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[Ch15]

[Structural Health Monitoring]

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[Columbia University, Civil Engineering and Engineering Mechanics]

[NON PRINT ITEMS]

Abstract:

Advances in sensors and information technologies have brought Structural Health Monitoring (SHM) as a data-driven remedy for civil infrastructure safety. Smart and mobile sensor systems have taken SHM discipline to a new era in the last two decades. Smartphones, in parallel, have paved the milestones of innovative SHM applications empowered by smart, distributed, wireless, mobile, and participatory sensor networks. This chapter introduces the advent of smartphones as an SHM technology and describes crowd/citizen engagement into an SHM framework. In contrast with the traditional monitoring approaches, there is a lack of control in sensor operation in terms of time, location, duration, and coupling conditions. These discrepancies are formulated as citizen-induced uncertainties, and smartphone-centric solutions are proposed. Smartphone-based SHM characterizes cyber-physical civil infrastructure systems, e.g. updating numerical bridge models with crowdsourced modal identification results. The chapter concludes with the state-of-the-art vision for smartphone usage in SHM, near future trends, and finally long-term research directions.

Key Words:

Citizen Science, Crowdsourcing, Mobile Sensing, Modal Identification, Model Updating, Smart Technologies, Smartphone Sensors, Structural Health Monitoring

[Structural Health Monitoring]

[15.1 Introduction]

Infrastructure safety and integrity has always been a fundamental concern for decision-maker authorities. Structural failure due to degradational and hazardous events has led to not only casualties but also direct and indirect economical losses, threatening societies' well-being in massive scales. To understand existing structures' behavior against natural and man-made demands, performance evaluation methods with structural analysis and local material sampling frameworks have been the main guidelines for the last few decades. However, these methods work heavily on a simulation basis which may deviate from the actual behavior due to the large uncertainty level of infrastructure systems.

Recent progresses made in sensor and information technology offered a data-driven alternative to incorporate actual global structural behavior through vibration-based SHM methodologies [1-2]. Sensor data from structures can be processed to assess dynamic characteristics of structure, update mathematical models with field information, diagnose if any damage exists, and prognose any future threats based on projection of identified system properties on existing trends or expected extreme events. In other words, SHM offers methodological frameworks to interpret structural status with the state-of-the-art algorithms, inverse dynamics theories, and real observations from the actual buildings and bridges through sensors.

Despite all the advantages proposed herein, SHM usage has been limited in infrastructure industry due to its costly instrumentation and labor as well as implementation difficulties. Fragile sensing equipment is susceptible to breakage under harsh field conditions which requires careful maintenance. Likewise, installation of conventional systems with cabling and dedicated positions require extensive time and labor efforts. In addition to all these, scalability has been an important problem due to large variety of infrastructure and limited observations.

To tackle aforementioned problems, low-cost and practical attempts have been made with the help of emerging mobile and smart technologies [3-4]. Advances in communications and microelectromechanical systems (MEMS) [5] has enabled widespread sensor network possibilities with minimal investment yet proposed large-scale real-time output from multiple structures. Substitutes or supplementary systems with wireless, mobile, and distributed networks have been proposed in contrast with cabled, stationary, and centralized instrumentation. What is more, such new-age sensing equipment is already embedded in personal devices such as smartphones. This opened a new frontier in SHM in terms of engagement of citizens into the civil infrastructure sensing process and reach out to a gigantic network scale through modern communities. Consequently, a large number of recent studies are conducted taking smartphones as a sensing platform for civil infrastructure monitoring purposes [6].

This chapter reflects the recent SHM initiatives exploring smartphone sensors as the main source of instrumentation. Parallel with a dissertation published in 2016 dedicated to multisensory smartphone applications in vibration-based SHM [7], Subsection 15.2 describes sensor evaluation phases at the early stages [8] and introduces the first crowdsourcing implementation in the field [9]. Subsection 15.3 idealizes citizen-induced uncertainties in terms of mobility [10-12] and Subsection 15.4 proposes a cyber-physical system formulation incorporating smartphone-based SHM [13]. Finally, Subsection 15.5 summarizes the current state with further examples and identifies future trends in this arena.

[15.2 Smartphones, Crowdsourcing, and Modal Identification]

Since the very first generations released in late 2010s, most of the smartphone models are equipped with built-in sensors. For example, triaxial MEMS accelerometers are embedded in smartphone makes and models with a variety of quality in sensitivity and accuracy. For example, one of the earliest models, iPhone 3GS contains LIS331DL accelerometer from ST Microelectronics with a sensitivity of 18 mg/digit for +-2g range. Approximately five years later, iPhone 5 model included a significantly improved accelerometer (LIS331DLH from ST Microelectronics) with 1mg/digit for +-2g range. Similar progress is observed in computational capabilities of smartphones with the arrival of new generations. Detailed introductory information including datasheet references can be found in [8].

As discussed, accelerometers, which are one of the main sensor technologies used in vibration-based SHM, show a variation among different phone models. As an SHM performance measure, measured amplitude accuracy and identified frequencies have been the introductory criteria for the feasibility assessment studies. To observe the vibration measurement performance of different smartphone models with an experimental approach, several tests are conducted in laboratory and field environments. Laboratory tests include sinusoidal-wave, white noise, and seismic shaking table tests conducted in Columbia University, Carleton Laboratory. Smartphones instrumented on shaking tables are compared with high quality piezoelectric accelerometers (PCB 393B04) for comparison.

The results show that two smartphone models (iPhone 3GS and iPhone 5) with a 5-year generation gap showed a significant difference in amplitude and frequency detection. For example, according to the sinusoidal-wave tests, vibration signal frequency is detected with only 1% error in iPhone 5 measurements, whereas earlier generation iPhone 3GS measurements show 5% error on a variety of wavelengths. Likewise, amplitude errors show similar performance, e.g. 44% to 8% for iPhone 3GS model, whereas 17% to 1% for newer generation iPhone 5 model. It is also observed that as measurement accuracy drops as vibration level decreases and gets close to ambient. Figure 15.1 shows exemplary sine wave tests comparing two smartphone generations with reference accelerometers.

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Early stage laboratory tests demonstrate a good indication of smartphone accelerometer performance, however, do not directly reflect vibration characteristics of a realistic structure. To address this issue, smartphone-based (iPhone 5) vibration measurements are collected from a pedestrian bridge in New Jersey, USA under varying loading conditions. These conditions include ambient vibration, random dynamic, and synchronized jump tests. Similar with the laboratory tests, as the vibration amplitude increases, smartphone accelerometer meets the reference signal with much better time series.

Figure 15.2 shows smartphone accelerometer time series compared with reference accelerometer under ambient vibrations and synchronized dynamic tests. For all different excitation types such as ambient, random, and synchronized vibrations, the phone data presents frequency identification errors not more than 1%. In summary, laboratory and field tests show that smartphones possess great potential for vibration measurement, however, phone model and signal-to-noise ratio are primarily decisive on measurement accuracy.

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Aforementioned laboratory and field tests encouraged the authors to develop a standalone platform which can automate data acquisition and processing phases implicitly. In other words, a multilayered computer platform including mobile and web software is developed to enable citizens collect vibration measurements with their smartphone accelerometers and submit data to cloud services. The acceleration signals are then processed for modal identification and results are stored on a web database. In other words, integrating mobile applications with a server-side web software, vibration-based SHM processes are conducted in a citizen-friendly manner or through crowdsourcing processes. Figure 15.3 shows the working principles of the multilayered crowdsourcing platform named Citizen Sensors for SHM (CS4SHM) [9].

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CS4SHM aims to bring all of the necessary information technology items together such that ordinary participants can contribute to an SHM database with the help of their smartphones. It comprises of a user-side platform which consists of the mobile software modules. This corresponds to an iOS application which is developed via XCode and published on Apple Store. Users can gather accelerometer data with their smartphones and submit to the server. Then, the server-side platform runs a set of PHP-based web scripts to conduct modal identification and save the results in a MySQL database which is accessible online. The communication between user and server is simply maintained by internet connection. Figure 15.4 shows user interfaces of CS4SHM from the mobile and web applications.

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Eventually, a pedestrian steel link bridge on Columbia University campus is taken as a testbed and students with their smart devices are assigned to acquire vibration measurements from the bridge. In summary, more than a hundred samples are received and peak frequencies from each record is autonomously obtained via Discrete Fourier Transform on the server. These findings are compared with the ones obtained under a controlled environment. Figure 15.5 shows distribution of identified frequencies from the crowd versus the controlled environment [9].

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In spite of the dispersion in the crowd tests, there is an apparent trend match between the first, second, and third modal frequencies obtained from crowdsourced and reference tests. It is an obvious fact that crowdsourced vibration measurements are susceptible to numerous sources of errors due to the uncontrolled instrumentation and sensor configuration. In the forthcoming subsections, these uncertainties are discussed within three idealization scenarios.

[15.3 Formulation of Citizen-Induced Uncertainties]

Following the first successful crowdsourcing-based SHM implementations named CS4SHM, the authors delved into fundamental error sources increasing uncertainties in smartphone measurements. According to the proposed framework, three fundamental instrumentation problems are investigated. These are 1) spatiotemporal uncertainties [10], 2) directional uncertainties [11], and 3) uncertainties associated with biomechanical inference of the crowdsourcer [12].

To explain with further details, spatiotemporal uncertainty corresponds to the lack of operational control on smartphone position in a timely manner. Similarly, distortions in the smartphone orientation before or during measurements are included as a citizen-induced uncertainty. Eventually, human biomechanical characteristics are studied as an intermediate medium between the sensor and the structure being monitored, and solutions are proposed. Figure 15.6 summarizes the three uncertainties due to the citizen involvement in the sensing process. In the following subsections, mobile and multisensory solutions to these uncertainties are investigated.

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[15.3.1 Identification under Spatiotemporal Errors]

Due to the lack of control in sensor position, duration, and timing, data extracted from multiple smartphone sensors involve heterogeneity in terms of vibration signal properties. Synthesis of heterogeneous signals from asynchronous multiple devices to get global dynamic characteristics of structures, is therefore, an uncommon case in SHM literature. To overcome this problem, the authors propose a signal processing scheme to eliminate location and time dependent heterogeneity through multisensory smartphone data [10].

The process can basically be classified into two phases: 1) detecting device position through location services or identity tags on the structure, 2) energy-to-power conversion with the help of measurement length or timestamped data. After these issues are resolved, accelerometer data with varying lengths and from multiple locations can be fused together in a uniform setting to compose structural dynamic characteristics, e.g. mode shapes. Figure 15.7 shows the flowchart of the method which is finalized with modal identification.

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In the field verification study, the same pedestrian bridge is addressed as a testbed. A single smartphone is positioned at 8 different locations on the bridge and acquired accelerometer data from each location. Figure 15.8 shows the modal identification results which shows 0.XX, 0.XX, and 0.XX MAC values for the proposed method's mode shape results compared with the reference measurement system.

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[15.3.1 Identification under Directional Errors]

In addition to spatiotemporal uncertainties studied in the previous section, incorrect sensor alignment or changes in orientation are possible consequences of uncontrolled instrumentation. To handle this error source, the authors propose a coordinate system transformation framework which implements additional sensor data such as gyroscope and magnetic compass into the citizen-engaged measurement processes. With multisensory smartphone data, changes in device orientation can be detected through accelerometer and gyroscope data and device coordinate system can be identified with global reference vectors such as gravity and the North Magnetic Pole [11].

The transformation procedure connects the link between sensor, structure, and the global coordinates through a smart monitoring scheme. Figure 15.9 depicts the flowchart explaining the methodology and sensor usage and Figure 15.10 demonstrate accelerometer waveforms before and after directional distortions and corrected signals through the coordinate system transformation procedure.

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[15.3.1 Identification under Biomechanical Errors]

The third source of uncertainty discussed in citizen-engaged SHM processes is related to human biomechanical nature, which corresponds to mobile and indirect sensor measurements. This can refer to phone carried or held by a pedestrian performing certain activities (e.g. walking, standing). In this case, two structure-relevant information lies beneath smartphone data: 1- information related to forces imposed on the structure 2- information related to structural dynamic characteristics [12].

The primary information type reflects pedestrian walking on a bridge, therefore, imposing dynamic forces on it. To depict this, Figure 15.11 shows theoretical forces vs. forces estimated by a smartphone accelerometer incorporating pedestrian weight and motion. In other words, keeping track of a pedestrian's position on a structure and measurement acceleration data attached to the pedestrian, one can dynamically idealize how a human body interacts on a structure.

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In addition to this highly active scenario, there can be relatively immobile scenarios such as a pedestrian resting in a stationary spot on a bridge. In this case, the authors propose to extract vibration data from the pedestrian smartphone, remove features associated with pedestrian, and insulate bridge-only vibration features. This can be done by developing transfer function of human body and filtering it out from the smartphone data while a pedestrian stands on a bridge.

Figure 15.12 shows how the vibration evolves through the structure and the pedestrian before reaching the mobile device. Figure 15.13 shows transfer functions obtained from analytical vs. smartphone-based approaches. Compatible with the figure, the results show that insulation process is highly effective for high frequency components where human biomechanics is not dominant, whereas frequency in the range of 5 to 10 Hz is susceptible to error due to transfer function peaks representing human body.

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[15.4 Cyber-Physical System Approach to Civil Infrastructure]

The final subsection introduces cyber-physical system concept into the CS4SHM processes through a finite element model updating and structural reliability estimation paradigm. With the ubiquitous usage of sensor technology in industrial processes combined with advanced computation, idea of cyber-physical processes emerged as a new era in science and engineering. In this study, cyber-physical system formulation is given from a structural perspective where mobile accelerometer data can contribute to the accuracy of mathematical models and associated computer-aided analyses [13].

Setting up a probabilistic analysis framework, stakeholders can be assisted with risk assessment and optimized decisions. Such decisions will incorporate future status of structural system which can again be sensed and modified by the sensor feedback, therefore will complete a loop behavior formulating structures' operational usage and management. Figure 15.14 shows the connection between cyber-physical system modules with CS4SHM approach.

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According to Figure 15.14, mobile sensor data from smartphones indicate vibration behavior of structures which represents the physical information related to the system. Such data recorded by crowdsourcers or citizens is transferred to the cyber platform for mathematical computations and data analytics. In particular, urban infrastructure conditions are generally represented with finite element models which do not fit actual behavior in many cases (for example, the difference between measured/identified modal characteristics vs. modal analysis of a finite element model). Therefore, smartphone accelerometer data can be a source to modulate finite element model which was developed on a theoretical basis, and at the end of modification process, can match the actual behavior better.

After the gap between the model and the experimental behavior is closed, further computational processes can be performed in an automated manner, e.g. residual reliability estimation. In this study, these processes are still covered in a local manner, however, the ideal scenario would be integrating these into the cloud services (as it is done in the modal identification process). Eventually, reliability results combined with loss estimation will propose a quantitative decision-making tool for the stakeholders. In other words, CS4SHM concept connects civil infrastructure with administrative features through a mobile and server-side platform and community participation. Figure 15.15 demonstrates the representative scheme for CS4SHM cyber-physical environment.

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To clarify the engagement between mobile sensor data with finite element model updating Figure 15.16 demonstrates the sensing and model updating phases of the platform. In the figure, uncertainties associated with modeling is solved by generating thousands of finite element models with a range of mass, stiffness, and boundary condition parameters. The subsets of generations are compared with the measured/identified results in terms of modal frequencies and the model with minimal error is determined as the updated finite element model. Figure 15.17 shows the combination of parameters which return minimal error in terms of individual modes in 2-D plots and combined modes in 3-D plot. The figure corresponds to the fixed-roller boundary condition case where all the error function scenarios lead to a similar optimal solution.

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Upon determination of the optimal model, the computational procedure continues with time history analyses under designated earthquake records. This study picks a set of earthquake records from 1994 Northridge Earthquake for illustrative purposes. As a result of 151 time history analysis results from under different ground motions, maximum displacement response of the bridge is collected as an indicator of structural performance. Looking at the results in Figure 15.18, there is a significant match between the analyses output and log-normal distribution. Based on the probabilistic distribution of structural response and a designated threshold, one can estimate the exceedance probability and therefore structural reliability according to a certain performance state [13].

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In summary, mobile sensor data obtained from citizens proposes valuable information regarding urban infrastructure conditions and can be integrated into the performance assessment and decision-making phases in an automated and remote form. Collecting such information at no or minimal cost imposes sustainable and resilient benefits not only on civil infrastructure but also monitoring and assessment systems themselves.

[15.5 Future Trends]

In conclusion, this chapter merges a number of mobile and smart SHM applications under citizen science and crowdsourcing umbrella to propose a futuristic smart city agenda from urban infrastructure safety point of view. The study starts with early-stage verification of smartphone accelerometer data and real crowdsourcing implementations as novel SHM prototypes. It continues with citizen-induced error sources such as spatiotemporal, directional, and biomechanical uncertainties, as well as smart, mobile and heterogeneous solutions to each of these problems. Eventually, it takes a step further to deploy cyber-physical system as an SHM formulation. All of the phases of the study are demonstrated on an actual structure, a pedestrian bridge, which makes it easier to understand the connection among each other.

To summarize, numerous case studies, successful deployment of participatory sensing software platforms with actual evidences, multisensory solutions to citizen engagement problems, and automation potential for further deep analyses offer a promising framework for scalable, cost-efficient, and self-sufficient SHM networks. What is mentioned, but not explicitly studied, is big data analytics when SHM data pools in variety, velocity, volume, and veracity. Likewise, distributed, multi-device, large-scale and asynchronous SHM forms -fitting smartphone sensor network endeavors to a better extent- require utmost attention according to the reviewers [14].

In addition to these materials, there is still a significant amount of smartphone research unexplored in SHM field from data heterogeneity and multisensory technology usage. Dissemination of computer vision in smartphone research also proposes advantageous monitoring tools thanks to the rapidly improving smartphone computational facilities. In fact, such hybrid solutions are already being developed, for example, combination of noncontact vision-based displacement data with invasive accelerometer data [15]. More examples within this direction engaging smartphone sensors alternative to accelerometers are expected to have interesting research output according to the authors.

What is not covered in this study is extension of smartphone technology into more practical and mobile sensing cases, e.g. vehicular sensor networks. Recent advancements in drive-by sensing offers possible methods to collect structural features from moving devices embedded in transportation modules. Early examples include modal identification and damage detection scenarios from moving vehicles [16-17] or pavement monitoring applications [18-19]. The authors encourage further research in this direction with real-world applications and opportunistic case studies.

It should be emphasized that these collections of studies are produced with a dominant contribution from Columbia University, Department of Civil Engineering and Engineering Mechanics. However, smartphone-based SHM literature is not limited to these approaches.

There is significant amount of research from Asia [20-24], America [25-26], and Europe [26-28] contributing to smartphone sensor literature and, in particularly, this rapidly advancing SHM subdiscipline.

Engaging smartphone data in SHM research has never been so deployable and so multidisciplinary with the contribution of engineering mechanics, information technologies, citizen sciences which, in conjunction, point out the smart city melting pot.

[15.6 References]

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[Chapter References]

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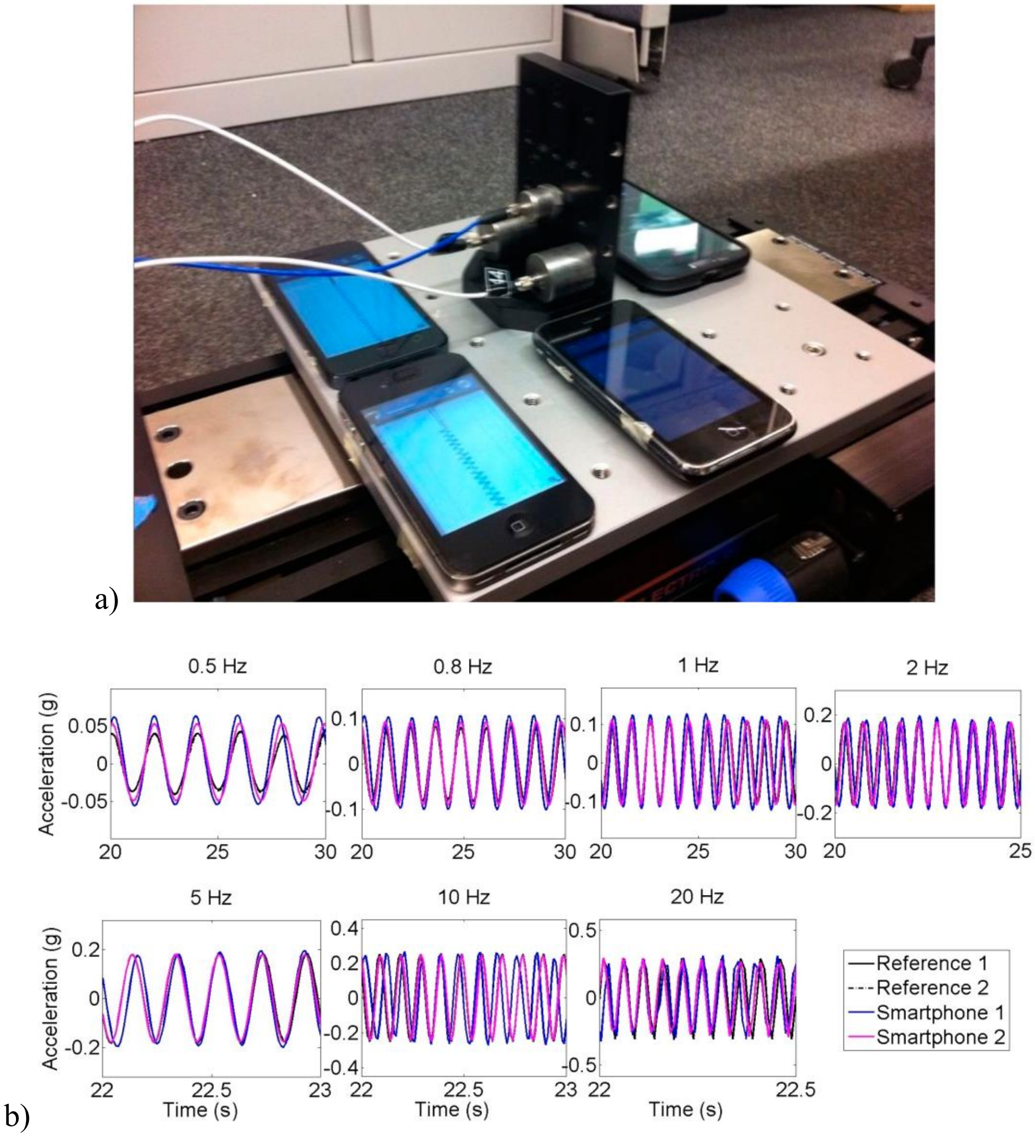

Figure 15.1 Shaking table tests: (a) exemplary setup and (b) waveforms.

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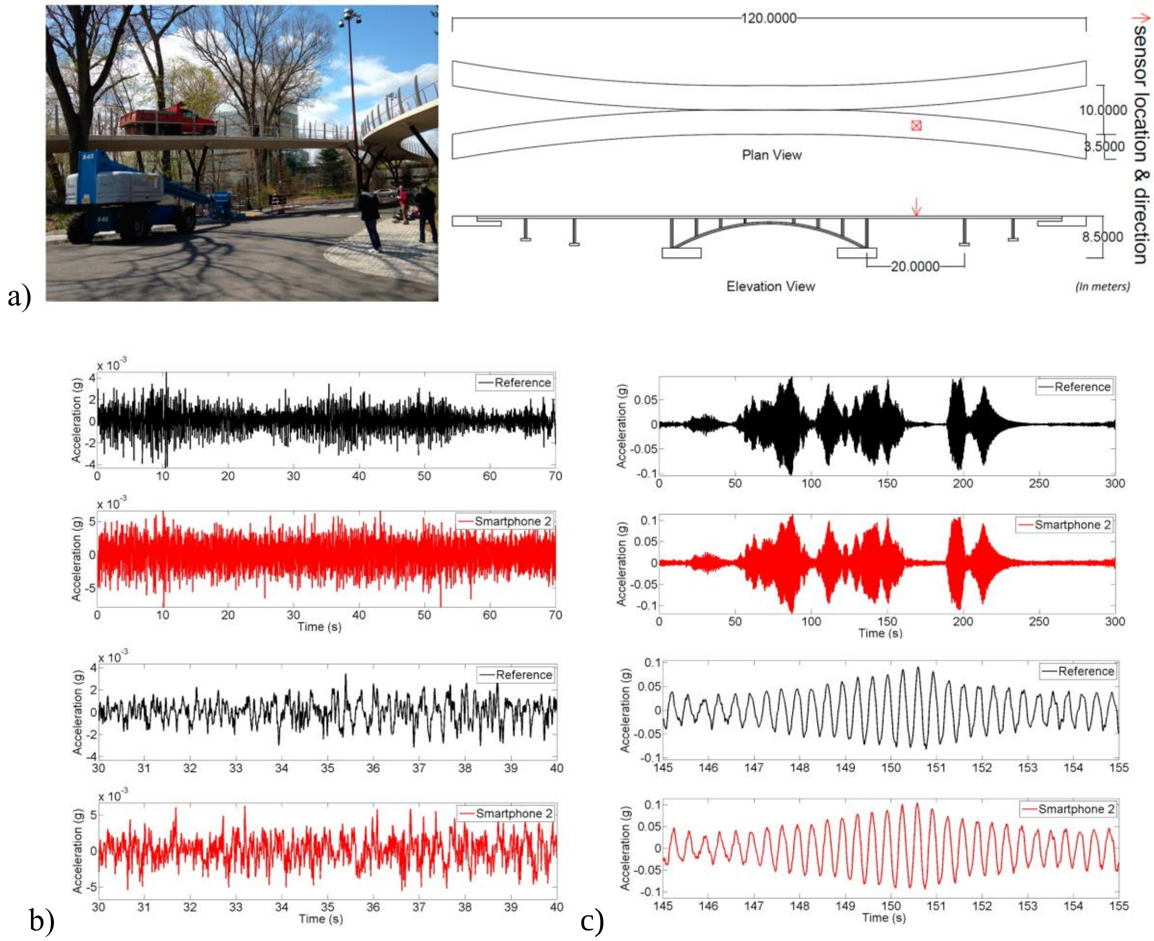

Figure 15.2 Field tests: (a) testbed, measurements under (b) ambient and (c) synched vibrations.

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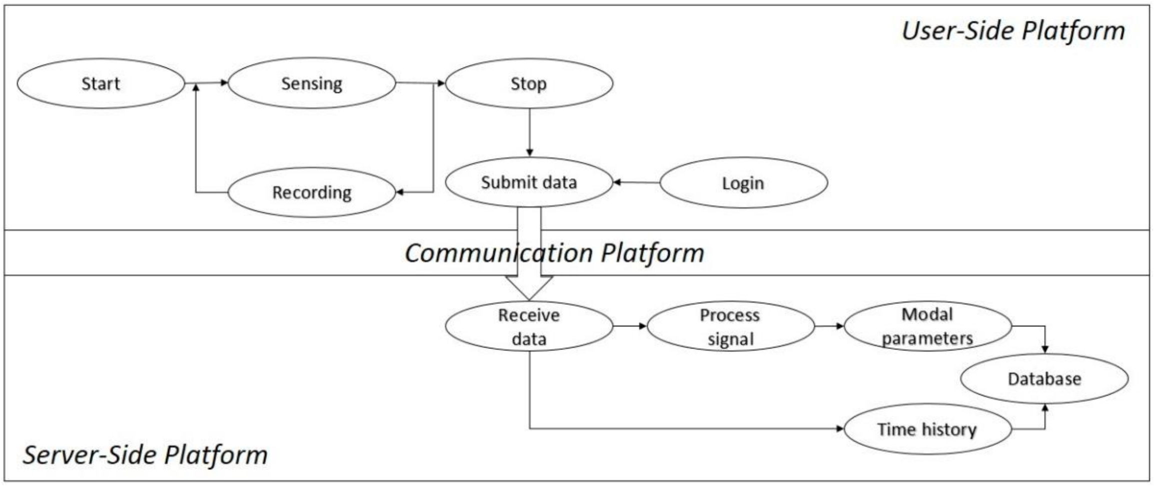

Figure 15.3 CS4SHM crowdsourcing platform architecture.

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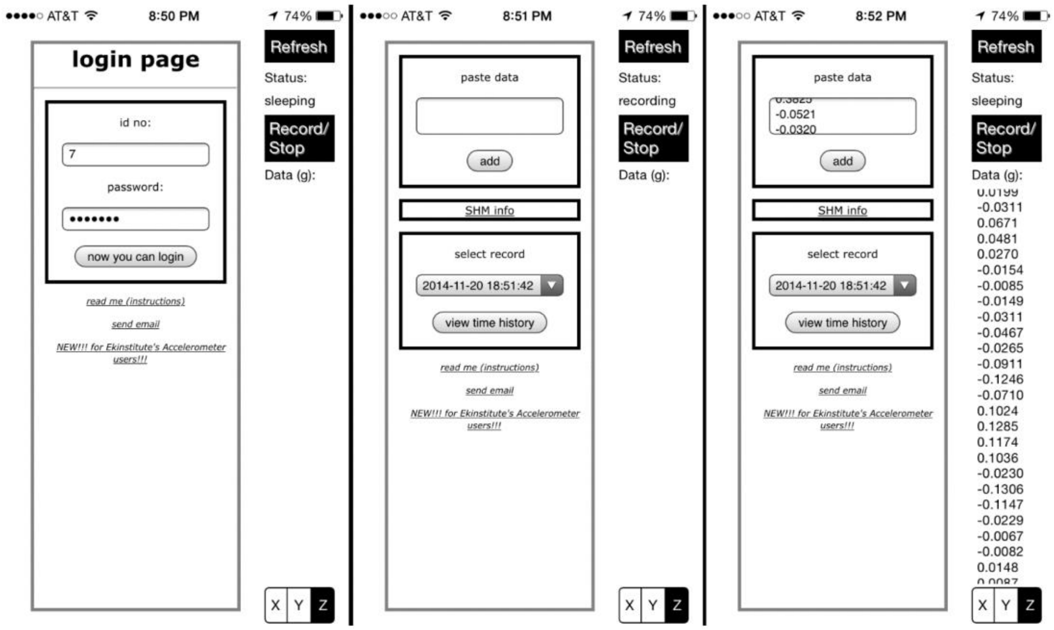

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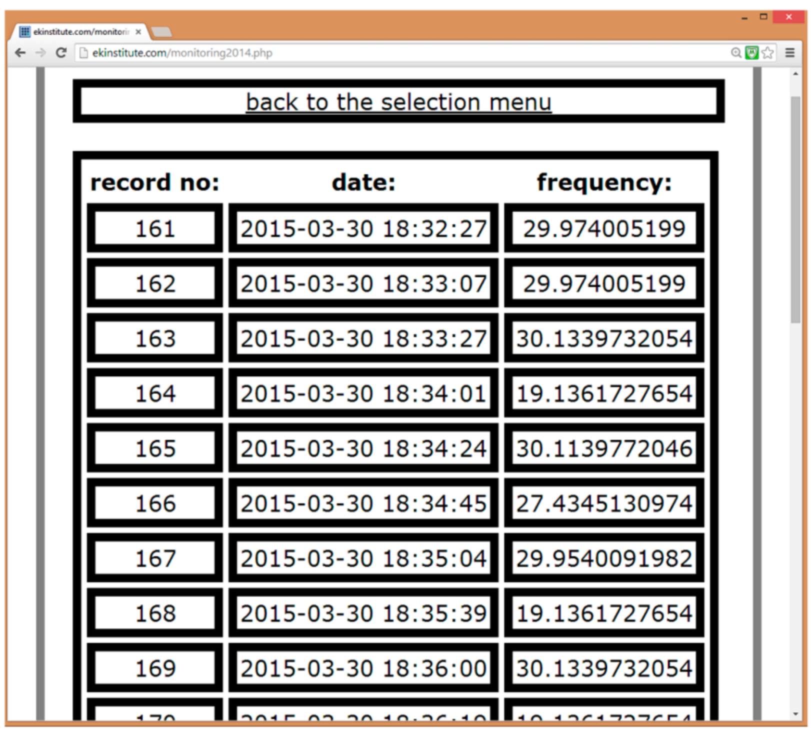

Figure 15.4 Screenshots from (a) mobile (b) web user interfaces.

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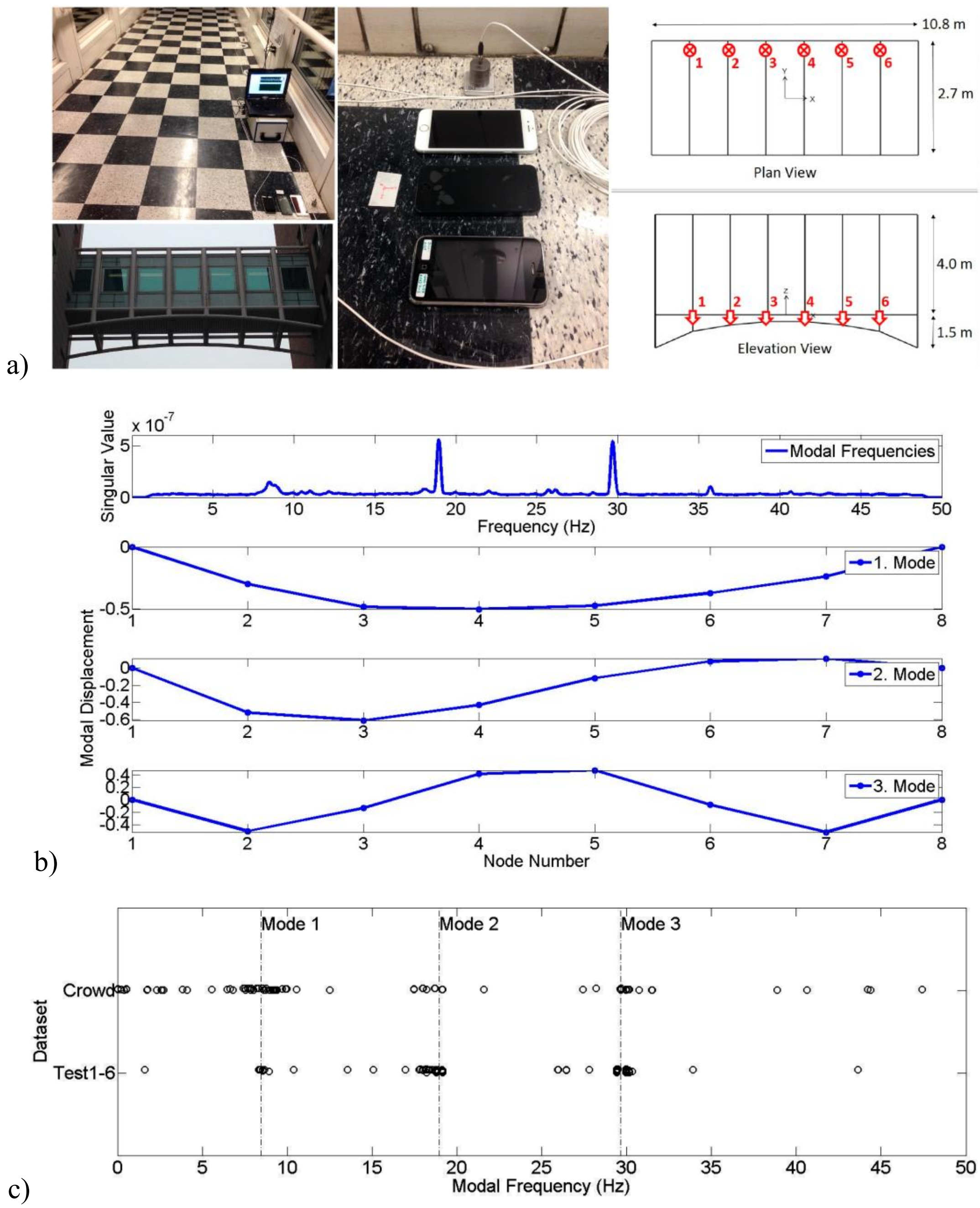

Figure 15.5 Mudd-Schapiro Bridge (a) outer view, (b) reference identification, and (c) crowd results.

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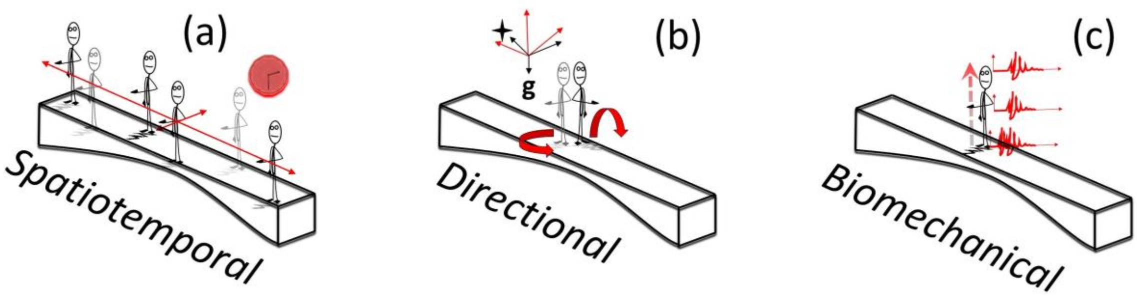

Figure 15.6 Errors due to (a) spatiotemporal, (b) directional, and (c) biomechanical uncertainties.

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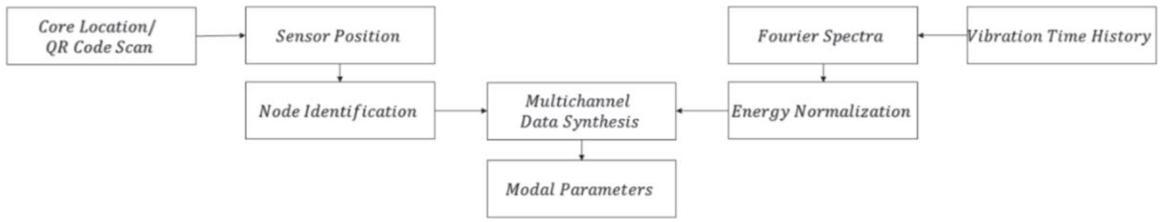
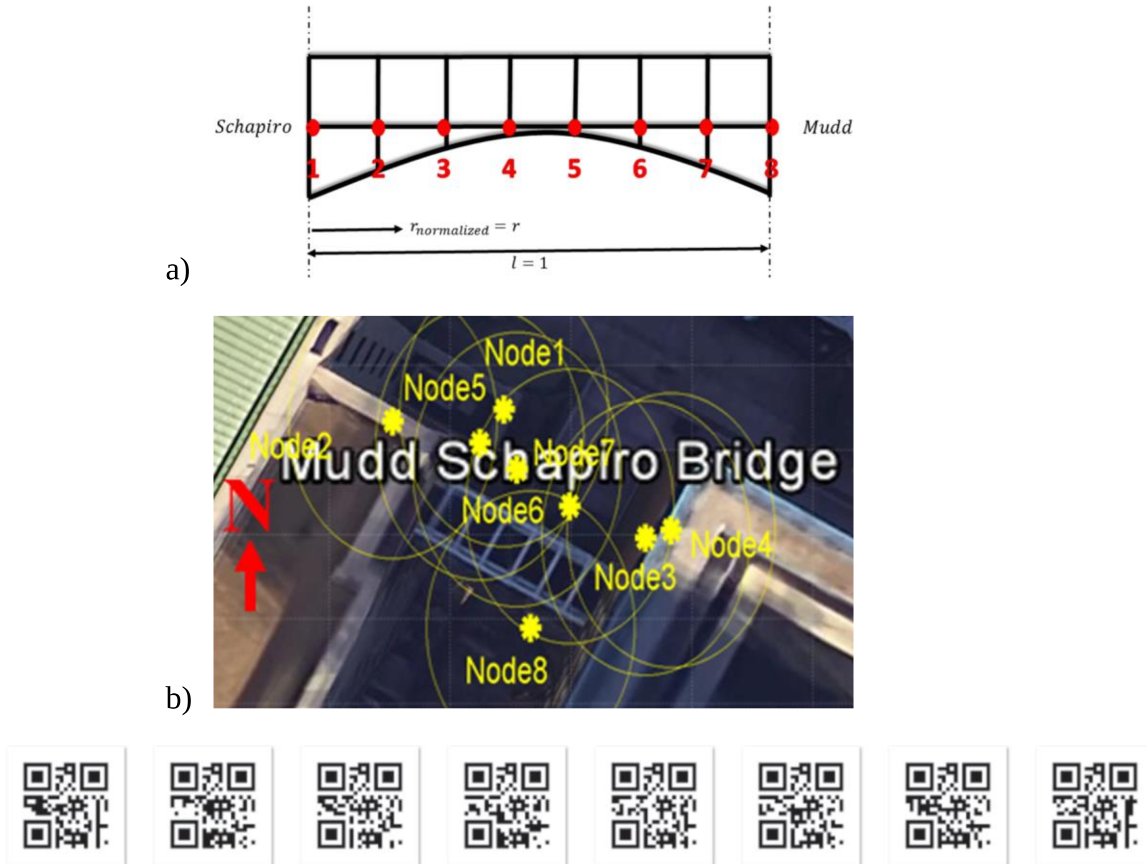


Figure 15.7 Flowchart addressing spatiotemporal heterogeneity in sensor data.



c)

Figure 15.8 Location identification: (a) nodes, (b) geolocation data, and (c) QR codes.

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

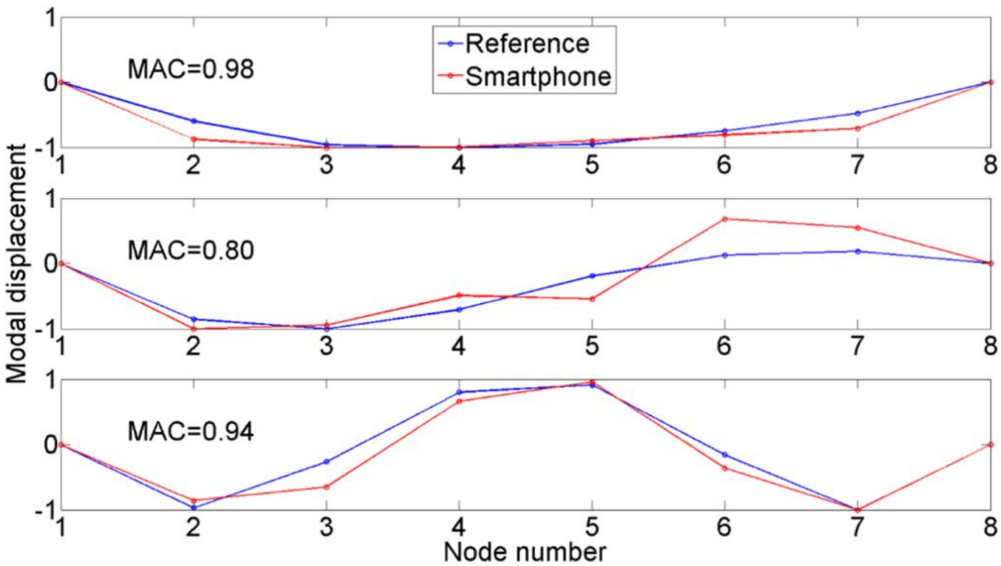


Figure 15.9 Identified mode shapes with a single smartphone.

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

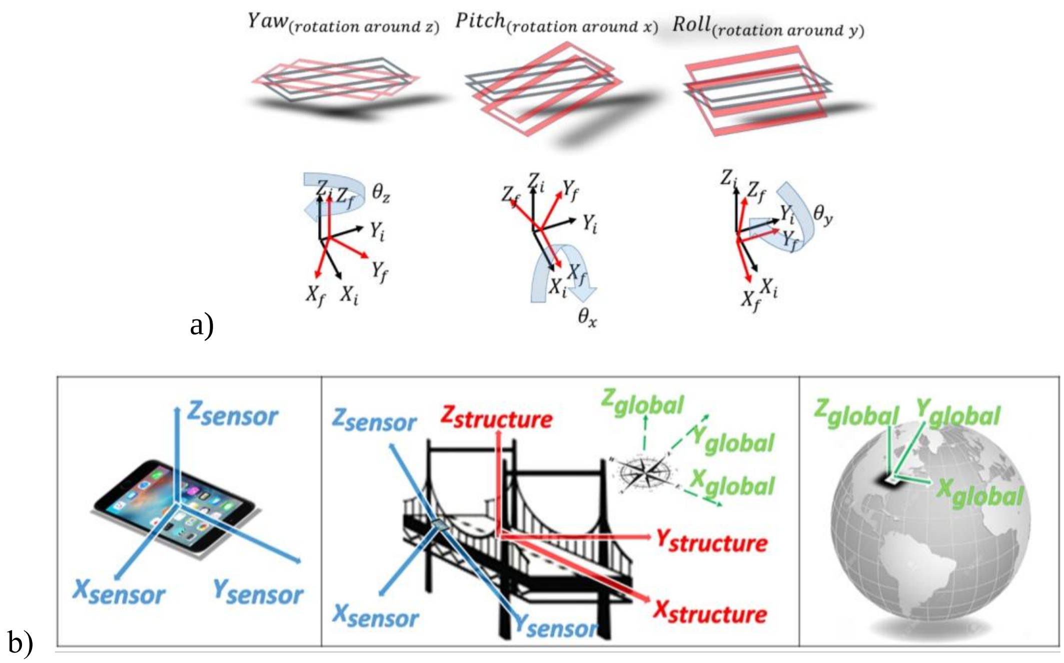
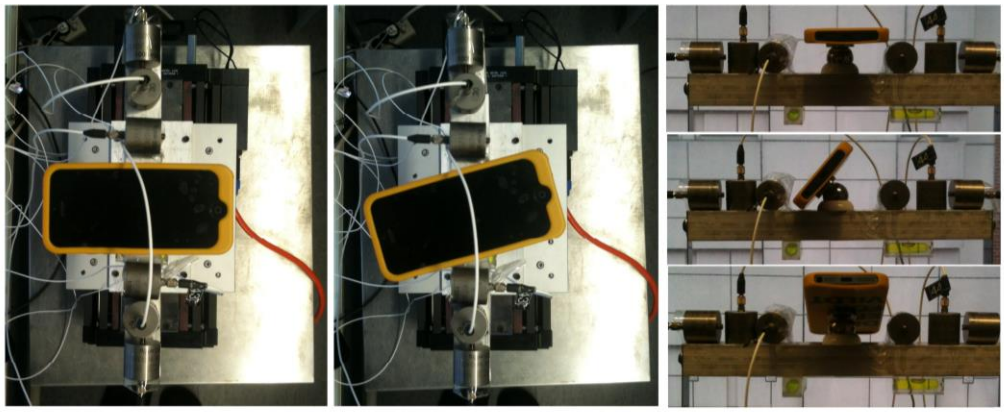


Figure 15.10 Direction uncertainties via (a) device orientation and (b) proposed coordinate systems.

Reprinted from 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(4), 045026. DOI: https://doi.org/10.1088/1361-665X/aa6298.

a) 

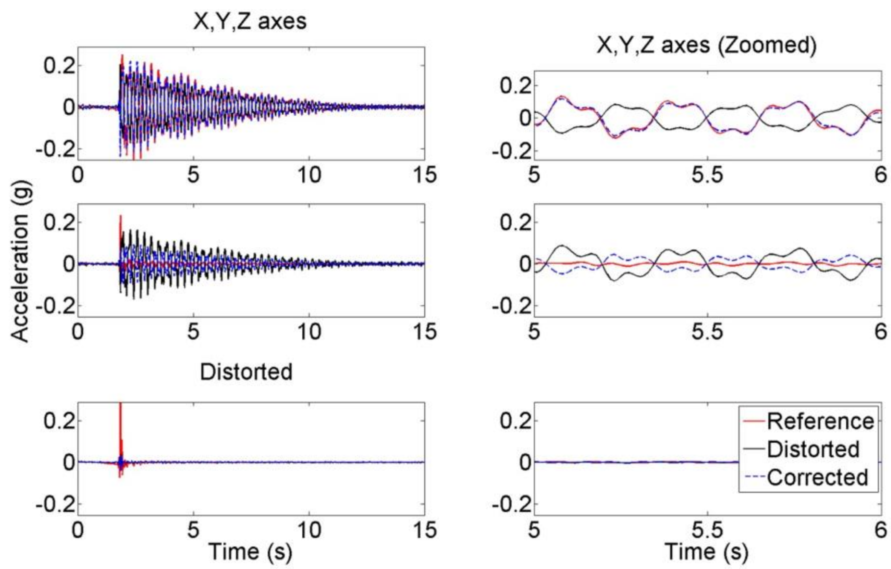
b) 

Figure 15.11 Orientation errors showing (a) test configurations and (b) accelerometer waveforms.

Reprinted from 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(4), 045026. DOI: https://doi.org/10.1088/1361-665X/aa6298.

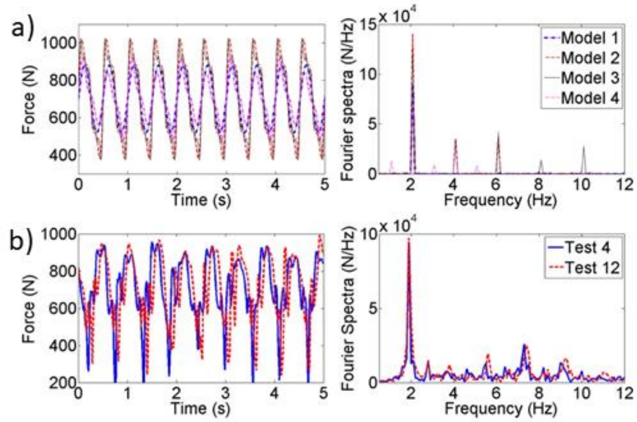


Figure 15.12 Pedestrian-induced forces from (a) theoretical model and (b) smartphone data.

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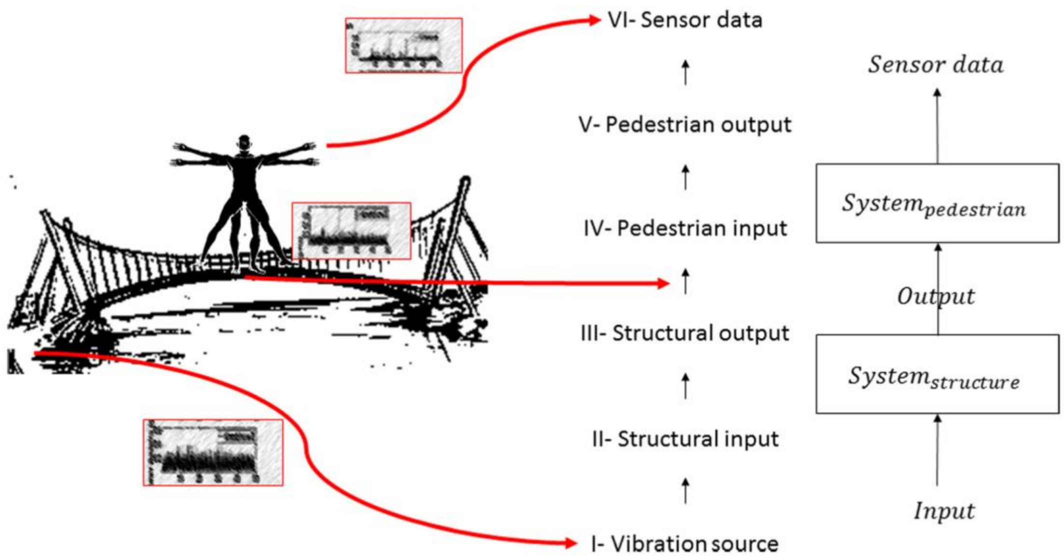

Figure 15.13 Indirect bridge vibration data influenced by pedestrian biomechanics.

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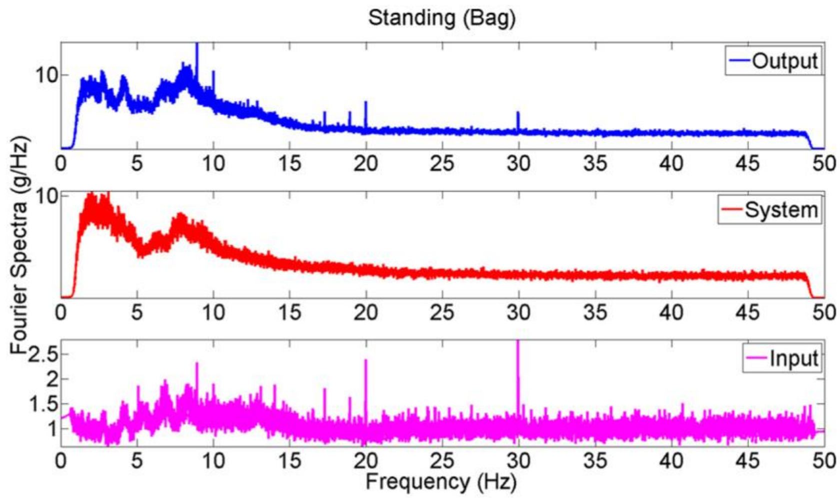

Figure 15.14 Biomechanical feature cancellation process through the frequency domain.

Reprinted from Ozer, E., & Feng, M. Q. (2017). Biomechanically influenced mobile and participatory pedestrian data for bridge monitoring. International Journal of Distributed Sensor Networks, 13(4), 1550147717705240. DOI: https://doi.org/10.1177/1550147717705240.

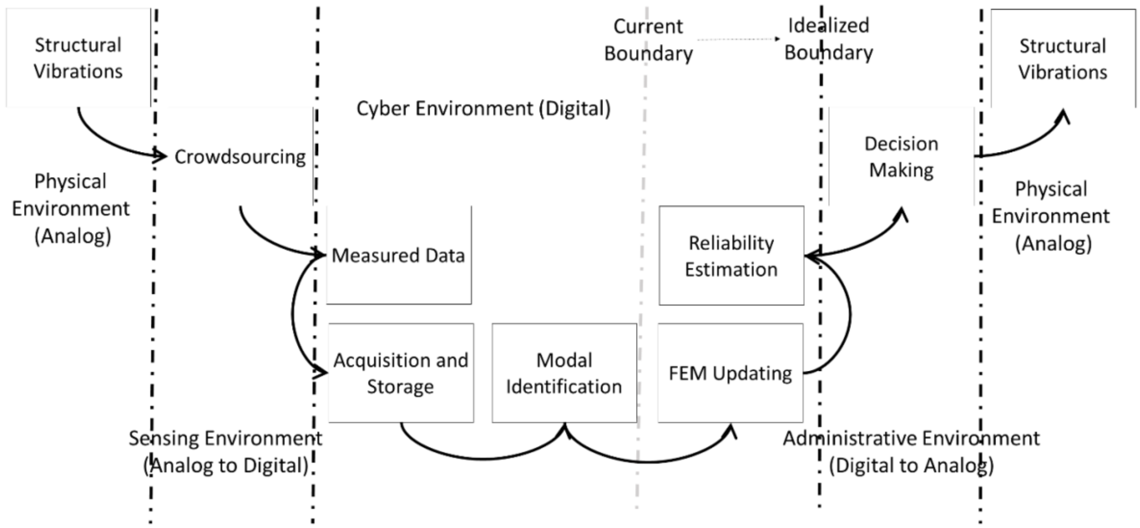

Figure 15.15 Cyberphysical system idealization from CS4SHM perspective.

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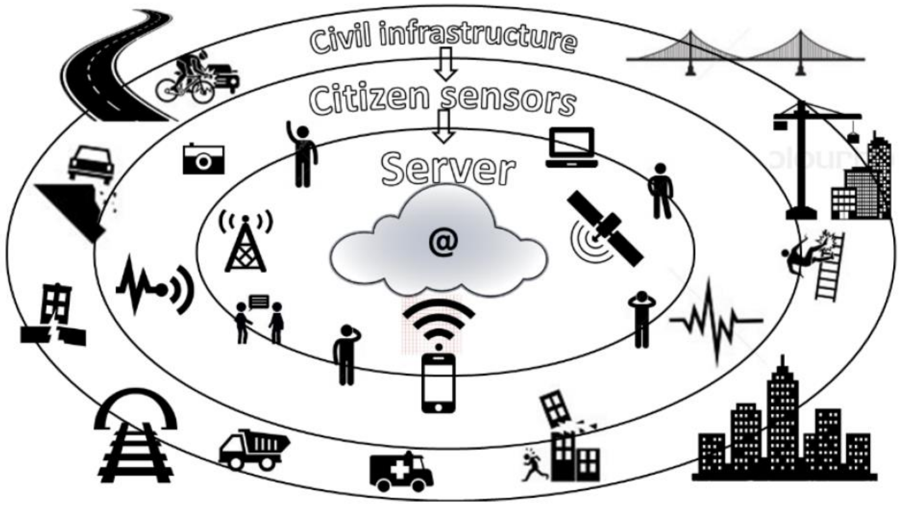

Figure 15.16 CS4SHM theme engaging crowd, infrastructure, and administrators.

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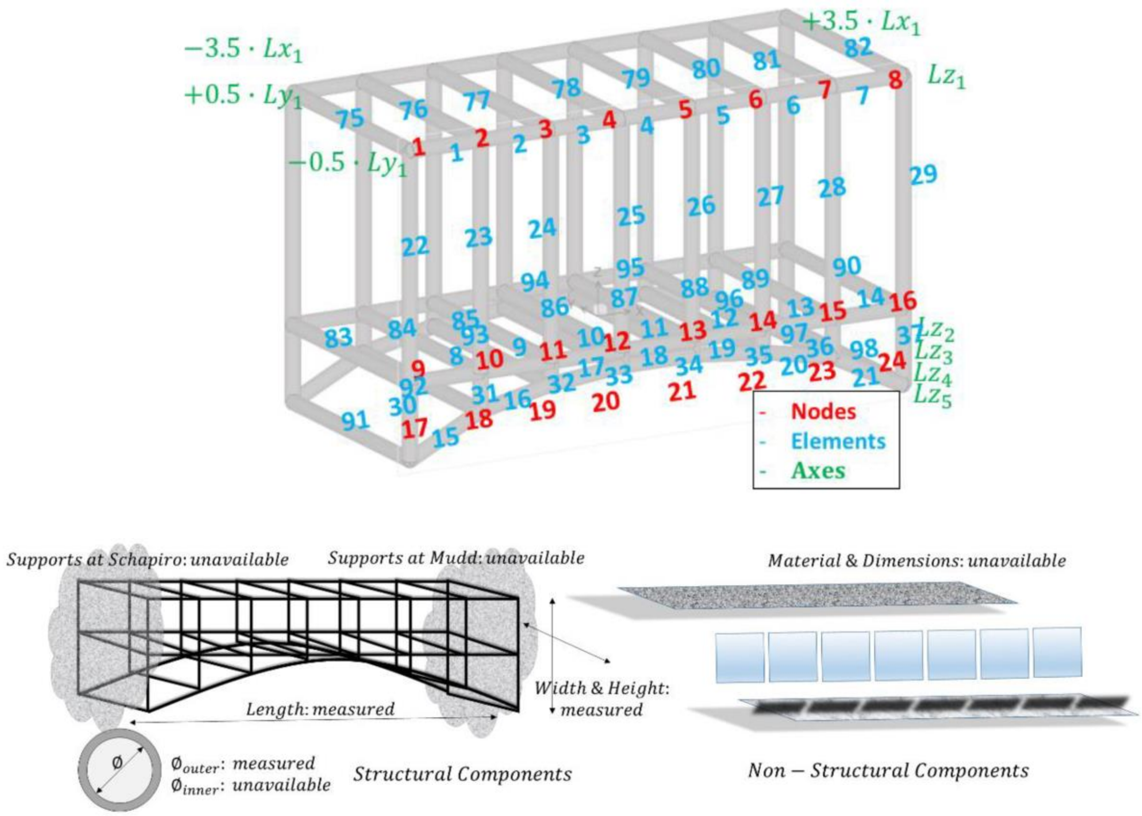

Figure 15.17 Finite-element model development and proposed updating parameters.

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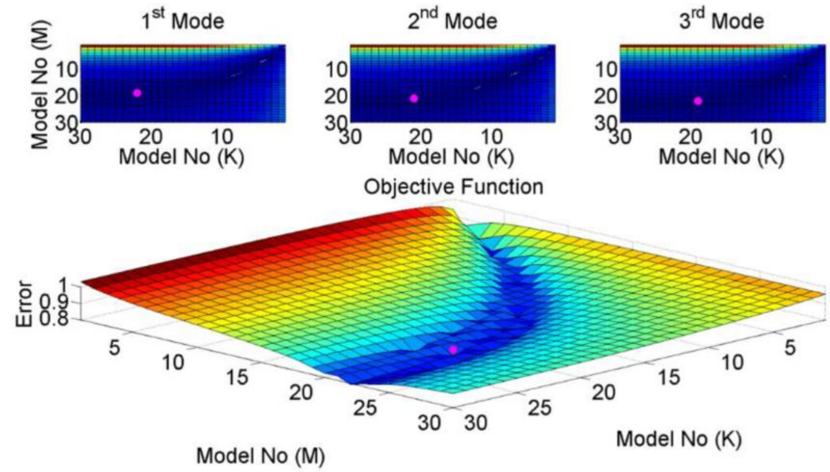

Figure 15.18 Objective function surfaces considering different vibration modes.

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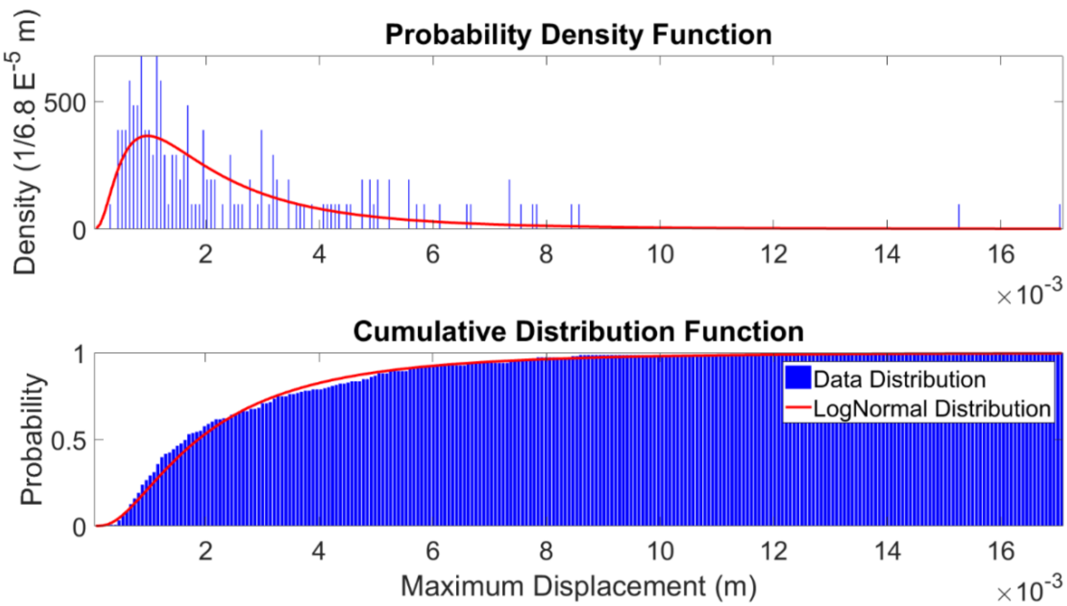

Figure 15.19 Probability distribution of structural response with updated model.

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