S with increased storage capacity; compute power and a strong network connection, together with created software, making it simple to employ cellphones in SHM applications.

Matarazzo et al. (2017) looked into the idea of crowdsensing bridge vibration data utilizing ubiquitous smartphones. To estimate projected crowdsourced data stream volumes, the number of cellphone journeys that cross the Harvard Bridge was analyzed. They estimated that 18,000 data points could be collected during weekdays, and 14,000 on Saturdays and Sundays.

2.4 Conclusions

The following conclusions are drawn based on this literature review:

1) Computing the dynamic properties of bridges could serve as a fingerprint or reference for monitoring purposes. A deviation of 5% in natural frequencies is significant to detect the presence of damage. Matching the fundamental frequencies to their mode of vibration could assist in locating damages. Further, a change in damping trend could also be a sign of fatigue or damage.
2) Smartphone's acceleration measurements are comparable to professional sensors (Ozer, 2015; Feldbusch, 2017; Zhao, 2017). Small errors that are acceptable for engineering purposes were observed with new generation smartphone (Ozer et al, 2015; Zhao, 2017).
3) There is a great potential to gather large masses of data from the crowd for bridge monitoring purposes (Matarazzo, 2017).
4) There are still gaps in using smartphone-based systems as a crowdsourcing tool for SHM: (i) Data should be collected automatically from passersby. (ii) There is no long-term study that compares smartphone measurements with field surveys and external loading conditions such as weather, temperature, and wind. (iii) Smartphones were placed on the bridge while gathering data. It is not a demonstration of crowdsourcing, as people do not usually place their smartphones on the bridge when crossing it. Often, they carry it in their pocket, in a bag, in a jacket, or holding it by hand.

The studies of Ozer (2015), Feldbusch (2017), and Zhao (2017) are evidence of the potential of using smartphone devices for vibration analysis and SHM. This research takes a step forward toward a crowdsensing platform by attempting to extract bridge dynamic properties with a smartphone in a pocket. In the next chapter, a methodology is proposed.

3. Methodology

An attempt to compute bridge dynamic properties from the smartphone data measured while crossing a footbridge follows a three-step methodology; Data gathering, Data analysis, and Data comparison. Figure 5 provides an overview of the methods used in each step. Three cases are performed: walking along the bridge (case 1), heel drops at the center of the bridge (case 2), and on its side (case 3). The smartphone is placed inside a pocket and measures live data at the bridge location. Acceleration and gyroscope data are analyzed with the Fast Fourier Transformation (FFT). Reference walking data is collected before and after the bridge. GPS provides position indications. Natural frequencies from the smartphone measurements are compared to reference frequencies with a threshold of 5% error. Within this chapter, the methods in each phase are explained in detail.

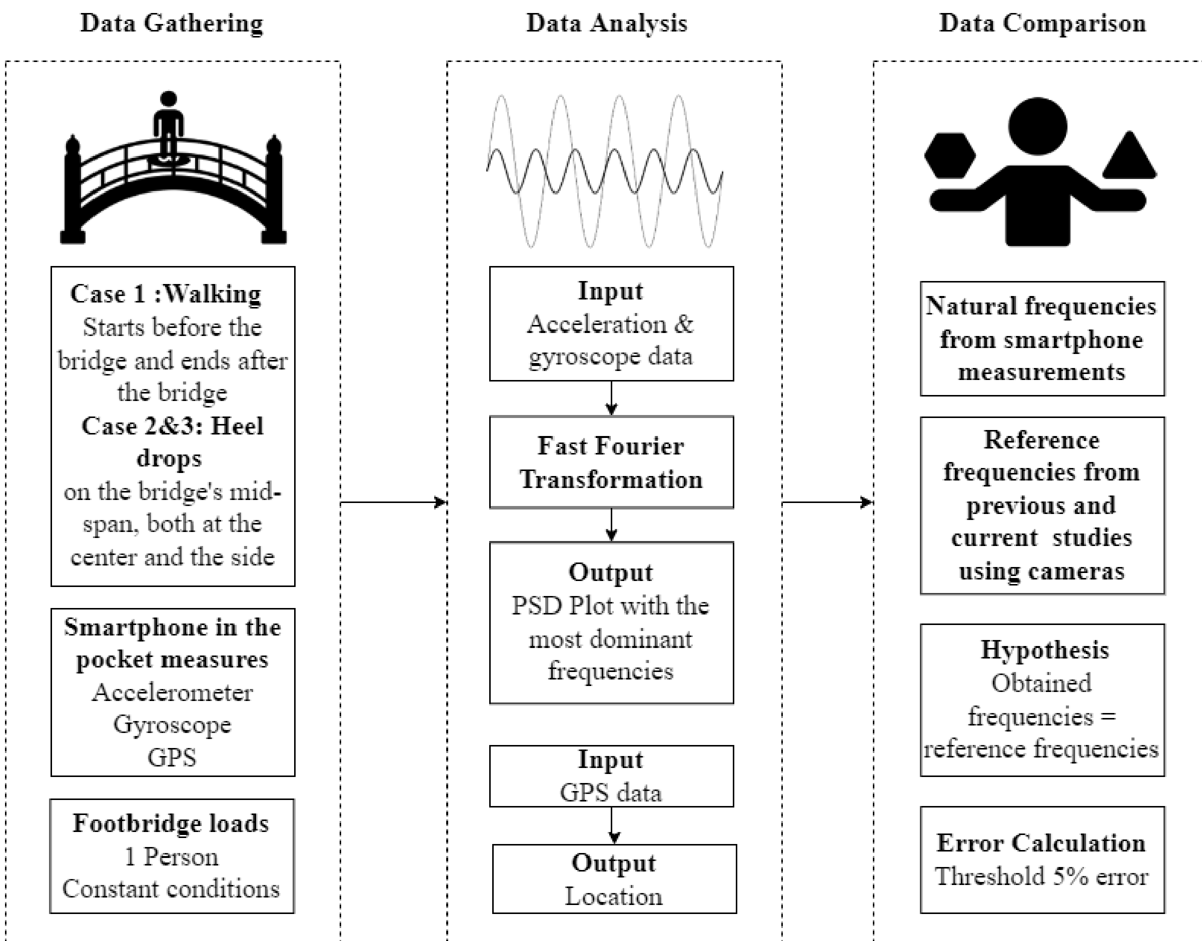


Figure 5 - Methodology Scheme

3.1 Data Gathering

Data is extracted from a footbridge when walking over it with a smartphone in the pocket. It is placed inside the pocket to demonstrate one natural behavior of a passerby. This is a step forward from previous studies by Ozer (2015), Feldbusch (2017), and Zhao (2017) that placed the smartphone on the bridge during the measurements. However, in this scenario, the smartphone is more sensitive to the walking movements rather than to the bridge responses, as it does not have direct contact with the footbridge. For that reason, reference walking data is measured before and after the bridge. This way, it is possible to compare measurements on the bridge with reference walking and isolate bridge responses. Moreover, the bridge is free from traffic during the measurements, except for the researcher himself. It ensures that only bridge dynamic responses and a controlled walking frequency of 2Hz (2 steps per sec) are measured. The walking frequency of 2Hz is chosen to make sure that one leg has direct contact with the bridge at any given moment. Important to notice that at least one leg should contact the bridge to capture its vibrations. Allowing random traffic such as walking/running/riding the bike with different frequencies would make it difficult to distinguish the bridge reactions. To ensure sufficient data set for the statistical analysis, the procedure is repeated 10 times. During these repetitions, it is assumed that all external loading conditions such as temperature and wind are constant. This assumption is based on the expectation that the duration of the measurements is short and that external forces should be almost identical. In addition to crossing the bridge, other loading cases are performed. Heel drops at the mid-span of a bridge on its center and the side. The aim is to excite the bridge in different modes and amplitudes. Heel drops at the side excite torsional modes whereas, at the center, bending is induced. Figure 6 shows the loading cases.

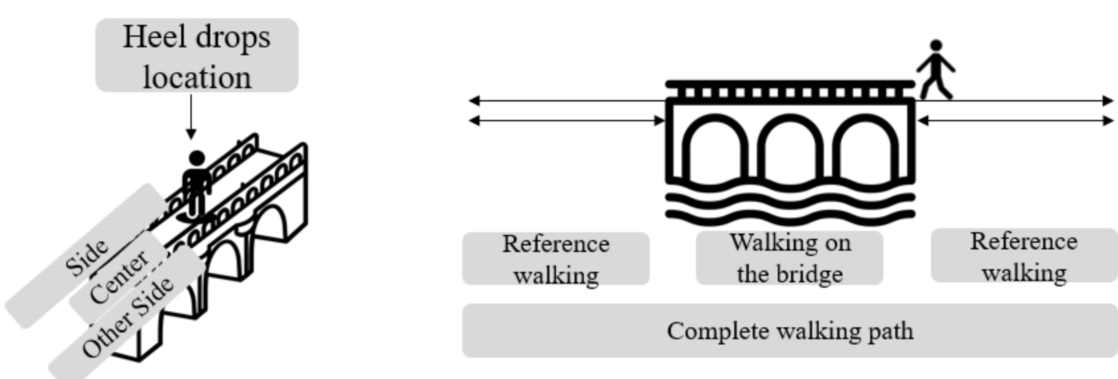
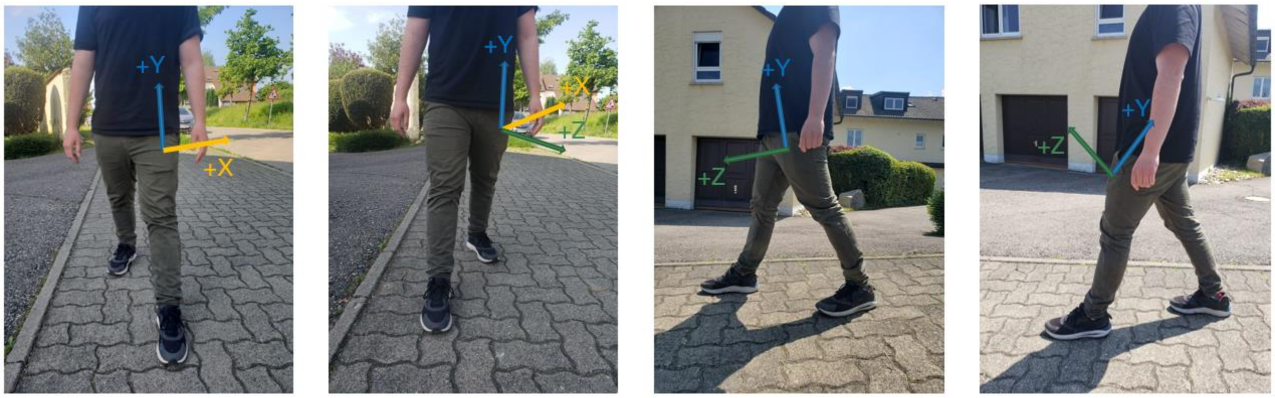


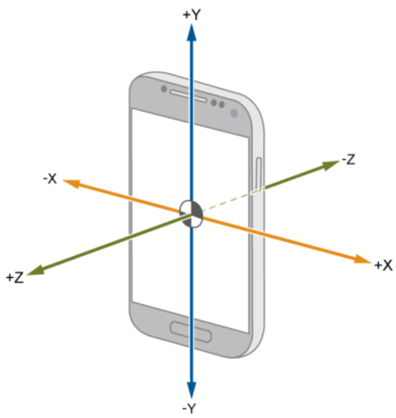
Figure 6 – Loading cases: (left) heel drops on the bridge's mid-span, (right) walking along the bridge

The following data is being measured while walking over the bridge: acceleration, gyroscope, and GPS. In the heel drops cases, only acceleration is collected because no walking is involved, and the location is constant. Acceleration data is used for vibration analysis while the gyroscope provides gait (manner of walking) cycles. GPS data could detect the location of the measurements and might assist with matching frequencies to their corresponding mode of shapes. Accelerometer, gyroscope, and GPS smartphone's built-in sensors measures acceleration (m/s^2), angular velocity (rad/s), and location, respectively. Acceleration (m/s^2) and angular velocity (rad/s) are measured and recorded in 3D, at a 500Hz sampling rate (data point every 0.002 sec or 500 data points per sec). GPS measures Latitude (°), Longitude (°), Height/ Altitude (m), Velocity (m/s), Direction (°), Horizontal Accuracy (m), and Vertical Accuracy (m), at approximately 1Hz sampling frequency (data point every 1sec). Horizontal accuracy is the radius representing the marginal error in coordinates (exact location), and vertical accuracy is the altitude margin error. Two applications are used for the measurements; a metronome application assists in pacing the walking rhythm to 2Hz (2 steps per second) by beeps. The App PhyPhox records the smartphone's sensors and generates an excel file with the corresponding time stamps. The excel file is then conveniently transferred to a computer for the data analysis.

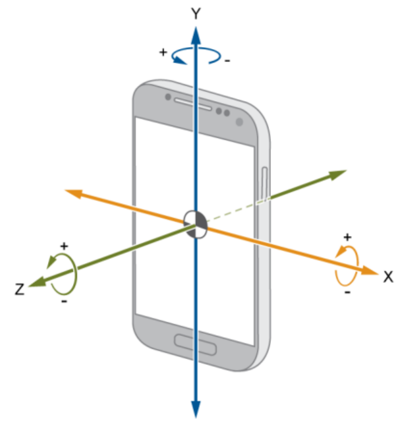
The smartphone position, its measurement orientation, and the recording App PhyPhox interfaces are shown in Figure 7. The placement of the smartphone in the left pocket can be seen both from front and side views. Moreover, the acceleration and gyroscope measurement directions are presented. Also, screenshots from the PhyPhox App show interfaces of acceleration, the gyroscope, and GPS recordings.



(a)

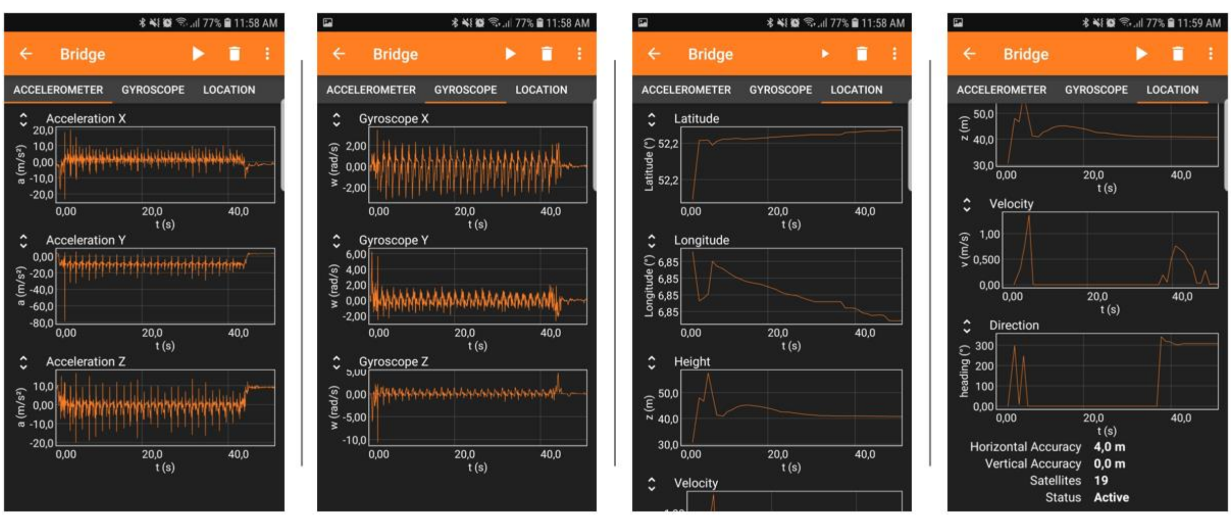


(b.1) Acceleration



(b.2) Gyroscope

(b)



(c.1) Accelerometer

(c.2) Gyroscope

(c.3) GPS

(c)

Figure 7 - Smartphone During Measurements: (a) Smartphone Position, (b) Smartphone Orientation (Simulink - MathWorks Benelux, 2022), (c) PhyPhox (2022) sensor recording App interface

3.2 Data Analysis

3.2.1 Acceleration Data

The raw acceleration data retrieved from the smartphone is used for vibration-based analysis. This analysis aims to compute the eigenfrequencies of the bridge. It is expected that the raw acceleration data measured by the smartphone consists of the walking frequency, noise, and bridge frequencies. The left side of Figure 8 shows the individual components of the signal; Frequency 1 is the walking frequency, frequencies 2 and 3 are the bridge frequencies, and noise. The right side of the figure shows a representation of the expected acceleration measurements. Important to note that a different amount of bridge frequencies might be captured in the actual measurements.

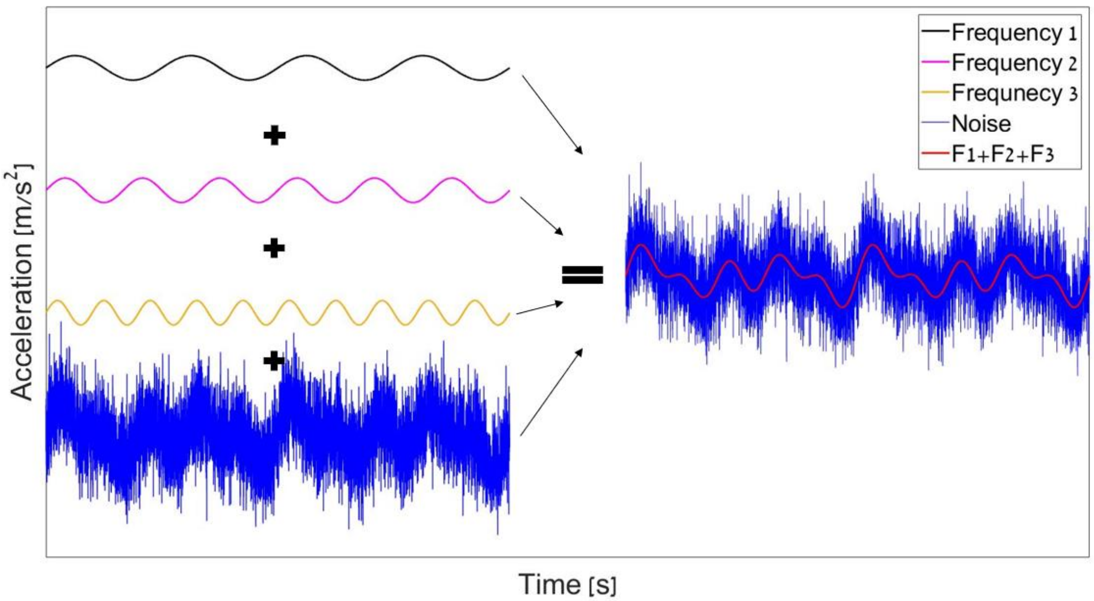


Figure 8 - Measurement Illustration: (left) Individual components (right) Expected measurement representation

After obtaining the raw acceleration data from the footbridge, the Fast Fourier Transformation (FFT) processes the signals. The FFT is used to convert a temporal signal (in time domain) into its different frequency components (frequency domain) (Dackermann, 2020). Figure 9 illustrates this transformation. On the left side, the same raw measurements representation from Figure 8 is shown. On the right side, the resulting Power Spectral Density (PSD) plot is presented. The PSD reflects how much power is presented at each frequency in the signal. Ultimately, assisting in identifying the most dominant frequencies in the signal. It is expected that the walking frequency is the most dominant pattern computed by the FFT, and therefore, its harmonics appears in the PSD (1Hz, 2Hz, 3Hz, …) (Martinelli et al., 2016; Urbanek et al., 2018; Yoneda, 2015).

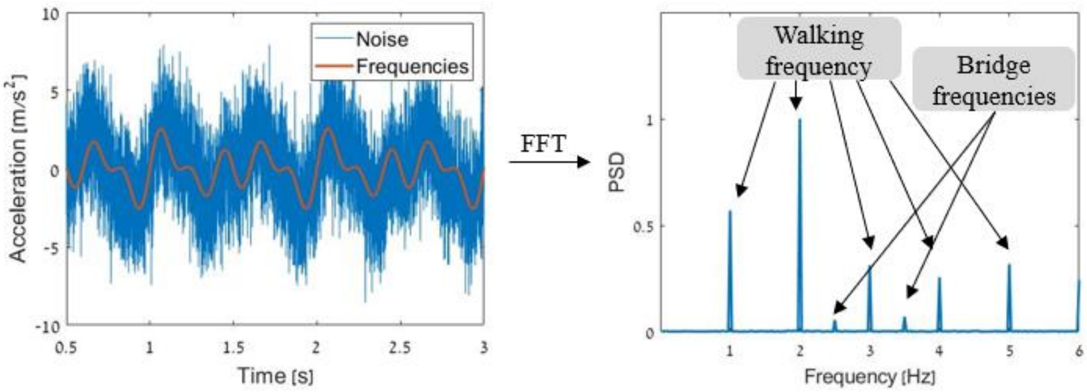


Figure 9 - Illustration of FFT: (left) Raw acceleration measurement representation, (right) Normalized PSD plot

In case the walking frequency is much more dominant and bridge responses cannot be observed from the PSD. The following procedure is carried out: The data is split into two, data that is measured on the bridge and data measured before and after the bridge (off the bridge) (Figure 10). It is expected that measurements before and after the bridge consist of the walking frequency and noise. However, data collected on the bridge consist of bridge responses in addition to the noise and walking frequency. Then, FFT is applied separately to each data set, resulting in two Power Spectral Density (PSD) plots. Finally, the difference in PSDs removes the walking frequency and adjusts the scale. As a result, the bridge responses can be recognized as they are more dominant than the noise.

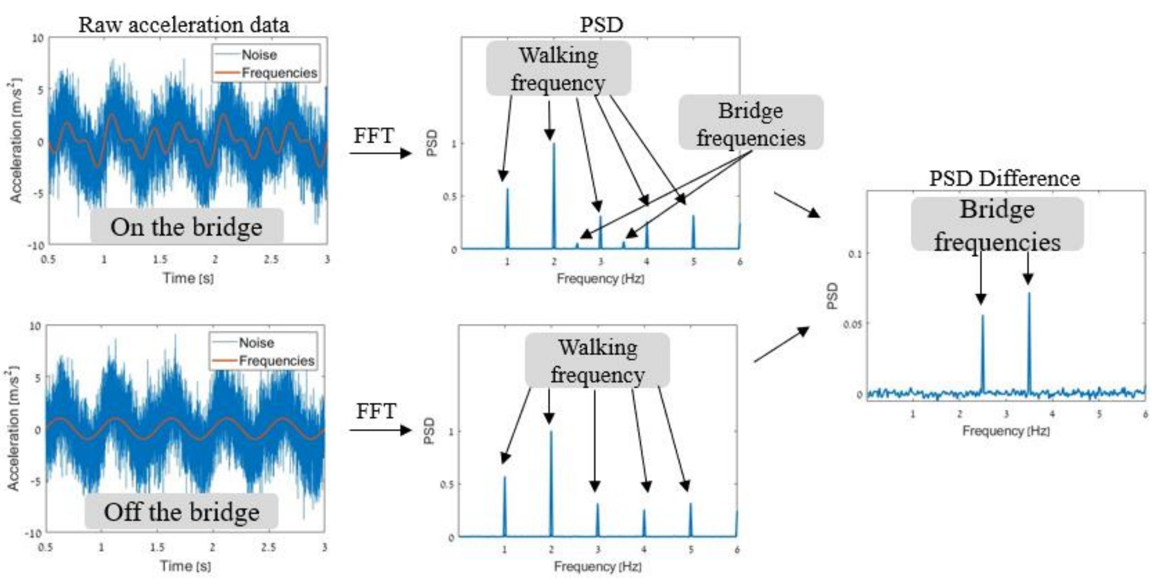


Figure 10 - Frequency Identification Illustration using PSD difference

3.2.2 Gyroscope Data

The gyroscope provides gait data (walking pattern). It could detect the angular movement of the left leg during the measurements. The aim is to check if there is any difference between the walking pattern when walking on the bridge compared to on the ground. Maybe the bridge reaction influences the angular velocity measured by the gyroscope. Also, the gyroscope data could verify the walking rhythm. Figure 11 demonstrate ~2.5sec of gyroscope measurements at 2Hz (2 steps per sec). The steps can be seen, and the leading leg can be determined depend on how the smartphone is placed inside the pocket. A full gait cycle is observed every approximately 1sec. The gyroscope data is analyzed similarly to the acceleration data with the FFT. The most dominant patterns captured on the bridge are compared with those captured before and after the bridge.

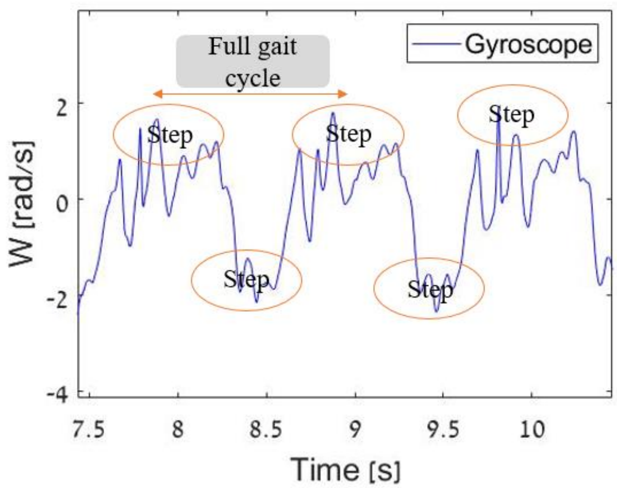


Figure 11 - Gyroscope illustration

3.2.3 GPS Data

GPS location measurements can be used to detect crowd movement on the bridge. This kind of information could indicate when people enter and exit the bridge. GPS data is aggregated and compared with Google Earth (2022) and Google Maps (2022) values. Longitude and latitude measurements are compared with known walking path coordinates. Height and direction readings could also improve position estimations. Especially, in the case that the bridge has height differences, or it is not straight.

3.3 Data Comparison

Natural frequencies obtained from the smartphone measurements are compared with reference frequencies. The hypothesis is that the frequencies are indeed the same and the following procedure is carried out. Error is calculated (equation 1), where A is the reference frequency and B is the frequency from the smartphone. Error is then maximized between obtained and reference frequencies. The hypothesis is rejected if $Error > 5\%$. Otherwise, the experiment gives confidence that the frequencies are indeed the same. Importantly, the trust in smartphone-based system for vibration analysis is increased.

Equation 1

$$Error = \max\left(\left|\frac{A - B}{A}\right| * 100\%\right)$$

To summarize, data is gathered while the bridge is excited with load cases. Three cases are executed: walking over the bridge, heel drops on the center, and heel drops on the side. The FFT algorithm processes the acceleration and gyroscope datasets to compute the most dominant frequencies and distinguish bridge vibrations. Data collected before and after the bridge serves as a baseline walking dataset. GPS provides position information. Natural frequencies extracted from the smartphone's measurement are compared with reference frequencies. In the next chapter, the proposed methodology is put to test in a case study.

4. Case Study

The University of Twente (UT), the Netherlands, campus footbridge serves as an experimental monitoring bridge in this study. It is 2 meters wide and spans a pond for 27 meters. Its timber deck is supported by three steel girders with diagonal bracing. The measuring tool is a Samsung Galaxy S7 edge. The bridge, the complete walking path, the reference walking, and the heel drop location are shown in Figure 12. Three loading cases are performed. In case 1 (walking along the bridge), acceleration, GPS, and gyroscope data are measured. The walking path starts ~15m before the bridge and ends ~15m after the bridge. While crossing the bridge, the path is on the northern side, between the midspan and the railings. The measurements before and after the bridge are served as a baseline for the walking rhythm. The differences between walking on the bridge and reference walking are the bridge responses. In case 2 (Heel drops at the center) and case 3 (Heel drops at the northern side), heel drops are performed on the mid-span of the bridge. Only acceleration data is collected, as no walking is included and location is constant. After each heel drop, the researcher stays still and captures the bridge vibrations damping (slowly decaying). The loading cases are listed in Table 1.

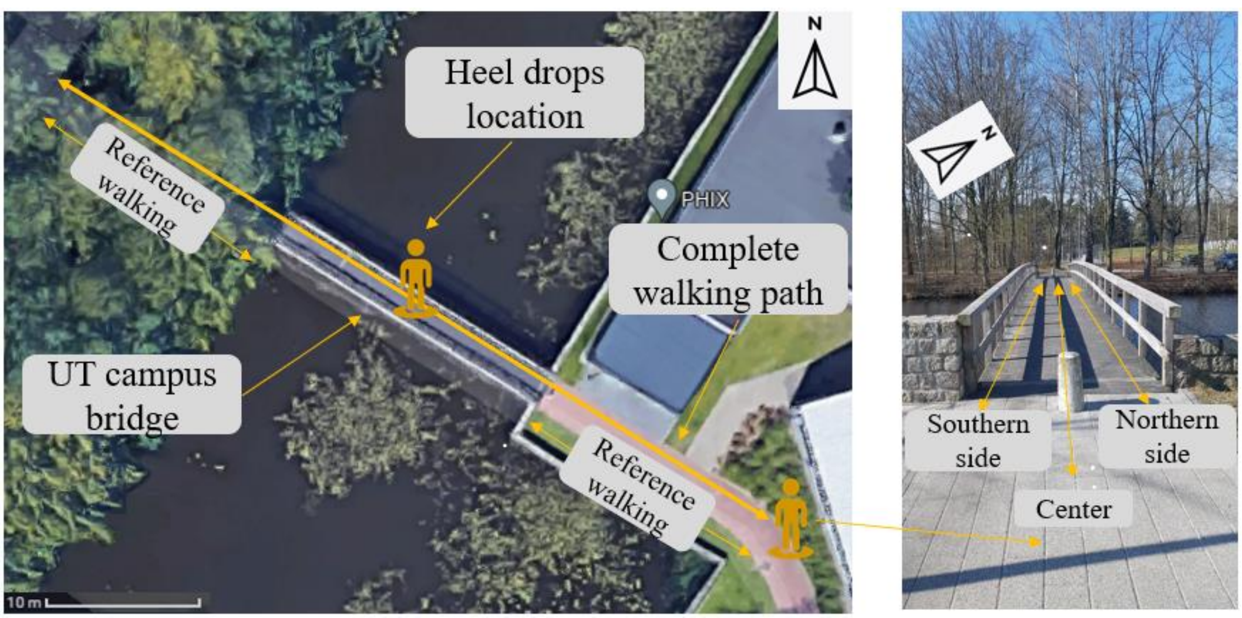


Figure 12 – The UT Footbridge: (left) Load cases (Google Maps, 2022), (right) view from SE

Table 1 - Bridge Load Cases

Case [#]	Description	Data	Repetitions
1	Walking across the bridge on its *Northern side*	Acceleration, GPS, gyroscope	10
2	Heel drops at the *center*	Acceleration	8
3	Heel drops at the *Northern side*	Acceleration	8

4.1 Case 1 – Walking Along the Footbridge

Acceleration, GPS, and Gyroscope data were collected while crossing the bridge ten times. The smartphone position in the left leg pocket and the walking path on the northern side can be seen in Figure 13. Smartphone z-axis measurements correspond with the bridge's longitudinal direction whereas the x-axis measures in the transverse direction of the bridge, and y-axis is the vertical direction. A hit was given to the smartphone device when entering and leaving the bridge. This way, it was possible to distinguish between data on and off the bridge regardless of GPS accuracy.

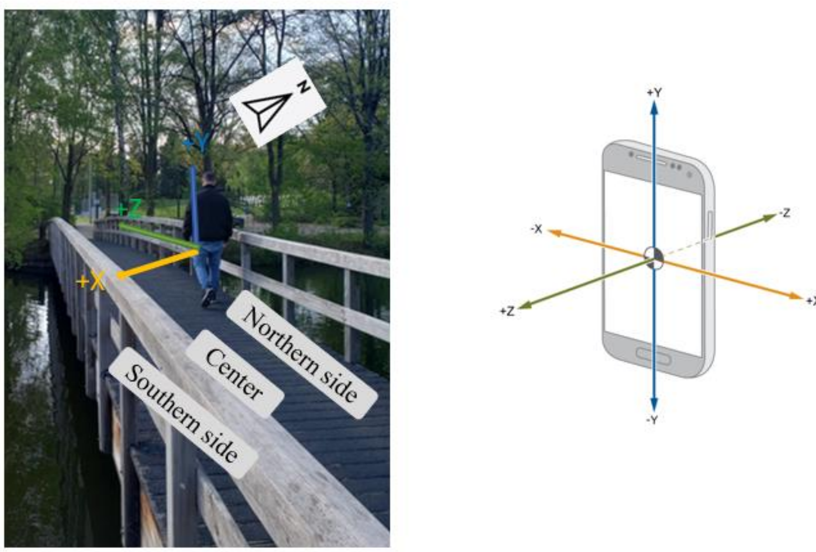


Figure 13 - Load case 1: walking along the bridge, and smartphone measurement directions

4.1.1 Acceleration Data Analysis

The raw acceleration data in x, y, and z directions, measured by the smartphone, is shown on the left side of Figure 14. The hit that was given to the smartphone when entering and exiting the bridge was effective. The interval for which data was measured on the bridge was recognized (~16sec – ~37sec), especially in the z-direction. On the right side of Figure 14, a zoomed view of acceleration data, measured on the bridge, in the z-direction, is presented. The positive peaks (green) correspond to the steps of the left leg, while the negative peaks (orange) to the right steps. The acceleration induced by the left leg is higher than the right one (the smartphone is in the left pocket). Two peaks, one positive and one negative every approximately 1 second, are an indicator of walking of 2Hz. Other patterns apart from the walking frequency and noise were not observed.

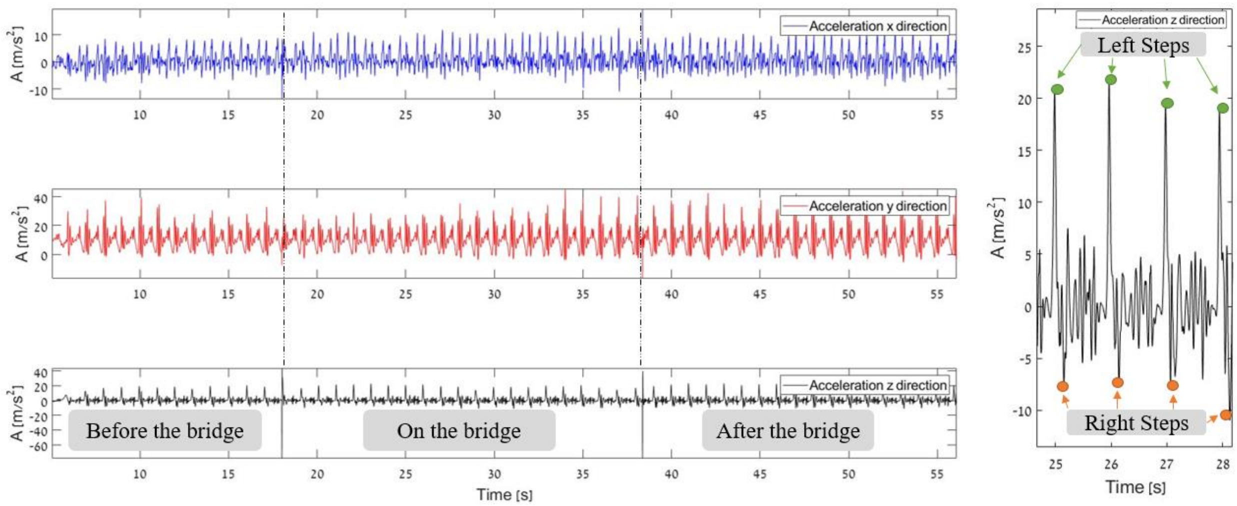


Figure 14 – (left) Raw Acceleration Data for the complete walking path in x, y, and z directions, (right) Zoomed view on acceleration in z direction

Acceleration data measured by the smartphone was computed with the FFT algorithm. First, the FFT was applied to the complete walking path. The resulting PSD graph for the whole walking path is presented on the left side of Figure 15. The walking frequency of 2Hz with its harmonics was the most dominant pattern. The large magnitude of the walking frequency created a situation where the bridge responses could not be distinguished from the noise. Then, the walking rhythm was removed utilizing the reference walking dataset. Also, the spectral scale was adjusted. As a result, the dominance of the bridge's natural frequencies compared to the noise was significant, as can be seen on the right side of Figure 15. Table 2 lists the natural frequencies of the bridge in Hz, the standard deviation, and the recognition times (Some vibrations were not present in every measurement). There was no correlation between the measurement direction and the frequencies.

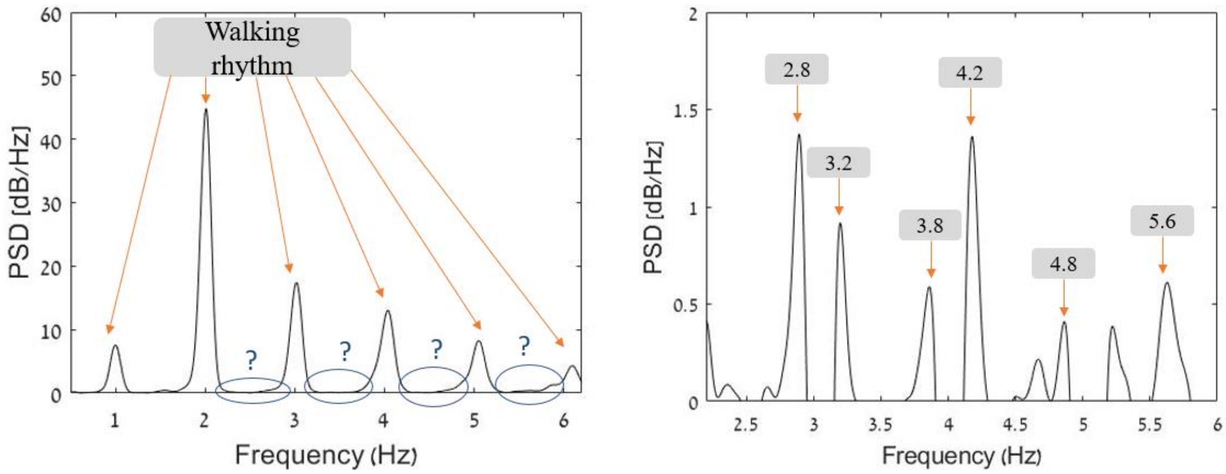


Figure 15 – (left) PSD of complete data set, (right) PSD difference

Table 2 - Identified natural frequencies from walking along the footbridge

f [Hz]	Std [Hz]	n [#] (30 max)
2.41	0.086	22
2.79	0.065	20
3.29	0.135	29
3.73	0.109	30
4.31	0.129	30
4.74	0.076	22
5.59	0.097	29

4.1.2 Gyroscope Data Analysis

Figure 16 presents the gyroscope data measured by the smartphone in 3D. The exact moments when entering and exiting the bridge were identified with the assistance of irregular angular velocities around 16 sec and 37 sec. On the right side of the figure, a zoomed view of the gyroscope measurements on the bridge is shown. Positive peaks (green) in the x-direction indicate left steps and negative peaks (orange) right steps. The angular velocities of left and right steps have comparable magnitude. A full gait cycle is observed every ~1 second.

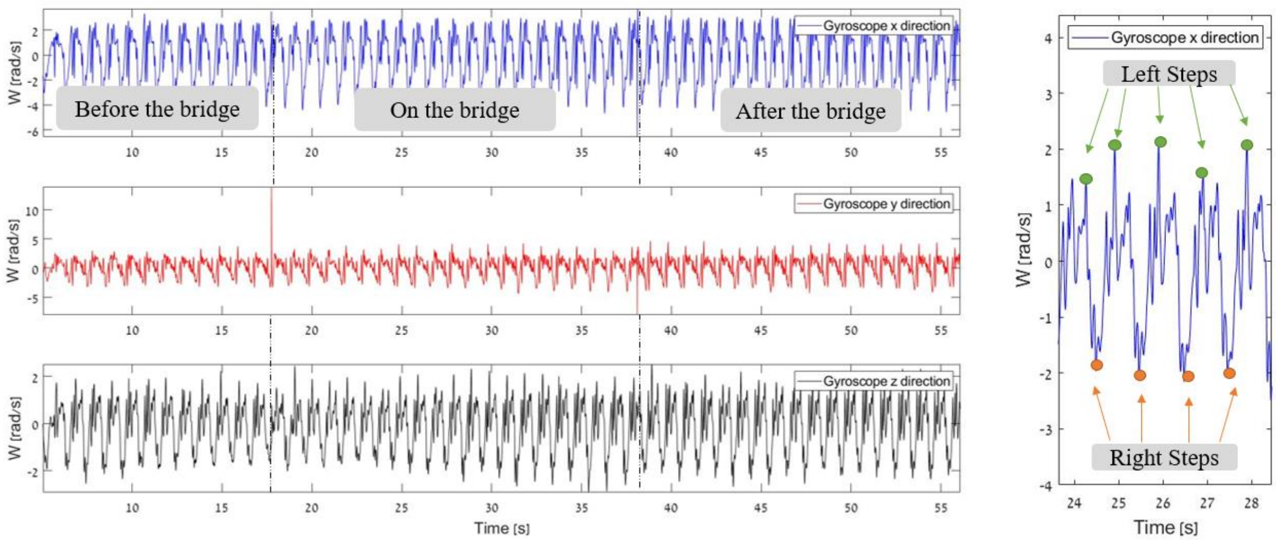


Figure 16 - (left) Raw gyroscope data for the complete walking path in x, y, and z directions, (right) Zoomed view on gyroscope in x direction

The raw gyroscope was analyzed with the FFT. The resulting PSD for the complete walking path is presented in Figure 17 (left side). The gyroscope picked the walking frequency (2Hz) and its harmonics while the smartphone device was placed in the pocket. However, it did not recognize the footbridge fundamental frequencies when removing the walking rhythm (right side). Only small deviations in the walking signal magnitude are observed.

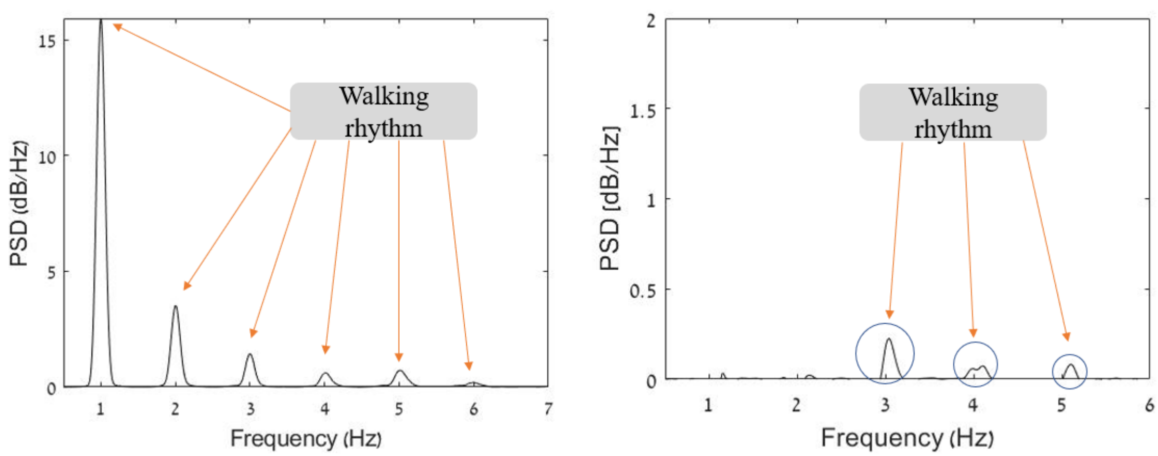


Figure 17 – (left) PSD gyroscope of complete data set, (right) PSD gyroscope difference

4.1.3 GPS Data Analysis

Figure 18 shows the GPS longitude and latitude coordinates during the ten measurements next to the actual walking path. In all repetitions, the coordinates are nearby the bridge. However, except for the 8^{th} data set, the GPS seems to deviate to a large extent from the actual walking path.

Further, in this study case, direction and altitude measurement could not assist in estimating the location because the walking path was straight, and there was no major height difference. For that reason, only GPS measurement accuracy was considered. Direction and altitude measurements were averaged and compared to values from Google Earth (2022). Table 3 list the average direction and height measurement. (-) is marked for outliers. As can be seen, altitude measurement deviated by over 20m on average from Google Earth value. Direction measurements were comparable in 60% of the cases, but 40% were outliers.

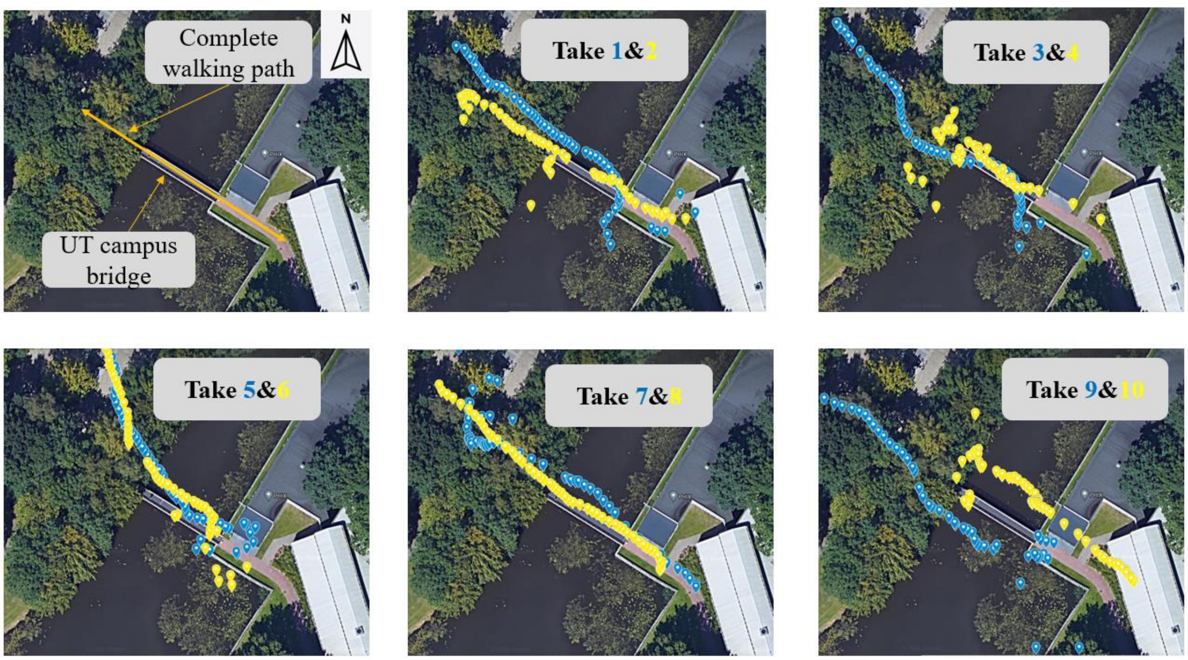


Figure 18 - GPS Location Measurements (Google Maps, 2022)

Table 3 - GPS Average altitude and direction measurements

Take	Height/Altitude [m]	Direction (°)
1	51.6	323.3
2	51.9	-
3	52.8	313.6
4	52.3	-
5	48.6	305.2
6	48.5	326
7	54.6	-
8	36.9	308.4
9	50.2	304.5
10	53.9	-
Average	50.13	313.5
Google Earth	27.22	301.74

4.2 Case 2 & 3 – Heel Drops

Heel drops were performed on the center of the bridge (case 2) and the northern side (case 3). The heel drops location, the phone position in the left pocket, and the measurement directions are shown in Figure 19. The smartphone device measured acceleration in 3D during these measurements. But it did not record gyroscope and GPS recordings, as the location was strictly at the mid-span of the bridge. After each heel drop, the smartphone captured the bridge vibrations damping. The researcher himself stood on his feet and let the bridge respond. The procedure was repeated eight times. Smartphone x-direction measurements correspond with the bridge longitudinal axis, and the z-direction measures the transverse axis. The y-direction of the smartphone represents the vertical axis of the bridge.

Figure 19 - Load cases 2&3: heel drop at the center (case 2) and at the northern side (case 3), and smartphone measurement directions

4.2.1 Acceleration data analysis

In both case 2 (heel drops at the center) and case 3 (at the northern side), the bridge was lightly damping. It can be seen in Figure 20 that the amplitude of the oscillations is decaying exponentially and aiming at equilibrium. It is noticeable both for positive and negative displacements (represented here with acceleration).

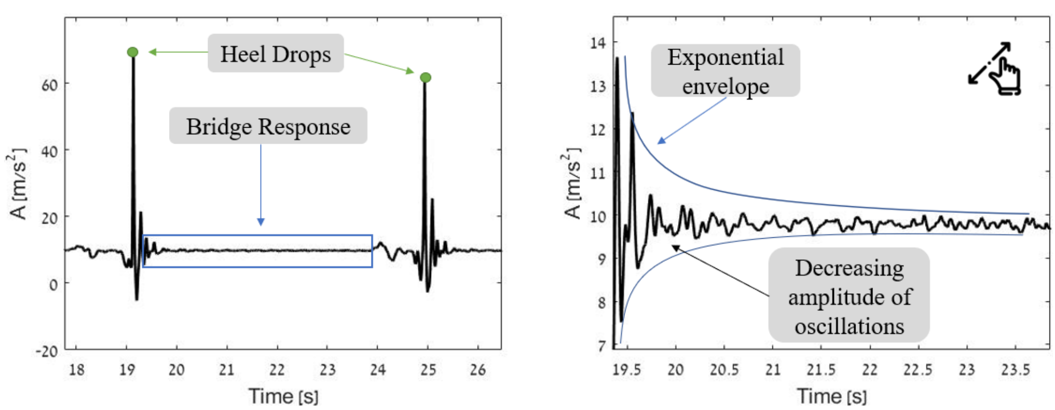
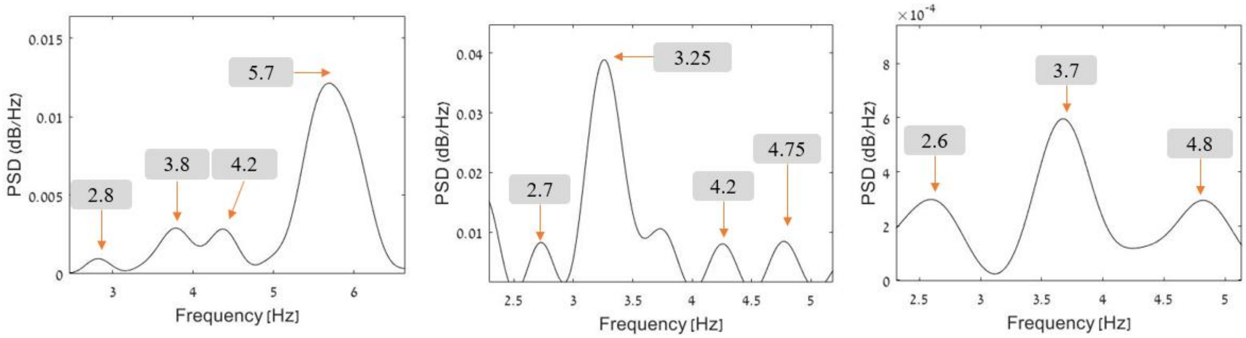


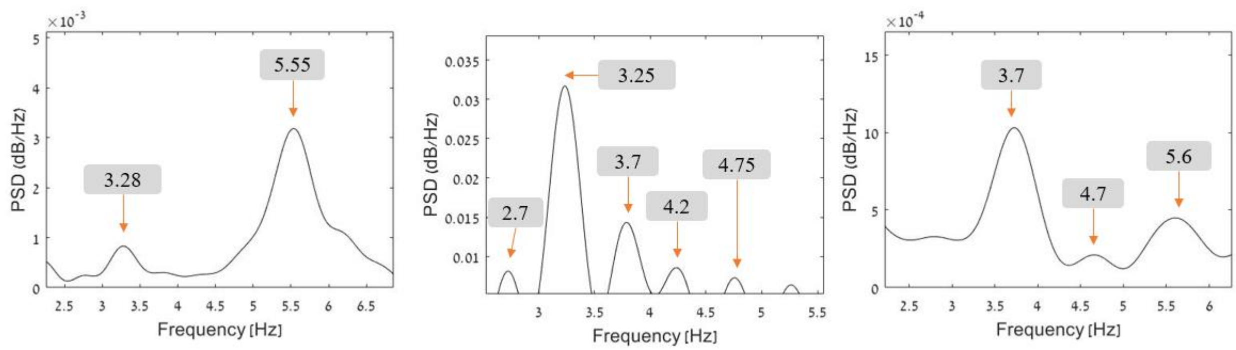
Figure 20 – (left) Raw acceleration data heel drops Y direction, (right) Zoomed view on bridge response (damping)

The frequencies for which the bridge vibrates after each heel drop were computed with the FFT. The most dominant frequencies for x, y, and z smartphone directions are 5.61Hz, 3.25Hz, and 3.81Hz, respectively (Figure 21 and Figure 22). Table 4 summarizes the corresponding natural frequencies estimated in cases 2 and 3 (at the center, and at the northern side), their standard deviation, and the number of recognitions (out of maximum 24). Interestingly, 2.41Hz (a frequency observed in case 1) was not identified.



21.a) X Direction 21.b) Y Direction 21.c) Z Direction

Figure 21 - PSD Heel Drops at the center (case 2)



22.a) X Direction 22.b) Y Direction 22.c) Z Direction

Figure 22 - PSD Heel Drops at the northern side (case 3)

Table 4 - Identified Natural Frequencies from Heel Drops on the Footbridge's mid-span

Center (case 2)			Northern Side (case 3)		
f [Hz]	**Std [Hz]**	**n [#] (max 24)**	**f [Hz]**	**Std [Hz]**	**n [#] (max 24)**
2.73	0.046	15	2.74	0.047	14
3.26	0.059	15	3.25	0.040	15
3.71	0.084	19	3.81	0.073	16
4.26	0.042	16	4.23	0.050	10
4.78	0.047	13	4.75	0.036	12
5.54	0.173	9	5.61	0.134	14

4.3 Frequency Comparison

The obtained frequencies are compared with three references. The references estimated eigenfrequencies of the UT footbridge utilizing a vision-based system (cameras). In reference 1, bridge responses were captured while cycling over the bridge, on its center and sides. In reference 2, the footbridge was subjected to walking and jogging diagonally on the bridge. Also, jumping at the bridge's mid-span was performed. In reference 3, bridge vibrations were measured while cycling, jogging, and jumping on the center and sides of the bridge. Table 5 lists the natural frequencies computed in the three load cases and reference frequencies. The maximum error between the references and the observed frequencies is displayed. In case 1, frequencies in the range 2Hz-3Hz were split into two natural frequencies; 2.41Hz and around 2.79Hz. In reference 3, however, frequencies in the same spectrum were averaged into one frequency, 2.6Hz. As a result, a large difference of 7.3% between the frequencies 2.79Hz (case 1) and 2.6Hz (Reference 3) is calculated. Except for this case, where frequency ranges were defined differently, the maximum error is 3.5%, between 3.68Hz (reference 3) and 3.81Hz (case 3). Moreover, the smartphone detected more vibration modes in comparison to cameras.

Table 5 - Identified Modal Frequencies

		f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**
Frequencies [Hz]	Case 1	2.41	2.79	3.29	3.73	4.31	4.74	5.60
	Case 2		2.73	3.26	3.71	4.26	4.78	5.54
	Case 3		2.74	3.25	3.81	4.23	4.75	5.61
	Reference 1	2.49		3.28	3.82			
	Reference 2	2.36	2.77		3.81			
	Reference 3		2.6	3.23	3.68			
Max Error [%]		3.3%	7.3%	2.0%	3.5%			

5. Discussion & Recommendations

The diffusion of smartphones into our society has created the opportunity to utilize crowdsourcing networks to gather big data for SHM. This data could provide input for structural monitoring over time and in changing conditions. This research explored applications of smartphones to collect bridge dynamic response and turn it into useful parameters for SHM. It takes a step forward on Ozer (2015), Feldbusch (2017), and Zhao (2017) that found the natural frequencies of bridges by placing a smartphone device on the bridge. In this research, the smartphone was placed in a pocket during the measurements, demonstrating crowdsourcing. Three questions were explored: the best ways to extract natural frequencies from the smartphone measurements, frequency accuracy, and methods to utilize gyroscope and GPS data for bridge monitoring.

In case 1 (walking along the footbridge), the reaction of the smartphone to the walking frequency was much more prominent than to the bridge vibration. The difference in response between walking on the bridge to the reference walking enabled the identification of the bridge's eigenfrequencies. Results show that smartphones can measure vibration responses from flexible structures such as footbridges while placed in a passersby pocket. However, the processing requires reference walking data. Bridge responses could not be computed with the gyroscope data. Yet, walking frequencies calculated from gyroscope data could be ruled out as bridge response. GPS data was not accurate enough to provide position measurements. Better measurements could assist in computing the mode shapes and possibly detecting damage locations. In cases 2 (heel drops at the center) & 3 (heel drops at the northern side), each measurement direction had a corresponding dominant frequency. The frequency of around 3.25Hz seems to be related to the bending mode shape of the bridge, as it was the most dominant in the vertical measurements. The frequency around 3.75Hz appears to correspond with torsional bridge vibration mode because it was the most powerful frequency in the transverse direction of the bridge. The findings suggest that the frequency 2.41Hz cannot be identified while exciting the bridge with a load acting on its mid-span. The comparison of natural frequencies from smartphones to vision-based systems measurements suggests the frequencies are indeed comparable. There was one case where frequencies were split into different ranges which resulted in a large error of 7.3%. Except for this case, the maximum error calculated was 3.5%. Some higher natural frequencies computed from the smartphone measurements could not be estimated with cameras. One explanation for this is that cameras capture 2D images of a specific location while the smartphone measures data in 3D along the bridge which allows it to detect additional modes of vibration.

Based on the findings presented, the following recommendation for further studies are suggested:

1) From a technical standpoint, crowdsourcing data needs to be analyzed automatically. Nevertheless, a multiple-step method is used in this research to obtain fundamental frequencies. A more automated way of analyzing the data is needed. A prediction model is proposed. That involves training a model to forecast the walking frequency. The difference between the prediction and the actual measurements could assist in identifying the bridge frequencies.
2) The bridge monitoring was around 45 min. This short duration represents better a condition assessment rather than structural monitoring. A longer monitoring period enables the discussion about smartphones' sensitivity to a variety of loading conditions such as load, temperature, wind, et cetera.
3) Other scenarios that represent crowdsourcing in a natural environment should be tested. For instance, carrying the smartphone differently (inside a backpack, in a jacket, et cetera), riding the bike, and measuring while random traffic is on the bridge.
4) To further explore recording alternatives besides Phyphox (2022), it is recommended to check other Apps and compare their results. For example, Simulink® Support Package for Android™ Devices (2022) or the App iDynamics (Feldbusch, 2017).

6. Conclusions

This chapter concludes the thesis by summarizing the key findings concerning the research aims and questions. It also discusses the contribution to the SHM field and reviews the limitations of this thesis. This study explored (i) applications of smartphones to measure acceleration, gyroscope, and GPS data and capture bridge dynamic responses, and (ii) methods to analyze the data for monitoring purposes. Techniques to extract eigenfrequencies from the smartphone measurements and methods to use gyroscope and GPS for bridge SHM were investigated. Also, the frequency accuracy achievable from the smartphone measurements was examined. The researcher measured acceleration, gyroscope, and GPS data while walking and performing heel drops on the bridge. During the data collection, the smartphone was inside the pocket to demonstrate crowdsourcing within a natural environment. After the data was gathered and transferred to a computer for further analysis, the FFT processed the acceleration and gyroscope data to identify the most predominant frequencies. GPS data were smartly aggregated and manually inspected. A comparison between smartphone measurements and vision-based system reference frequencies was carried out. Based on the findings of this thesis, the following conclusions are drawn:

1) Utilizing crowdsourcing and built-in smartphone sensors is a unique, cost-effective, and most importantly, convenient way to gather data and translate it into useful information regarding bridges' structural integrity.
2) Smartphones can measure vibration responses from flexible structures such as footbridges while placed in a passersby pocket. The process of extracting the natural frequencies from the smartphone measurement requires reference walking data.
3) The gyroscope data could be used to detect gait and walking rhythm.
4) GPS data is currently insufficiently precise to detect exact location and assist in pairing frequencies with their mode shapes.
5) The comparison of natural frequencies calculated from the smartphone data to reference frequencies has shown that the results are comparable. Except for one case where the frequency range was defined differently, the maximum error was 3.5%.
6) Averaging small data sets from the crowd could serve as a database for monitoring purposes.

Identifying the dynamic properties of a footbridge with a smartphone in a pocket is an advancement toward a crowdsourcing platform for SHM. A platform that receives data from passersby and transforms it into valuable information about our infrastructure. It is a unique participatory process that has the potential to gather Bigdata, cost-effectively and collaboratively. Some issues are yet to be addressed: the privacy issue, the practical issue; how to extract data from passersby's smartphones, and the financial issue; who the data belongs to. Nevertheless, this study shows the applicability of smartphones to measure bridge dynamic characteristics and create a database. With this information, it is possible to monitor flexible structures over time without installing and maintaining complex sensor networks.

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8. Appendices

Identified frequencies in all cases are listed.

Table 6 - Natural Frequencies Identified Case 1 (Walking Along the UT bridge)

Take	Direction	Frequency identified [Hz]							
1	x	1.7	2.4	2.6	3.3	3.8	4.3	4.6	5.72
	y	1.6	2.3	2.9	3.2	3.4	4.4	5.62	
	z	1.5	2.5	3.2	3.4	3.9	4.2	4.4	5.48
2	x	2.86	3.8	4.13	4.6	4.8	5.75		
	y	2.4	3.13	3.8	4.13	4.33	4.8	5.64	
	z	2.46	2.8	3.13	3.8	4.13	4.8	5.45	
3	x	2.1	2.5	3.3	3.7	4.2	4.7	5.63	
	y	2.2	2.8	3.1	3.8	4.3	5.45		
	z	2.2	2.9	3.2	3.5	3.9	4.2	4.9	5.47
4	x	2.46	2.8	4.46	4.73	5.5			
	y	2.4	2.8	3.4	3.66	4.4	5.69		
	z	2.4	3.4	3.733	4.4	4.733	5.77		
5	x	2.2	2.5	2.8	3.3	3.8	4.3	5.55	
	y	1.7	2.4	2.8	3.6	4.5	5.61		
	z	2.2	2.4	2.7	3.4	3.8	4.4	4.8	5.59
6	x	2.66	3.26	3.73	4.2	5.57			
	y	2.26	2.73	3.2	3.73	4.2	4.73	5.45	
	z	1.73	2.2	2.733	3.2	3.733	4.2	4.73	5.67
7	x	2.5	3.2	3.4	3.8	4.3	4.8	5.51	
	y	1.9	2.3	2.8	3.2	3.7	4.2	4.7	5.49
	z	1.9	2.3	2.8	3.3	3.7	4.3	4.7	5.7
8	x	3.86	4.53	4.8	5.5				
	y	3.13	3.53	4.13	4.53	5.64			
	z	2.13	2.866	3.13	3.46	3.86	4.13	4.6	
9	x	2.2	2.4	3.7	4.3	4.5	4.7	5.53	
	y	2.4	2.8	3.4	3.8	4.4	4.8	5.56	
	z	2.5	2.8	3.2	3.5	3.8	4.5	4.8	5.68
10	x	2.3	2.7	3.46	3.73	4.33	4.73	5.67	
	y	2.3	3.46	3.66	4.3	4.733	5.7		
	z	2.3	2.73	3.52	3.73	4.46	5.62		

Table 7 - Natural Frequencies Identified Case 2 (Heel Drops at the Middle)

Take	**Direction**	**Identified Frequencies**					
1	Y	2.72	3.25	3.75	4.24	4.75	
2		2.72	3.26	3.77	4.25	4.77	
3		2.72	3.26	3.73	4.26	4.77	
4		2.73	3.23	3.68	4.24	4.76	
5		2.76	3.23	3.7	4.25	4.73	
6		2.74	3.26	3.73	4.24	4.75	
7		2.73	3.26	3.73	4.25	4.75	
8		2.72	3.26	3.72	4.25	4.76	
1	X		3.22	3.85			
2				3.6	4.32		5.44
3		2.74	3.27		4.3		5.55
4		2.81		3.78	4.37		5.75
5		2.75	3.22		4.27		5.78
6		2.76	3.27	3.69	4.24		5.38
7			3.3		4.2	4.86	5.4
8			3.2	3.766	4.25	4.751	5.35
1	Z			3.85			
2				3.51			5.75
3				3.58			5.5
4				3.74			
5		2.74					
6				3.66		4.82	
7		2.59		3.69		4.84	
8		2.7	3.46		4.2	4.87	
Avg		2.728667	3.263333	3.711895	4.258125	4.783154	5.544444
Std		0.046116	0.05996	0.084284	0.042146	0.047092	0.172707
n		15	15	19	16	13	9

Table 8 - Natural Frequencies Identified Case 3 (Heel Drops at the northern side)

Take	**Direction**	**Identified Frequencies [Hz]**					
1	Y	2.74	3.23	3.79	4.25	4.76	
2		2.73	3.24	3.81	4.2	4.74	
3		2.77	3.26	3.72	4.21	4.75	
4		2.76	3.26	3.85	4.17	4.73	
5		2.73	3.24	3.79	4.23	4.76	
6		2.76	3.26	3.76	4.23	4.75	
7		2.73	3.24	3.77	4.25	4.74	
8		2.77	3.24	3.7	4.21	4.74	
1	X						5.58
2							5.66
3			3.28				5.52
4							
5			3.22	3.82			5.46
6		2.73	3.32	3.84	4.34		5.67
7		2.71	3.2			4.72	5.75
8		2.69	3.16	3.78			5.73
1	Z	2.87					5.89
2				3.91			5.63
3		2.67		3.88			5.57
4			3.28	3.93			
5		2.71	3.31		4.16	4.79	5.44
6				3.93		4.82	5.71
7				3.72		4.67	5.59
8							5.4
Avg		2.740714	3.249333	3.8125	4.225	4.7475	5.614286
Std		0.047307	0.040438	0.073166	0.050387	0.036463	0.134491
n		14	15	16	10	12	14