Health monitoring of bridges

14

Rolands Kromanis
Department of Construction Management and Engineering, Faculty of Engineering Technology, University of Twente, Enschede, The Netherlands

14.1 Introduction

Bridges are elements of infrastructure linking two or more distant sites and providing access over obstacles. They provide the means for our society to operate efficiently and at all. Their health (i.e., fitness for purpose, safety, conditions), soundness, and functionality are prioritized. Bridges are exposed to continuously applied loads such as traffic, wind, and temperature, which accelerate their and their component wear and tear. General and principal bridge investigations are scheduled every 2 and 6 years, respectively, to assess bridge conditions. Inspections might be subjective and are infrequent, thus rising a need for implementation of robust and frequent structural health monitoring (SHM). The purpose of SHM is to assess the performance of the bridge and support asset owner's decisions for required interventions.

Developments of sensing technologies and advances in signal processing algorithms enable asset owners and engineers to obtain useful information about bridge performance using appropriate monitoring systems. Sensor systems are selected depending on the size of a bridge, measured structural response, measurement of collection frequency, and cost, which has become a very important factor. Sensing systems providing high accuracy such as fiber optic sensors are expensive. Wireless sensor networks (WSNs) consisting of wireless sensor nodes (usually measuring accelerations with microelectromechanical components) could be a good solution. WSNs are said to be low cost, which is around $200 per sensor node (Chae et al., 2012). However, they have the following shortcomings: (1) overall costs of a WSN are still high, (2) short life span of a battery (Noel et al., 2017), and (3) access requirements, which is a common challenge to contact sensors (i.e., devices that need to be physically attached to the structure or its component). The need for a cost-efficient, available, and easily operable bridge monitoring means still exists.

Modern smartphones are mini computers equipped with sensors such as accelerometers, global positioning system (GPS), gyroscopes, and cameras. They offer high processing power and smartphone applications (apps) with a user-friendly interface. Their availability, software, and hardware scope opportunities for the engineering community to use them as low-cost sensors and/or sensor networks for bridge monitoring. Smartphones are considered as next-generation smart sensors, which are affordable, easy to install, capable of collecting and storing large datasets, and offering real-time monitoring (Sony et al., 2019). Besides, when overcoming privacy and data sharing/protection challenges, smartphones are ideal for citizen-centered monitoring of

Start-Up Creation. https://doi.org/10.1016/B978-0-12-819946-6.00014-X

civil infrastructure (Alavi and Buttlar, 2019). Smartphone availability, in comparison with conventional sensor systems, and aforementioned features make them an attractive chose in bridge monitoring applications.

The suitability of smartphone technology for the collection of accurate engineering measurements is a hot research topic. A decade ago, Mohan et al. (2008) proposed monitoring road and traffic conditions using smartphones. Since then (predominantly starting from 2015), many scholars piloted applications of smartphones for measuring response of laboratory test beds and full-scale bridges. In addition to hardware enhancements, which are driven by manufacturers, smartphone app developers and researchers have taken opportunity to develop free and proprietary apps that utilize smartphone-integrated sensors for acquisition of structure's response. This chapter reviews current methods and applications of smartphones for bridge monitoring, provides a case study, and discusses future trends and challenges.

This chapter is organized as follows. The next section introduces health monitoring of bridges, which includes bridge management and collection and analysis of bridge response for condition assessment. It is followed by a section on bridge health monitoring using smartphones. Although the main emphasis of the section is on smartphone applications for measuring bridge response, examples on laboratory test beds, which are specifically designed to mimic bridges, are also presented. A case study section demonstrates applications of smartphones, specifically their cameras, for ultrahigh-resolution image stream for measuring deformations of a pedestrian footbridge. The concluding section provides an insight into current challenges and future perspectives of smartphone applications in bridge health monitoring.

14.2 Characterizing bridge response

Efficient and effective bridge management (e.g., decision-making process providing save operational conditions) strategies overview the entire bridge system with traffic, applied loads and surrounding environment, and plan for condition assessments and interventions to reduce life cycle costs (Catbas and Aktan, 2002). A bridge management paradigm, where measurements of bridge response are collected using smartphones, is envisioned in Fig. 14.1. A bridge is a structural system that (1) is exposed to applied

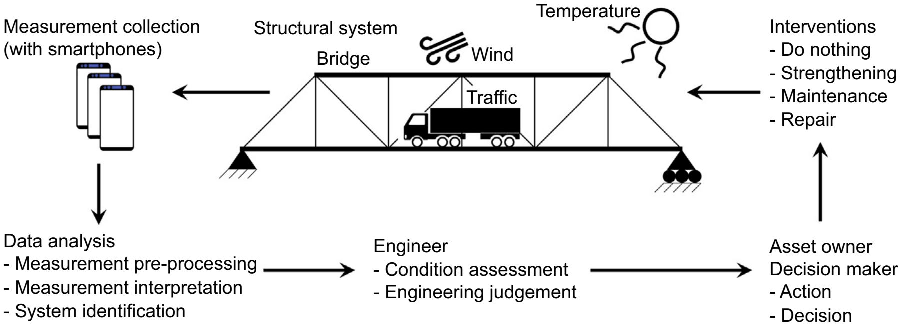

Figure 14.1 A bridge management paradigm involving smartphones-driven bridge monitoring.

loads such as traffic, wind, and temperature, (2) has a defined geometry and boundary conditions, and (3) is safe to use and fit for purpose. To characterize its performance, detecting and locating rust, erosion, cracks, and pot holes is not enough. Instead, knowledge of load-response mechanism is required.

A sensing system measures bridge response such as deflections induced by vehicular loads. Response measurements, which could be displacement time histories or signals, are firstly preprocessed and only then interpreted for the purpose of structural system (i.e., bridge) identification. Engineers scrutinize the analyzed data and provide their judgment on bridge conditions. Information on bridge performance is communicated to asset owners who can also be decision-makers. They plan for necessary interventions if any deviations from previously observed bridge behavior are detected.

To arrive to a stage when bridge response can be characterized, engineers have to (1) understand bridge response, (2) measure the response using a suitable sensing system, and (3) perform data analysis. These three topics are discussed in the following subsections.

14.2.1 Bridge response

Bridge response can be static, quasi-static, and dynamic. Static response, in its simple form, is easy to visualize and understand. It results from a load applied to the structure, which deforms correspondingly. Such load can be applied slowly at desired locations or can be induced by traffic (i.e., moving vehicles). Bridge response to moving loads is more complex than that to static loads at strategic locations. Typically measured deformations are displacements (lateral, transverse, and longitudinal), strains, and tilts. An important factor influencing bridge deformations to static loads is temperature (Nguyen et al., 2016). For example, when ambient temperature increases, the bridge (such as shown in Fig. 14.1) lengthens, thus slightly changing its geometry and response to static loads.

Quasi-static bridge response is generated by slowly applied loads such as variations in ambient temperature. This response might seem insignificant in short term; however, in long term, it governs deformations of bridges. For example, Catbas et al. (2008) observed that maximum peak-to-peak strains of a long span truss bridge induced by traffic are approximately 10 times smaller than strains resulting from yearly temperature variations. Temperature loads create the same deformations as static loads. However, to understand phenomena of temperature-induced response, distributed temperature needs to be measured.

Bridge dynamic response is very complex. It includes bridge damping and natural frequencies with their associated mode shapes. Capturing dynamic (or vibration) properties may require more sophisticated sensing system than for capturing static response. Bridge dynamics are obtained from accelerations and/or displacements of structural nodes, from which the majority of natural frequencies can be measured and fundamental mode shapes can be constructed. Similarly to static response, temperature effect has to be considered for a reliable characterization of bridge dynamic response (Xia et al., 2012).

14.2.2 Sensing systems

Accurate and reliable response measurements are of utmost importance for meaningful data interpretation and bridge response characterization. Fig. 14.1 envisions smartphones, instead of a conventional sensor system typically consisting of contact sensors, for measurement collection. Sensors and their configuration (such as location and measurement frequency) are chosen based on monitoring requirements, type of response, and budget.

An accelerometer is a device measuring accelerations (i.e., dissipated forces) of a bridge under excitations. Multiple accelerometers form a WSN, which can provide much information on bridge dynamic properties. Global navigation satellite systems (GNSS) and robotic total stations are frequently employed for short- and long-term displacement monitoring. A long-term GPS monitoring system on the Humber Bridge has provided engineers with useful data on the behavior of large-span suspension bridges (Brownjohn et al., 2010). Fiber optic sensors are a very good option to collect strains, which can be converted to displacements and tilts, at high and low frequencies. They have been used for more than two decades in bridge monitoring (Casas and Cruz, 2003). Their accuracy, reliability, and robustness, especially in long-term monitoring, are outstanding, so is the high cost of a fiber optic system.

Applications of computer vision have been widely considered and employed for short-term bridge monitoring (Feng and Feng, 2018). The majority of affordable cameras offer recording ultrahigh or 4k resolution (i.e., 3840×2160 pixels) videos at 30 frames per second (fps). With the aid of appropriate image processing algorithms, small changes in structural response, which is captured at high rates and from far, can be computed.

Smartphones have integrated accelerometers, gyroscopes, magnetometers, GPS, and cameras, which could be deployed to replace aforementioned sensors/sensing systems.

14.2.3 Data analysis

Response measurements are meaningless, unless they are correctly interpreted. Much research has been devoted to derive approaches, techniques, strategies, and methodologies for data analysis. The main focus is to characterize the performance of the structure and, in a way, "make sense" of the data. The first step is measurement preprocessing, in which

(i) outliers are removed or replaced with statistical values derived from neighboring measurement points;
(ii) noisy data are smoothed with moving average or low-pass filters;
(iii) high-frequency data sets are downsampled (if needed) to a frequency required for fast and, at the same time, accurate data interpretation.

Dynamic analysis focuses on structure's frequencies and corresponding mode shapes. Frequently numerical or finite element models are developed. These are calibrated to mimic response of full-scale bridges for system identification, and damage and anomaly event detections.

Static response is very useful for short-term measurement interpretation. For example, vertical displacement and strain measurements of bridges at events of train or truck passages can provide information on axel loads. In some countries, overweight vehicles expose bridges to loads that can even result in its collapse (Yu et al., 2013). It has been a challenge for the bridge monitoring community to develop systems detecting extreme loads and identifying vehicle owners.

Quasi-static measurements form time histories or signals requiring sophisticated preprocessing approaches, which involve either removal or characterization of traffic and thermal loads. Many methodologies are proposed to analyze long-term monitoring data. Some methodologies are output only (i.e., response measurements alone are considered) such as cointegration (Cross et al., 2011) and moving principal component analysis (Posenato et al., 2010); others, in contrary, focus on temperature-based strategies, which seek solutions for characterizing thermal response (Kromanis and Kripakaran, 2014; Yarnold and Moon, 2015).

Less complicated data processing can be accommodated by smartphones; however, for more complicated and computationally expensive data analyses, cloud-based computing could suffice.

14.3 Bridge monitoring with smartphones

When considering bridge monitoring with smartphones, they can be considered as

- contact sensors when they are attached to a bridge or bridge component,
- noncontact sensors when they face a bridge or bridge component and record videos or capture images,
- part of a smartphone network or crowdsourcing (e.g., bridge data are obtained from citizen smartphones), in which bridge dynamic parameters are collected.

A flowchart of smartphone applications in bridge monitoring is shown in Fig. 14.2.

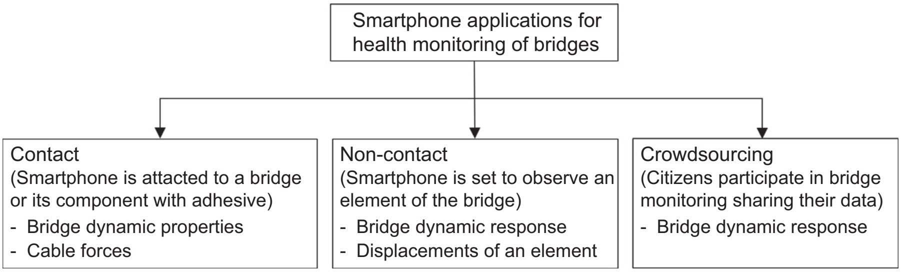

Figure 14.2 Smartphone applications in bridge health monitoring.

These three main smartphone applications (smartphones as contact and noncontact sensors and mobile sensor networks) for bridge health monitoring are further reviewed, discussed, and presented in the following sections.

14.3.1 Contact sensors

Smartphone-integrated accelerometer can be set to measure structural movements, specifically dynamic response. High accuracies are achieved when phones are attached (by adhesive or double-sided tape) to an element of the bridge. This approach has been researched extensively for measuring accelerations. Morgenthal and Höpfner (2012), and Höpfner et al. (2013) piloted applications for measuring structural displacements with accelerometers and GPS. In motion monitoring tests, smartphones were attached to a shaking rig. The maximum reliable oscillation frequency was determined to be around 6 Hz. Although the actual acceleration range of smartphones was found to be ± 2g resulting in slightly noisy spectral analysis, the physical frequency of the shaking table was correctly computed.

With enhancements in smartphone accelerometers, the number of studies on their applications has significantly increased since 2015. Yu et al. (2015) proposed a Mobile-SHM method that uses gyroscope and accelerometer to obtain dynamic response of structural elements. A pendulum test, in which an iPhone and an inclinometer were put on a swing, demonstrated that the iPhone's gyroscope measures accurately dynamic angles (inclinations). The natural frequency of the swing was accurately calculated from smartphone inclination data. The drawback is that the swing frequency was only 0.515 Hz, and higher frequency swing tests were not performed.

Short-term bridge monitoring (e.g., during the construction phase) is important for quality assurance as demonstrated by Han et al. (2016). They proposed to employ smartphones for girder hoisting monitoring. Hoisting is predominantly referred to the positioning or placement of a deck/girder in suspension bridges. High-strength slings connect a girder to cranes, which control its orientation and position along the length of the main cable. The monitoring is required to ensure the girder leveled correctly and prevent a drop of one of its ends. In this study, two iPhones were used. One phone was placed on the girder to measure its rotation angle and accelerations. The other controlled the monitoring process by communicating to the phone that recorded angles and accelerations. Results show that this approach can be implemented in hoisting monitoring and enhancing current practices.

Acceleration data can also be used to estimate the cable force. The cable force can be computed using the vibration theory of a tensioned string, for which cable geometric properties (i.e., linear mass and length) and frequency difference of the frequency spectrum (obtained from power spectrum density [PSD] peaks) are needed. Frequency difference of 4 Hz or less can be accurately measured. PSD plots of cables with frequencies over 5 Hz are noisy. Orion-CC is a popular iPhone app for measuring accelerations and frequently employed in bridge monitoring (Zhao et al., 2016b). Overall, the fundamental frequencies obtained with industry standard accelerometers and smartphones deviate by no more than 3%, thus making smartphones a robust and reliable tool for estimating cable forces (Yu et al., 2015; Zhao et al., 2015b; 2017a).

Attaching a smartphone to the deck has been practiced to measure frequencies and mode shapes. Shrestha et al. (2018) used a remote trigger function to collect simultaneously accelerations of multiple smartphones on a cable-stayed bridge.

The error between smartphones and servo velocity sensors for the first vertical frequency of the bridge was 0.36/0.38, i.e., 5%. In other studies, some success has been achieved capturing mode shapes of reinforced concrete and timber bridges with distributed smartphones (Elhattab et al., 2019; Hester and Keenan, 2017). Guzman-Acevedo et al. (2019) compared frequencies collected with a GPS antenna, accelerometer, and smartphone of a reinforced concrete bridge. All sensors were fused into a "smart sensor" attached to the tripod, which is placed on a bridge to measure accelerations. Only a single frequency (at 9.37 Hz) coincided with a high confidence for all sensors. Ndong et al. (2019) found that error between smartphones and professional accelerometers peaked up to 15.8% for ambient vibration test and 5.6% for the impact hammer tests of concrete deck bridges. Besides, ambient excitation was noisy with hardly distinguishable peaks.

Castellanos-Toro et al. (2018) have conducted an extensive study collecting accelerations of 682 bridges using Vibsensor app. Data from 231 bridges were discarded due to failing requirements of measurement resolution level. They initially tested accelerometer performance of 25 smartphones from LG, Motorola, and Huawei. Smartphones performed well in three sweeping tests. Frequency was changed from 0.3 to 30 Hz, for the period between 60 and 120 s. Smartphone performance on a test footbridge was also evaluated. The frequency of the first five modes (ranging from 3.88 to 23.8 Hz) was accurately calculated from accelerations collected with all smartphones. Frequencies obtained from 12 test bridges with seismic accelerometers and smartphones in the worst case deviated only by 4%. Parameters such as span length, natural frequency, material, and type of bridge (i.e., pedestrian or vehicular) were compared. The collected data were used to carry out multivariate statistics analysis (Millán et al., 2019).

The following conclusions are drawn from smartphone applications as contact sensor:

- Smartphones can be considered as reliable and accurate tools for dynamic structural monitoring of bridges and their components such as cables and decks.
- Smartphones (especially the latest versions) and apps can collect accurate acceleration, especially below 20 Hz. The collection of higher frequencies remains a challenge.

So far, damage detection studies have been carried out only on laboratory structures. Xie et al. (2019) used a three-dimensional steel frame. Smartphones were attached at strategic locations. The structure was subjected to earthquake excitations simulated on a shaking table. Several levels of damage were created by removing ridge beams. Damages, which were exaggerated and unlikely to present realistic scenarios, were detected using smartphone data.

14.3.2 Noncontact sensors

Smartphones, when they are used to obtain response without being physically attached to the structure, are considered being noncontact sensors. In the majority of applications, smartphone cameras are used; however, smartphone microphone and speakers can also act as a sensor. Höpfner et al. (2013) tested if oscillations could be measured with the sonar distance measurement method, which records time for the sound to reflect from a source. Smartphone speaker transmits the sound, whereas the microphone receives it. The time for the sound reflection is equal to the distance. A wooden plate subjected to harmonic oscillations served as the reflecting surface. The excitation frequency was identified correctly. However, very few data points were captured; hence, only two displacement distances (i.e., distance to the receiver) were measured.

Smartphone cameras and video/image quality that they offer have developed significantly. Much of the research has been conducted using high-definition (HD) videos (1920×1080) at 30 or 60 fps. However, many modern smartphones can record 4k videos at 60 fps or 1280×720 videos at 240 fps. Computer vision in deformation monitoring of structures has been well researched (Feng and Feng, 2018). The fundamental concept is to follow the movement or displacement of a target, marker, or object of interest such as a template or pattern with known dimensions, a bolt in a structural joint and laser spot in a sequence of image frames or video. The pixel information is translated (if needed) to engineering units such as millimeters. Dynamic properties of the structure are obtained from high-frequency displacements, which result from ambient or forced excitations.

Zhao et al. (2015a; 2017a, 2016a,b) have researched the application of an Android app D-Viewer for calculations of cable force and bridge dynamic as well as static response. Calculations for the cable force are exactly the same described in Section 14.3.1. One of the approaches to measure displacements is tracking a laser spot (in a form of a blob) on the reflected surface. The setup requires a laser pointer, reflection plate, and smartphone, which captures a single laser spot. Accurate measurements of static and dynamic response as evaluated on a laboratory suspension bridge can be obtained (Zhao et al., 2016a,b). Zhao et al. (2017c) also measured distributed response using several setups on both laboratory and full-scale bridges. Main drawbacks for this method are as follows:

- Need for a laser, which has to be fixed on an object that is not moving
- Installation of a plate at 30 degrees to the laser beam
- Single target in a smartphone field of view

Zhao et al. (2017b) compared cable forces calculated from (1) accelerations measured with Orion-CC of a smartphone attached to a cable, (2) displacements of a black circle target, which was printed on a white sheet attached to a cable, computed with D-Viewer app from a video stream of a smartphone set on a tripod, and (3) vibrations of a cable (no targets) recorded with a handheld smartphone and smartphone set on a tripod. The latter approach had 3.4%–3.7% error in comparison with the first approach. Wang et al. (2018) proposed to use D-Viewer to obtain 3D structural displacement by tracking out-of-plane and horizontal as well as vertical displacements of a black circle. A paper sheet with a black circle was placed on the deck at the midspan of a scaled suspension bridge. A smartphone is attached to a supporting structure, which is set on the laboratory floor, a few centimeters above the deck. This setup is unrealistic for full-scale bridge monitoring. Another drawback in the app is that it tracks one or two closely placed circles, i.e., no other object/shapes can be tracked.

Another technique for monitoring column or deck movements is setting smartphones away from the structure or its component. Kalasapudi et al. (2016) collected dynamic response of a reinforced concrete bridge column at 240 fps. They developed an algorithm automatizing scour assessment. The video data were accurate enough to compute the first two resonant frequencies of columns. Kromanis and Forbs (2019a) validated the performance of the multiepoch location-independent measurement collection approach, which initially proposed and validated on a laboratory structure (Kromanis and Liang, 2018), on a full-scale pedestrian bridge. Two smartphones recorded 4k videos from opposite river banks of forced bridge excitations. Bridge deformations and first vertical frequency computed from the videos were in a good agreement with GNSS results and previous studies. Vertical displacements at the midspan were more than 15 mm, thus favoring the approach. Smaller displacements would have been hard to detect. However, mounting a smartphone to a zoom lens and focusing it at a very localized region of interest on the structure is a solution to measure small and localized displacements (Kromanis and Al-Habaibeh, 2017).

In the past decade, many computationally intensive algorithms were made available for real-time image processing. The computational speed and capacity have grown. Smartphones are not yet powerful enough to replace proprietary PC software and mature hardware (cameras). Being aware of current developments, there is no doubt that these devices will become ubiquitous in all ways. However, there is still a room for improvement as it can be seen from the studies mentioned previously:

- Measurements are accurate in a close range applications.
- Mainly, only a single target is tracked.
- High-resolution and frame rate videos, in which multiple targets are tracked, are not processed in real time.

14.3.3 Mobile sensor networks

An activity when an individual, group, or company actively, with genuine intentions, and voluntarily participate in data collection and share it is one way how to define data crowdsourcing (Estellés-Arolas and González-Ladrón-De-Guevara, 2012). Today, almost all citizens have a smartphone in their pockets. The acquisition and interpretation of data such as accelerations from citizen smartphones crossing a bridge on foot or by car is termed crowdsensing. A crowdsensing approach, in which a citizen's device starts/stops recording accelerations, when the citizen approaches a bridge (citizen's location is tracked by GPS) and sends data to a server where it is processed, sounds indeed attractive and could be a low-cost bridge-monitoring solution. Large data sets could be processed using statistical and probabilistic big data analysis tools assessing bridge performance and identifying anomaly events.

The first steps in applications of citizen sensors in bridge monitoring date back only to 2015, when Feng et al. (2015) proposed the idea of collecting data from citizen smartphones for acceleration measurements of structures. Similarly to studies, where smartphones were used as contact sensors, acceleration tests were initially performed in the laboratory and only then in on the Streicker Bridge in Princeton, United States.

A smartphone was attached with a double-sided tape to the deck of the bridge. Natural frequency of the bridge derived by smartphone and standard accelerometer data varied by only 1%. Ozer et al. (2015) furthered research of Feng et al. (2015) and developed iOS app *Citizen Sensors for SHM*. A pedestrian link bridge, which spans 11 m between two buildings, was a test bed for the vibration-based SHM crowdsensing approach. Bridge vibrations were measured with standard accelerometers and two crowdsourcing strategies: (1) placing smartphones with different fixities in strategic locations (modal nodes) and (2) obtaining data from 135 pedestrians crossing the bridge. Collected bridge frequencies, in general, compared well, although a high dispersion in crowdsourcing frequencies was observed. Other tests explored accelerations collected when pedestrians are walking over or standing on the bridge (Ozer, 2018). Bridge frequencies above 10 Hz were accurately identified. Furthermore, from accelerations of

(i) walking pedestrians, bridge dynamics due to human activities were estimated;
(ii) standing pedestrians, human biomechanical models were developed and eliminated from acceleration signals to obtain bridge dynamics.

Ozer and Feng (2016) collected smartphone geolocation data and accelerations of the aforementioned pedestrian link bridge for its modal identification. Overall, modal frequencies deviated by only 3% from the ones derived using specialized accelerometers. Ozer and Feng (2017) also demonstrated how heterogeneous sensor (smartphone accelerometer, magnetometer, gyroscope, and GPS) data can be converted to the structure and then global coordinate system. This method can be encapsulated in crowdsensing approach for bridge modal identification.

Drive-by approaches, in which measurements are collected from vehicles crossing a bridge, are also widely studied. Departments for transportation keep close records of traffic data, which, in conjunction with other statistical data records, can be used to estimate smartphone trips over a bridge. For example, based on data collected in 2009, it was estimated that on average the Harvard Bridge, United States, has 18,000 smartphone daily trips (Matarazzo et al., 2017). Such data amount could provide meaningful information about bridge conditions when correctly analyzed and interpreted. Matarazzo and Pakzad (2018) introduced an extended structural identification using expectation maximization algorithm for accurate modal identification using a dynamic sensor network (e.g., moving vehicles). In an experimental setup, a mobile sensor network provided accurate modal frequencies and high-resolution mode shapes (with 248 mode shape points) for a 3.66-m-long laboratory bridge specimen. Matarazzo et al. (2018) collected accelerations of the Harvard Bridge from a moving vehicle. The first three modal frequencies of the bridge computed from collected data were consistent with a fixed wired accelerometer network. Their study confirms that bridge modal frequencies can be detected accurately using smartphones from moving vehicles.

Crowdsensing can be implemented to monitor health of bridges using data from crossing vehicles. Mei and Gül (2018) proposed a framework for damage detection of bridges using smartphones in moving vehicles. A laboratory bridge (platelike beam) and an Arduino-controlled vehicle with a smartphone attached to it were used for the framework evaluation. Damages and their extents were identified at various vehicle configurations (i.e., weight, suspension spring, and speed). Real-life examples have not yet been employed for damage detection. McGetrick et al. (2017) drove a van equipped with specialized equipment (accelerometers and GNSS receivers) and smartphones along predetermined routes to study the feasibility of smartphone applications for drive-by monitoring of transport infrastructure. Vehicle accelerations were collected to identify bridge frequencies and expansion joints. Results from specialized equipment and smartphones compared well. The low mass of the vehicle as well as its excitations by expansion joint and short signal length are listed as a few factors affecting measurement quality.

Another way to engage citizens in crowdsensing is using a smartphone to collect data from low-cost sensor nodes. Morgenthal et al. (2018) proposed to employ off-the-shelf electronic components such as Raspberry Pi and MPU-6050 accelerometer, which costs €5, to build a low-cost WSN. Accurate cable dynamic properties and forces as well as mode shapes of horizontal structures can be calculated from accelerations collected with the Raspberry Pi-based monitoring system (Morgenthal et al., 2018, 2019a). A single node in the system costs below €50.

Gibbs et al. (2019) suggest to involve citizens in rural areas to assess conditions of bridges using a citizen sensing approach. The premise is that citizens in rural areas deploy a low-cost, easy-to-install sensing system to establish database for dynamic response of rural bridges. A data-enabled framework is employed to predict dynamic properties of bridges at their conceptual design, thus improving their safety under winds. The downside of this attractive method is that citizens performing tests need the testing kit, which consists of smartphone(s) and/or the Vibration Sentry data logger, USB cables, laptop, 10-m rope for plucking test, notebook and pen, wood screws, screwdriver, and a timing device.

Smartphone crowdsourcing has a vast potential for bridge monitoring applications; however, there are still grounds to cover. Besides, data privacy is an issue. The current studies conclude that

- bridge drive-by data acquisition using smartphones is much cheaper than the conventional system, which can cost around €26,000 (McGetrick et al., 2017);
- specialist training is not required in crowdsensing;
- crowdsourcing acceleration signals is a feasible solution for drive-by bridge monitoring;
- there is a need for a large population data from many smartphones to effectively evaluate crowdsensing approaches for bridge monitoring;
- low-cost WSNs controlled with smartphones are accurate and accessible solution for acquisition of dynamic properties.

14.3.4 Summary and discussion

Main applications of smartphones for bridge monitoring were discussed. Many case studies provide useful insights in the technology and its application. Research gaps still need filling, and solutions for fundamental problems/questions need addressing:

- Attaching smartphones to bridges is not much different from installing contact sensors, which might involve working at height and cause traffic disruptions. Contact sensing also does not support long-term monitoring. It can be carried out only during inspections.

If multiple smartphones are considered for collection of dynamic properties, ideally measurement collection should be made synchronous. This requires an app, which enables the control smartphone operated by an engineer, to initiate synchronized measurement collection.

- Crowdsourcing provides useful information and proves to work well in laboratory environments. However, not all users are willing to share their data or use their smartphones to obtain bridge data or collect it themselves.
- Computer vision for bridge monitoring has gained large popularity in the field of SHM and measurement collection. It needs further implementation in smartphones especially for collecting real-time measurements.
- The majority of research is focused on measurement collection, especially when using smartphones as contact sensors; however, there is a gap of developing and implementing strategies of data archiving, storage, and review for smartphone-driven bridge health monitoring.

Ozer et al. (2017) proposed a hybrid monitoring approach fusing dynamic measurements from smartphone accelerometer and camera. Although measurements from both sensors were in good agreement, imperfections were observed in the sampling rate. There is much scope in fusing sensor data. For example, a smartphone can be attached to the bridge or its element to record a video and collect accelerations, while the bridge is excited. In such scenario, the smartphone is focused away from the bridge at a target in the distance. Many smartphone cameras can record videos at 240 fps (with a boost of up to 960 fps). This property is not yet explored in bridge health monitoring. Another important consideration is equipping computer vision algorithms with artificial intelligence (AI) tools. Today, smartphone processors might not be powerful enough to analyze large data files; however, with the emerging 5G communication technologies, large data files could be uploaded to the server where data analysis can take place. The bridge monitoring community, which develops apps and uses smartphones for measuring response, has to follow hardware and software developments. A few comments are provided in the following.

Software. The smartphone processing power limits the complexity of algorithms that can analyze real-time data stream, thus demanding optimized algorithms capable of coping with large data sets. The competition between app developers also creates uncertainty when selecting the appropriate app for bridge SHM. Cahill et al. (2019) explored the performance of 12 smartphone accelerometer apps using Motorola Moto G (1st Generation); however, a commonly used iOS app Orion-CC was not included in the comparison study. There is a need to thoroughly and critically study many apps (and their compatibility with smartphones) to find and comment on apps (and smartphones) that provide reliable measurement collection and interpretation. Besides, some apps are only available for Android or iOS devices.

Hardware. An existing difference between low-cost smartphones and more expensive ones needs to be understood and investigated. Expensive devices may have more robust and reliable integrated sensors. The latest smartphones such as Samsung Galaxy S10 Plus, Huawei Mate 30 Pro, and iPhone 11 Pro have multiple rear cameras. This feature could be both an advantage and disadvantage when using only the device to record videos of structures subjected to loading. It can get difficult attaching a smartphone with multiple cameras to a telescope when monitoring small displacements from far.

14.4 Case studies

This section demonstrates smartphone applications for measuring bridge response using a noncontact approach. The bridge and the monitoring system are introduced. Image processing techniques, which measure vertical deflections of the bridge while it was exposed to forced excitations, are discussed and explained. The bridge fundamental frequency computed from smartphone videos and calculated from GNSS data is in a good agreement.

14.4.1 Pedestrian suspension bridge

The Wilford Suspension Bridge (see Fig. 14.3), which has a status of Grade II listed heritage buildings, is located in Nottingham, the United Kingdom. It is a pedestrian bridge, which also serves as a water aqueduct. The suspended span is 69 m long, crosses the River Trent, and links Nottingham and West Bridgford. The bridge has two main cables, in which a steel structure covered with a timber deck is suspended. The bridge was rebuilt/renovated between 2008 and 2010. The bridge dynamic displacement and modal properties were studied using a multimode GNSS processing (Yu et al., 2014) and combination of GPS and robotic total station (Psimoulis et al., 2016). The natural vertical frequency of the bridge was found to be around 1.69 Hz.

In this study, Samsung S9 plus (S1) and Samsung S8 (S2) are selected to capture dynamic properties of the bridge. Smartphones are positioned at slightly different locations approximately 45 m away from the bridge on the left bank of the river. Fig. 14.3 shows smartphone monitoring setup. Smartphones record 4k videos at 30 fps. The experiment is organized by the University of Nottingham as a part of student assignment. GNSS collects vertical displacements at the midspan and 1/3-span (or 23 m from the left end of the suspended superstructure) of the bridge. The bridge is

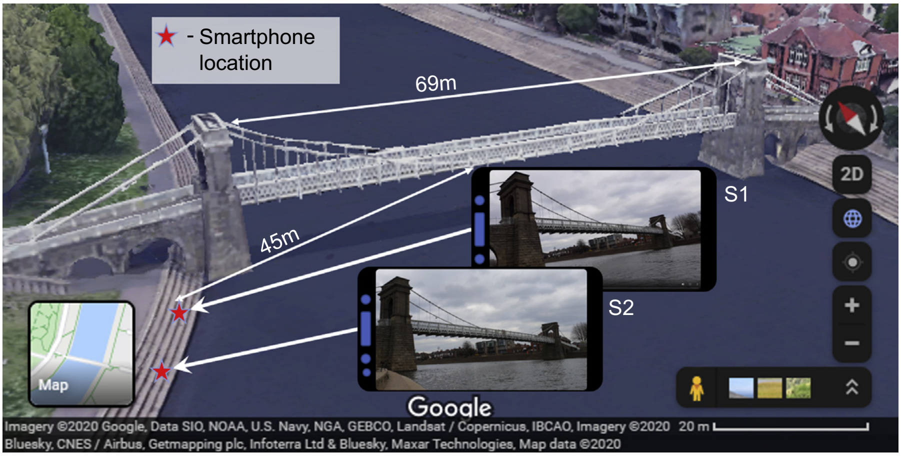

Figure 14.3 Smartphone monitoring setup for the Wilford Suspension Bridge.

excited by 10 students jumping near GNSS locations. In this example, the bridge dynamic response is analyzed for a period when the jumping took place at the 1/3-span of the bridge.

An image frame as recorded with S1 is shown in Fig. 14.4. Four reference points on the structure are selected to derive a transformation matrix (see Fig. 14.4 (left)). The matrix converts any given coordinate point to the defined coordinate system requiring no additional scale factors. The bottom and top left points (bottom and top of the hanger) are set to [0, 0] and [0, 6] x and y coordinates (in meters), respectively. x coordinates for the bottom and top left points are 65 m, and y coordinates are kept the same as for the points on the left side. A region of interest (ROI) includes both GNSS antenna locations. Targets T-1 and T-2 are selected close to the antenna locations. Mini eigenvalue algorithm is chosen to detect features in the targets. Targets with their features and centers (calculated as an average value from feature coordinates) are shown in Fig. 14.4 (right).

Vertical displacement histories of T-1 for the duration of excitations, which lasted approximately 40 s, computed from the video recorded with S1 are plotted in Fig. 14.5(a) The signal is preprocessed with a low-pass filter, and camera movements

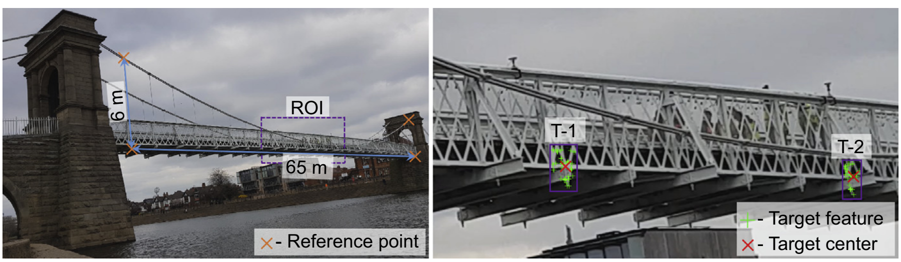

Figure 14.4 Image processing approach. Selection of (left) reference points and ROI, and (right) targets.

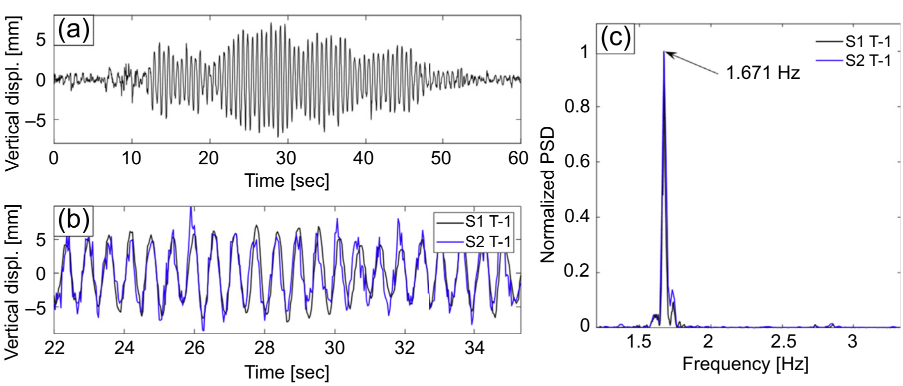

Figure 14.5 The bridge dynamic response: T-1 vertical displacements form (a) S1 for the duration of excitation and (b) both S1 and S2 for 13 s period; (c) PSD of T-1.

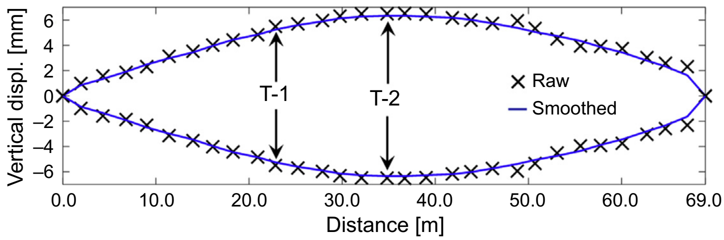

Figure 14.6 Bridge vertical displacements at hanger connections to the deck.

are removed. The signal has either noise or human-induced vibrations before and after forced excitations (see displacements before 10 s and after 55 s). Maximum peak-to-peak displacements are around 14 mm, which are similar to GNSS measurements. Fig. 14.5(b) gives a closer look at the period between 22 and 35.5 s for T-1 displacements from S1 and S2. The plot shows that S1 provides a better quality video than S2, resulting in smoother displacements. Measurement plots are synchronized/merged manually. S2 T-1 oscillations between 27 and 32 s are lagging behind S1 T-2, resulting in a high root mean square deviation (i.e., 2.5 mm for the period between 22 and 35.5 s). PSD is computed to find the first vertical frequency of the bridge. For both smartphone signals, the fundamental frequency at T-1 location is 1.671 Hz (see Fig. 14.5(c)). GNSS measured 1.675 Hz.

S1 video allows the computation of vertical displacements of the deck at hanger connections along the length of the bridge. Fig. 14.6 depicts upward (positive) and downward (negative) displacements at the 24th second. The deck displacement curve for the first 48 m from the left side of the bridge (i.e., side that is closer to the camera) is a parabolic and realistic. The part of the deck further away from the camera view has large measurement discrepancies. The vertical distance between the selected reference points (as shown in Fig. 14.4) is equal to 682 and 309 px on the left and right sides, respectively, leading to larger measurement error.

The Wilford Suspension Bridge study demonstrates that accurate dynamic response can be obtained using smartphone cameras. The difference between the first frequency calculated from GNSS and smartphones measurements is only 0.2%. Small displacements can be measured. In Fig. 14.6, the maximum peak-to-peak vertical displacement of the first hanger from the right side is ± 0.85 mm, which is $\frac{682[\text{px}]}{6000[\text{mm}]} \times 0.85[\text{mm}] \cong \frac{1}{10}[\text{px}]$. With more sophisticated image processing algorithms, accuracies smaller than 1/50 px can be achieved.

14.5 Current challenges and future perspectives and directions

There is no best solution or approach using smartphones in bridge SHM. Attaching a smartphone to an element of the bridge might seem as an unattractive option; however, it provides useful information about cable forces and frequencies of bridge deck.

For these reasons, this still remains an option. Besides, attaching a smartphone is practical and easy. Recording a video (with a smartphone) of a bridge subjected to excitations and later analyzing it does not support real-time monitoring. With more sophisticated and efficient algorithms and powerful processors, this, however, measuring accurately real-time deformation, could be made possible. Crowdsensing sounds as a fantastic solution for bridge SHM. However, data privacy and lack of large data sets for evaluating crowdsensing capabilities on full-scale bridges, which is beyond obtaining approximate dynamic response, are still challenging. Government and local authorities should encourage citizens to share their data for good purposes. This, however, could lead to a danger of hacking into such important data and manipulating it. This topic is outside of this chapter's scope.

Data sharing and upload permissions could be issued to practicing engineers or responsible personnel involved in asset management. This consortium could use crowdsensing applications and also upload images of structural defects to a specified bridge inventory directory. However, today, a platform, where one with given clearances would be able to contribute and share relevant data, does not exist. This leads to another issue that needs addressing—creation of a unified bridge management platform/live database. Participants with granted access could share and upload relevant data for selected bridges. The data would be automatically archived, reviewed, and analyzed using some predefined deep learning tools.

Smartphones have not yet been extensively exploited in long-term monitoring applications, although they are becoming ruggedized and waterproofed. Park et al. (2015) employed two smartphones, which took an image every 10 min for a duration of 2 weeks capturing thermal movements of a bridge at its bearings. Measured displacements were only 3.11% different from those obtained with a displacement transducer. Kromanis et al. (2019) captured temperature-induced strains from time-lapse images (captured with Samsung A5) of a laboratory beam subjected to accelerated temperature variations for more than a 26 h. Demonstrations of long-term smartphone functionality are seen; however, they are very limited in bridge monitoring studies.

Smartphones could be fixed to a zoom lens attached to a robotic platform, which rotates and points the camera to a desired location and captures images or records videos. Examples of robotic platforms for smartphones are seen for artistic video montages, but not in bridge monitoring studies. Besides, they do not include a zoom lens. The performance of a robotic system with a modified action camera was evaluated on a laboratory structure (Kromanis and Forbes, 2019b). Its performance was compared with a smartphone camera that captured the entire structure. Although the robotic system outperformed smartphone in the measurement accuracy, if the action camera were replaced with the smartphone, comparable results between two camera systems could be achieved. The latest smartphones have two or more rear cameras, which could improve or reduce the practicality of their application. No studies have yet explored this new feature opening scope for further research.

Bridge inspections. Smartphones could support bridge visual inspections with image-based data and augmented reality. Ideally, a 3D model of a bridge is preferred. The model could be created with LiDAR or images from a drone

(Morgenthal et al., 2019b). The digital replica of the bridge serves as a platform, on which monitoring and visual information of bridge conditions are uploaded. It is envisioned that an inspector would use a virtual reality (VR) tool. The location of the smartphone is detected using GPS. From here, a camera can be used as a VR to see information such as images and monitoring data collected in previous inspections. Inspector can then place the smartphone on identified structural nodes and record accelerations. Or an image of a location with a defect can be captured. Augmented reality helps identify the locations of interest. The newly acquired data are uploaded to the server/cloud, where (1) monitored parameters are analyzed and compared with the baseline data using unsupervised and autonomous measurement interpretation techniques, and (2) images of joints with defects are project over time, and, using artificial intelligence and deep learning tools, their propagation/severity is characterized. The acquired data supports bridge condition assessment.

Acknowledgments

The financial support from Global Heritage, Nottingham Trent University, for the equipment used during the collection of videos of the Wilford Suspension Bridge is gratefully acknowledged. The bridge testing was organized by Dr Panos Psimoulis, Mr Sean Ince, and Dr Lukasz Bonenberg from Nottingham Geospatial Institute of the University of Nottingham.

References

Alavi, A.H., Buttlar, W.G., 2019. An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring. Future Generation Computer Systems 93, 651−672. https://doi.org/10.1016/j.future.2018.10.059.

Brownjohn, J.M.W., Magalhaes, F., Caetano, E., Cunha, A., 2010. Ambient vibration re-testing and operational modal analysis of the Humber Bridge. Engineering Structures 32, 2003−2018. https://doi.org/10.1016/j.engstruct.2010.02.034.

Cahill, P., Quirk, L., Dewan, P., Pakrashi, V., 2019. Comparison of smartphone accelerometer applications for structural vibration monitoring. Advances in Computationl Design. https://doi.org/10.12989/acd.2019.4.1.001.

Casas, J., Cruz, P., 2003. Fiber optic sensors for bridge monitoring. Journal of Bridge Engineering 362−373.

Castellanos-Toro, S., Marmolejo, M., Marulanda, J., Cruz, A., Thomson, P., 2018. Frequencies and damping ratios of bridges through Operational Modal Analysis using smartphones. Construction and Building Materials 188, 490−504. https://doi.org/10.1016/j.conbuildmat.2018.08.089.

Catbas, F.N., Aktan, A.E., 2002. Condition and damage assessment: issues and some promising indices. Journal of Structural Engineering 128, 1026−1036. https://doi.org/10.1061/(asce)0733-9445(2002)128:8(1026).

Catbas, F.N., Susoy, M., Frangopol, D.M., 2008. Structural health monitoring and reliability estimation: long span truss bridge application with environmental monitoring data. Engineering Structures 30, 2347−2359.

Chae, M.J., Yoo, H.S., Kim, J.Y., Cho, M.Y., 2012. Development of a wireless sensor network system for suspension bridge health monitoring. Automation in Construction 21, 237−252. https://doi.org/10.1016/j.autcon.2011.06.008.

Cross, E.J., Worden, K., Chen, Q., 2011. Cointegration: a novel approach for the removal of environmental trends in structural health monitoring data. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 467, 2712−2732. https://doi.org/10.1098/rspa.2011.0023.

Elhattab, A., Uddin, N., OBrien, E., 2019. Extraction of bridge dynamic characteristic utilizing handheld devices. In: SHMII 2019 - 9th Int. Conf. Struct. Heal. Monit. Intell. Infrastructure, Proc., pp. 1−6. St. Louis, USA.

Estellés-Arolas, E., González-Ladrón-De-Guevara, F., 2012. Towards an integrated crowdsourcing definition. Journal of Information Science 38, 189−200. https://doi.org/10.1177/0165551512437638.

Feng, D., Feng, M.Q., 2018. Computer vision for SHM of civil infrastructure: from dynamic response measurement to damage detection − a review. Engineering Structures 156, 105−117. https://doi.org/10.1016/j.engstruct.2017.11.018.

Feng, M., Fukuda, Y., Mizuta, M., Ozer, E., 2015. Citizen sensors for SHM: use of accelerometer data from smartphones. Sensors 15, 2980−2998. https://doi.org/10.3390/s150202980.

Gibbs, M.M., Kwon, D.K., Kareem, A., 2019. Data-enabled prediction framework of dynamic characteristics of rural footbridges using novel citizen sensing approach. Frontiers in Built Environment 5, 1−18. https://doi.org/10.3389/fbuil.2019.00038.

Guzman-Acevedo, G.M., Vazquez-Becerra, G.E., Millan-Almaraz, J.R., Rodriguez-Lozoya, H.E., Reyes-Salazar, A., Gaxiola-Camacho, J.R., et al., 2019. GPS, accelerometer, and smartphone fused smart sensor for SHM on real-scale bridges. Advances in Civil Engineering 2019. https://doi.org/10.1155/2019/6429430.

Han, R., Zhao, X., Yu, Y., Guan, Q., Hu, W., Li, M., 2016. A cyber-physical system for girder hoisting monitoring based on smartphones. Sensors 16. https://doi.org/10.3390/s16071048.

Hester, D., Keenan, C., 2017. Using mobile phones to capture mode Shapes : a feasibility study. In: SHMII 2017 - 8th Int. Conf. Struct. Heal. Monit. Intell. Infrastructure, Proc., pp. 121−130.

Höpfner, H., Morgenthal, G., Schirmer, M., Naujoks, M., Halang, C., 2013. On measuring mechanical oscillations using smartphone sensors. ACM SIGMOBILE Mobile Computing and Communications Review 17, 29−41. https://doi.org/10.1145/2557968.2557972.

Kalasapudi, V.S., Tang, P., Du, J., 2016. Automatic correlated vibration pattern analysis for a rapid remote scour assessment of civil infrastructure. In: Constr. Res. Congr. 2016 Old New Constr. Technol. Converg. Hist. San Juan - Proc. 2016 Constr. Res. Congr. CRC 2016. https://doi.org/10.1061/9780784479827.083.

Kromanis, R., Al-Habaibeh, A., 2017. Low cost vision-based systems using smartphones for measuring deformation in structures for condition monitoring and asset management. In: 8th Int. Conf. Struct. Heal. Monit. Intell. Infrastruct. Brisbane. http://toc.proceedings.com/39899webtoc.pdf.

Kromanis, R., Forbes, C., 2019a. Multi-angle measurement collection and analysis approach of bridge dynamic response using smartphones. In: SHMII 2019 - 9th Int. Conf. Struct. Heal. Monit. Intell. Infrastructure, Proc, pp. 1−6. St. Louis, USA: ISHMII.

Kromanis, R., Forbes, C., 2019b. A low-cost robotic camera system for accurate collection of structural response. Inventions 4, 47. https://doi.org/10.3390/inventions4030047.

Kromanis, R., Kripakaran, P., 2014. Predicting thermal response of bridges using regression models derived from measurement histories. Computers and Structures 136, 64–77. https://doi.org/10.1016/j.compstruc.2014.01.026.

Kromanis, R., Liang, H., 2018. Condition Assessment of Structures Using Smartphones: A Position Independent Multi-Epoch Imaging Approach. http://www.ultrasonic.de/article/ewshm2018/papers/0082-Kromanis.pdf.

Kromanis, R., Xu, Y., Lydon, D., Martinez del Rincon, J., Al-Habaibeh, A., 2019. Measuring structural deformations in the laboratory environment using smartphones. Frontiers in Built Environment 5. https://doi.org/10.3389/fbuil.2019.00044.

Matarazzo, T., Vazifeh, M., Pakzad, S., Santi, P., Ratti, C., 2017. Smartphone data streams for bridge health monitoring. Procedia Engineering 199, 966–971. https://doi.org/10.1016/j.proeng.2017.09.203.

Matarazzo, T.J., Pakzad, S.N., 2018. Scalable structural modal identification using dynamic sensor network data with STRIDEX. Computer Aided Civil and Infrastructure Engineering 33, 4–20. https://doi.org/10.1111/mice.12298.

Matarazzo, T.J., Santi, P., Pakzad, S.N., Carter, K., Ratti, C., Moaveni, B., et al., 2018. Crowdsensing framework for monitoring bridge vibrations using moving smartphones. Proceedings of the IEEE 106, 577–593. https://doi.org/10.1109/JPROC.2018.2808759.

McGetrick, P.J., Hester, D., Taylor, S.E., 2017. Implementation of a drive-by monitoring system for transport infrastructure utilising smartphone technology and GNSS. Journal of Civil Structural Health Monitoring 7, 175–189. https://doi.org/10.1007/s13349-017-0218-7.

Mei, Q., Gül, M., 2018. A crowdsourcing-based methodology using smartphones for bridge health monitoring. Structural Health Monitoring. https://doi.org/10.1177/1475921718815457.

Millán, D., Castellanos, S., Tovar, J.R., Marulanda, J., Thomson, P., 2019. Multivariate statistical analysis of operational frequencies and damping ratios of bridges in cali-Colombia. In: SHMII 2019 - 9th Int. Conf. Struct. Heal. Monit. Intell. Infrastructure, Proc., pp. 1–6. St. Louis, USA.

Mohan, P., Padmanabhan, V.N., Ramjee, R., 2008. Nericell: rich monitoring of road and traffic conditions using mobile smartphones Prashanth. In: 6th ACM Conf. Embed. Netw. Sens. Syst., pp. 323–336.

Morgenthal, G., Eick, J.F., Rau, S., Taraben, J., 2019a. Wireless sensor networks composed of standard microcomputers and smartphones for applications in structural health monitoring. Sensors 19. https://doi.org/10.3390/s19092070.

Morgenthal, G., Hallermann, N., Kersten, J., Taraben, J., Debus, P., Helmrich, M., et al., 2019b. Framework for automated UAS-based structural condition assessment of bridges. Automation in Construction 97, 77–95. https://doi.org/10.1016/j.autcon.2018.10.006.

Morgenthal, G., Höpfner, H., 2012. The application of smartphones to measuring transient structural displacements. Journal of Civil Structural Health Monitoring 2, 149–161. https://doi.org/10.1007/s13349-012-0025-0.

Morgenthal, G., Rau, S., Taraben, J., Abbas, T., Hallermann, N., 2018. Determination of stay cable forces using highly mobile vibration measurement devices. Maintenance, Safety, Risk, Manag. Life-Cycle Perform. Bridg. In: Proc. 9th Int. Conf. Bridg. Maintenance, Saf. Manag. IABMAS, 2018.

Ndong, A.K., Ozbulut, O.E., Harris, D.K., 2019. Identifying modal characteristics of reinforced concrete bridges using smartphones. In: Conf. Proc. Soc. Exp. Mech. Ser. https://doi.org/10.1007/978-3-319-74421-6_46.

Nguyen, V.H., Schommer, S., Maas, S., Zürbes, A., 2016. Static load testing with temperature compensation for structural health monitoring of bridges. Engineering Structures 127, 700−718. https://doi.org/10.1016/j.engstruct.2016.09.018.

Noel, A.B., Abdaoui, A., Elfouly, T., Ahmed, M.H., Badawy, A., Shehata, M.S., 2017. Structural health monitoring using wireless sensor networks: a comprehensive survey. IEEE Communications Surveys & Tutorials 19 (3), 1403−1423.

Ozer, E., 2018. Monitoring bridge vibrations via pedestrians and mobile sensing. In: 9th Eur. Work. Struct. Heal. Monit. Ser., pp. 1−8. Manchester.

Ozer, E., Feng, D., Feng, M.Q., 2017. Hybrid motion sensing and experimental modal analysis using collocated smartphone camera and accelerometers. Measurement Science and Technology 28. https://doi.org/10.1088/1361-6501/aa82ac.

Ozer, E., Feng, M.Q., 2017. Direction-sensitive smart monitoring of structures using heterogeneous smartphone sensor data and coordinate system transformation. Smart Materials and Structures 26. https://doi.org/10.1088/1361-665X/aa6298.

Ozer, E., Feng, M.Q., 2016. Synthesizing spatiotemporally sparse smartphone sensor data for bridge modal identification. Smart Materials and Structures 25. https://doi.org/10.1088/0964-1726/25/8/085007.

Ozer, E., Feng, M.Q., Feng, D., 2015. Citizen sensors for SHM: towards a crowdsourcing platform. Sensors 15, 14591−14614. https://doi.org/10.3390/s150614591.

Park, J.C., Cho, J.S., Gil, H.B., Shin, J.I., 2015. Measurement and evaluation of thermal movements of existing bridges using a series of two-dimensional images. In: 7th Int. Conf. Struct. Heal. Monit. Intell. Infrastruct., pp. 1378−1385. Torino, Italy.

Posenato, D., Kripakaran, P., Inaudi, D., Smith, I.F.C., 2010. Methodologies for model-free data interpretation of civil engineering structures. Computers and Structures 88, 467−482.

Psimoulis, P.A., Peppa, I., Bonenberg, L., Ince, S., Meng, X., 2016. Combination of GPS and RTS measurements for the monitoring of semi-static and dynamic motion of pedestrian bridge. 3 Joint International Symposium on Deformation Monitoring 1−7.

Shrestha, A., Dang, J., Wang, X., 2018. Development of a smart-device-based vibration-measurement system: effectiveness examination and application cases to existing structure. Structural Control and Health Monitoring 25, 1−18. https://doi.org/10.1002/stc.2120.

Sony, S., Laventure, S., Sadhu, A., 2019. A literature review of next - generation smart sensing technology in structural health monitoring. Structural Control and Health Monitoring 26 (3), 1−22. https://doi.org/10.1002/stc.2321.

Wang, N., Ri, K., Liu, H., Zhao, X., 2018. Structural displacement monitoring using smartphone camera and digital image correlation. IEEE Sensors Journal 18, 4664−4672. https://doi.org/10.1109/JSEN.2018.2828139.

Xia, Y., Chen, B., Weng, S., Ni, Y.Q., Xu, Y.L., 2012. Temperature effect on vibration properties of civil structures: a literature review and case studies. Journal of Civil Structrual Health Monitoring 2, 29−46.

Xie, B., Li, J., Zhao, X., 2019. Research on damage detection of a 3D steel frame model using smartphones. Sensors 19, 1−17. https://doi.org/10.3390/s19030745.

Yarnold, M.T., Moon, F.L., 2015. Temperature-based structural health monitoring baseline for long-span bridges. Engineering Structures 86, 157−167. https://doi.org/10.1016/j.engstruct.2014.12.042.

Yu, J., Meng, X., Shao, X., Yan, B., Yang, L., 2014. Identification of dynamic displacements and modal frequencies of a medium-span suspension bridge using multimode GNSS processing. Engineering Structures 81, 432−443. https://doi.org/10.1016/j.engstruct.2014.10.010.

Yu, Y., Han, R., Zhao, X., Mao, X., Hu, W., Jiao, D., et al., 2015. Initial validation of mobile-structural health monitoring method using smartphones. International Journal of Distributed Sensor Networks 11, 274391. https://doi.org/10.1155/2015/274391.

Yu, Y., Zhao, X., Shi, Y., Ou, J., 2013. Design of a real-time overload monitoring system for bridges and roads based on structural response. Measurement and Journal of the International Measurement Confederation 46, 345−352. https://doi.org/10.1016/j.measurement.2012.07.006.

Zhao, X., Han, R., Yu, Y., Hu, W., Jiao, D., Mao, X., et al., 2017a. Smartphone-based mobile testing technique for quick bridge cable-force measurement. Journal of Bridge Engineering. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001011.

Zhao, X., Liu, H., Yu, Y., Zhu, Q., Hu, W., Li, M., et al., 2016a. Displacement monitoring technique using a smartphone based on the laser projection-sensing method. Sensors and Actuators, A: Physical 246, 35−47. https://doi.org/10.1016/j.sna.2016.05.012.

Zhao, X., Liu, H., Yu, Y., Zhu, Q., Hu, W., Li, M., et al., 2015a. Convenient displacement monitoring technique using smartphone. Vibroengineering Procedia 26−28.

Zhao, X., Ri, K., Han, R., Yu, Y., Li, M., Ou, J., 2016b. Experimental research on quick structural health monitoring technique for bridges using smartphone. Annals of Materials Science and Engineering. https://doi.org/10.1155/2016/1871230, 2016.

Zhao, X., Ri, K., Wang, N., 2017b. Experimental verification for cable force estimation using handheld shooting of smartphones. Journal of Sensors 2017. https://doi.org/10.1155/2017/5625396.

Zhao, X., Yu, Y., Hu, W., Jiao, D., Han, R., Mao, X., et al., 2015b. Cable force monitoring system of cable stayed bridges using accelerometers inside mobile smart phone. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 9435, 94351H. https://doi.org/10.1117/12.2084068.

Zhao, X., Zhao, Q., Yu, Y., Chen, Y., Liu, H., Li, M., et al., 2017c. Distributed displacement response investigation technique for bridge structures using smartphones. Journal of Performance of Constructed Facilities 31. https://doi.org/10.1061/(ASCE)CF.1943-5509.0001025.