Biomechanically influenced mobile and participatory pedestrian data for bridge monitoring

Ekin Ozer and Maria Q Feng

Abstract

Future structural health monitoring systems are evolving toward crowdsourced, autonomous, sustainable forms based on which damage-indicative structural features can be identified. Unlike conventional sensor systems, they serve as non-stationary, mobile, and distributed sensor network components. For example, smartphone sensors carried by pedestrians decouple from the structure of interest, making it difficult to measure structural vibration. Taking bridges as instances, smartphone sensor data contain not only the bridge vibration but also the pedestrians’ biomechanical features. In this article, pedestrians’ smartphone data are used to conduct force estimation and modal identification for structural health monitoring purposes. Two major pedestrian activities, walking and standing, are adopted to estimate walk-induced forces on structures and identify modal parameters, respectively. First, vibration time history of a walking pedestrian combined with pedestrian weight is a measure of dynamic forces imposed on the structure. Second, standing pedestrian’s smartphone sensors provide spectral peaks which are mixtures of structural and biomechanical vibrations. Eliminating biomechanical content reveals structural modal properties which are sensitive to structural integrity. This study presents the first structural health monitoring application recruiting pedestrians in a testbed bridge monitoring example. Orchestrating pervasive and participatory pedestrian data might bring new frontiers to structural health monitoring through a smart, mobile, and urban sensing framework.

Keywords

Structural health monitoring, mobile sensing, modal identification, biomechanical systems, transfer functions, force identification, smartphone sensors, pedestrian bridges

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Introduction

Advances in system identification, statistical learning, and sensor technologies have boosted the influence of structural health monitoring (SHM) on civil infrastructure assessment in the past three decades.1,2 SHM has brought opportunities to support and improve conventional methods by means of structural response prediction, damage detection, performance evaluation, and reliability assessment.3,4 As new mobile,5–8 heterogeneous,9–12 smart,13–16 wireless, and distributed17–22 sensing technologies emerge, SHM systems have become more practical, cost-effective, and sustainable not only for laboratory but also for field applications. With their embedded batteries, various sensors, and on-board computing capabilities, smartphones have brought a new possibility to compose novel mobile sensor networks for SHM applications.23–30 Engaging citizens through “Citizens for SHM” (CS4SHM) for structural vibration response measurement, as

Civil Engineering and Engineering Mechanics, Columbia University, New York, NY, USA

Corresponding author:

Ekin Ozer, Civil Engineering and Engineering Mechanics, Columbia University, 500 W. 120th Street, 610 Mudd, New York, NY 10027, USA. Email: eo2327@columbia.edu

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proposed by the authors, opens a new avenue of sustainable sensor systems but faces significant technical challenges due to numerous uncertainties in the measurement process. Uncertainties in the device orientation as well as in the time and the space domains can be eliminated by multisensory data as long as the sensor is in direct contact with the structure of interest. Yet, the usability of sensor data carried or worn by human is still of question. For example, when a pedestrian’s smartphone is used to measure vibration of a bridge, the measurement data not only contain the structural vibration but also the pedestrian’s biomechanical features. Using human biomechanical models, isolation of pedestrian features from smartphone data could reflect structure’s actual vibration characteristics.

Biomechanical models are widely used in automotive and aircraft industry as well as medical studies to understand vibratory effects on human bodies. Standing, seated, or both human body vibrations were studied with the consideration of posture effects. Yet, these models were prone to variation stemming from numerous sources of uncertainties including individual subject characteristics. Numerous multi degree of freedom (MDOF) and single degree of freedom (SDOF) biomechanical models are introduced to represent human bodies, but the variation among different individuals makes it difficult to adopt deterministic models for particular cases. Besides, modeling human body and activities plays an important role on defining pedestrian and crowd loads on civil infrastructure, where the human-induced motion and structural response is not independent of each other and should be examined together to involve human–structure interaction.

For these reasons, it might be beneficial to avoid generalized models and instead collect customized sensor data in order to build pedestrian’s biomechanical features. For example, studies have shown the possibility of using sensor data to identify posture and activity. Likewise, similar vibration data collected from a pedestrian can be used to develop data-driven transfer functions and later on filter human content out of on-site measurements. An advantage of smartphones is that they can be used to identify biomechanical properties in a mobile and individual-oriented framework. As mentioned previously, considering crowdsourcing as a data source for structural vibrations, citizen initiative and control in the measurement process produce numerous challenges in sensor positioning, orientation, and mobility. Pedestrians as crowd participants may be in various postures and be engaged in different activities, and depending on the action type, mobile data can be utilized in different ways. For example, the vibration data measured by walking pedestrians’ smartphones or other wearable devices (e.g. smartwatches, activity trackers) can be used to identify the human-induced forces on a structure, which would be helpful to determine the demand on the structure.

The vibration data by the pedestrians’ phones can also be used to estimate the bridge vibration and identify these modal properties, if the human body effects can be eliminated. Modal parameters such as natural frequencies reflect a structural system’s properties that are linked to the health conditions or the capacity of the structural system. In summary, pedestrian participation using smartphone sensors represents an innovative approach to SHM considering its cost-effectiveness, citizen engagement, and sustainability as well as completely decoupled vibration measurement instruments from the structure.

This article aims at understanding structural vibration behavior and pedestrian forces imposed on the bridge through mobile pedestrian data measured by smartphones. First, accelerometer time history of a walking pedestrian is used to estimate forces imposed to the bridge. Second, a smartphone user standing on a rigid platform is employed to develop transfer functions representing pedestrian biomechanical system. Later on, these transfer functions are used to extract the bridge structural vibration from the mobile accelerometer data. Section “Methodology and framework” introduces the methodology and framework involving the biomechanical models, transfer functions, and walk-induced forces and describes field tests on a pedestrian bridge. Section “Results and discussion” applies the proposed methodology to analyze the bridge test results. Finally, section “Conclusion” summarizes the findings and draws conclusions from this study.

Methodology and framework

A fundamental difference between CS4SHM and a conventional monitoring system is that structural vibrations are indirectly measured through smartphone users rather than sensors fixed on the structure. In other words, smartphone users appear as an intermediary medium between the sensors and the structure. Smartphone users may play different roles during a structural vibration measurement process depending on structural type and service needs. For example, for buildings, smartphone users are building occupants, who likely maintain a stationary position for a long time interval. In contrast, for bridges, smartphone users are moving pedestrians whose presence is transitional and whose position spatiotemporally varies. Monitoring of building structures can utilize smartphone sensors as stationary devices, since phone position and fixity can be predetermined and maintained throughout long measurement durations. The building occupants may leave their phones at the prescribed locations to directly collect vibration data. In contrast
with the building occupants, bridge pedestrians are unlikely to leave their smartphones on the bridge unattended for a long time for bridge monitoring purposes. For this reason, it is more feasible to collect sensor data from smartphones held in hands or carried in bags by the pedestrians. As a result, the sensor data contain not only bridge vibration but also the pedestrian’s biomechanical features.

The human body (pedestrian) standing on a bridge can be considered as an intermediary mechanical system, in which (1) the vibration data measured by his or her smartphone are the output, (2) the bridge structural vibration is the input, and (3) the human body is the system. And this mechanical system can be represented with transfer functions or signal filters. If the system (i.e. the transfer function) is known and the output can be measured, eventually, the system input (i.e. the bridge vibration) can be obtained.

In this article, stationary human-induced effects are considered as the effects of a biomechanical system, which can be modeled as transfer functions. Likewise, motion record of a pedestrian moving on a bridge can serve as a tool for dynamic force measurement. To make a distinction between these two major cases, two pedestrian mobility scenarios are taken into consideration, which are (1) standing and (2) walking. The following sections introduce exemplary biomechanical models existing in the literature and then use these models to define characteristics of the pedestrian vibrations. In addition, a citizen-centric biomechanical model development procedure is proposed with the help of the mobile data characterizing their individual users. Then, a pedestrian bridge is implemented as a testbed to discuss the presented methodology’s validity through experimental verification.

**Biomechanical models**

As discussed previously, pedestrians, in other words, human body and their accessories, can act as mechanical systems modifying the structural vibrations into vibrations indirectly measured by the smartphone user. To add, a smartphone in a backpack, pocket, bag, or luggage might have a different transformation procedure as well as pedestrian’s posture such as sitting, standing, or walking. Figure 1 illustrates certain citizen posture and activity states which might have different biomechanical effects and accordingly transform structural vibrations into a modified signal. Depending on the pedestrian posture, activity, and the coupling between the smartphone and the user, the vibration signals can be converted into a different character. Considering all of these effects as the pedestrian system, if the mechanical properties are well defined, the final output or the pedestrian-measured data can be converted back into the structural data as the input source. In order to do that, human body biomechanical models are investigated as follows.

In literature, human body vibratory effects are commonly represented with biomechanical systems which are extensively studied in a wide range of fields from mechanical engineering to biomedical sciences. A variety of biomechanical human models are proposed by researchers considering stationary postures such as seated, and standing, or systems in action such as jumping or running. Likewise, there is a significant variation in modeling details; for example, the same posture, i.e. seated pedestrian, is represented with models of MDOFs or SDOFs. Figure 2 illustrates exemplary human biomechanical models varying extensively in the modeling abstraction, showing that the model complexity might change depending on the developer’s choice and modeling purpose. In this article, pedestrian biomechanical behavior is approximated with an MDOF system of unknown spectral features, considering the highly uncertain model identification problem. These spectral features are to be determined as a result of the mobile sensing test results and are assigned to find the pedestrian transfer functions. Yet, in the future, as more advancements in mobile sensing literature proceed, more detailed or hybridized models can be implemented into the same framework.

Spatiotemporal variation or changes in the device orientation are previously discussed scenarios in a citizen-centric mobile SHM framework. Likewise, in smartphone-based SHM systems, it is expected that the monitoring results are significantly affected by the uncontrollable sensing environment due to crowdsourcing initiatives. These initiatives can result from pedestrian identity (height, weight, age, gender, etc.), mobility (stationary, walking, running, etc.) as well as wearables and accessories (bag, backpack, pocket, etc.). In addition, these uncertainties are likely to interact with each other, and therefore, representation of such complex behavior might be cumbersome. This problem is decisive in the identification process due to the fact that detailed and predefined theoretical models may not be sufficient to investigate indirect and highly uncertain structural vibration signal characteristics obtained from pedestrians. Likewise, the parameters
defining a pedestrian’s model may have unique features which are not captured by the benchmark approaches in the literature. For this reason, it might be beneficial to define biomechanical characteristics of a pedestrian in an individual-oriented scope.

To paraphrase, rather than relying on generic definitions existing in the literature, smartphone data are utilized to identify the pedestrian’s biomechanical system and extract useful information for SHM purposes. In addition, for multiple scenarios, such as different postures and activities, customized biomechanical models can be developed with the help of vibration data obtained from smartphone sensors. In other words, according to the proposed method, smartphones are first used to describe biomechanical features of individual pedestrian for various posture and activity cases and then are used to diminish these features from the smartphone data when the pedestrian conducts vibration measurements on civil infrastructure. With this data-driven approach, neither detailed nor simplified generic analytical models do not need to be pursued; yet, individual and unique pedestrian features can be distinguished. Next sections investigate existing pedestrian force models as well as transfer functions representing human biomechanical features.

Walk-induced vibrations

This section addresses the first pedestrian mobility scenario which is related to the walk-induced forces on a bridge structure. Early modeling principles in pedestrian loads assumed that the motion imposed to the structure by the human body is independent of structure’s characteristics, and a variety of pedestrian-induced force models exist in literature. One of the most widely used model is a deterministic expression representing pedestrian forces with Fourier series

\[
F_p(t) = G + \sum_{i=1}^{n} G \cdot \alpha_i \cdot \sin(2\pi f_p t - \varphi_i)
\]

where \(G\) is the person’s weight, \(\alpha_i\) is the Fourier coefficient of the \(i\)th harmonic, \(f_p\) is the activity rate, and \(\varphi_i\) is the phase shift of the \(i\)th harmonic. Some exemplary values used to define walk-induced vibrations in the literature are Model 1 (Vertical: \(\alpha_1 = 0.257\)); Model 2 (Vertical: \(\alpha_1 = 0.400, \alpha_2 = 0.100, \alpha_3 = 0.100\)); Model 3 (Vertical: \(\alpha_1 = 0.37, \alpha_2 = 0.10, \alpha_3 = 0.12, \alpha_4 = 0.04, \alpha_5 = 0.08\)); and Model 4 (Longitudinal: \(\alpha_1 = 0.204, \alpha_2 = 0.083, \alpha_{1/2} = 0.100, \alpha_{3/2} = 0.026, \alpha_{5/2} = 0.024\)).
Figure 3 shows the deterministic model time histories with different coefficients presented above as Models 1–4 for $G = 700$ N and $f_p = 2.0$ Hz. According to the figure, similar to the biomechanical model abstraction variety, some methods simplify the pedestrian-induced vibration as a single sine function, whereas others include harmonics with decreasing amplitudes, and some considering longitudinal and transverse directions as well. As previously mentioned, these models constitute a reliable base for pedestrian modeling, yet, may not be perfectly representative of individual pedestrians in real life. Therefore, extraction of human body acceleration time history from smartphone sensors while walking may be a novel and promising approach to estimate pedestrian forces directly related to that particular smartphone user.

The logic behind smartphone-based force identification is related to the pedestrian’s weight and harmonic motion captured by the smartphone accelerometer. In other words, if the summation term given in the theoretical force model is replaced with the pedestrian mass and acceleration time history sensed by the smartphone during pedestrian walk, loads on the bridge can be estimated without any advanced formulation. As a result, the smartphone sensor data can be processed to deduce the dynamic component of the walk-induced force time histories and then can be merged with the static component which is directly related to the pedestrian weight.

The walk-induced force modeling approaches discussed so far exclude the effects of pedestrians and structures on each other. After numerous studies, it is found out that the interaction between the pedestrian’s and the structure’s mechanical systems recursively affect each other. In other words, similar to the transition from rigid support models to soil–structure interaction, or from simplified moving vehicle loads to vehicle–structure interaction, conventional pedestrian load models evolved into comprehensive approaches introducing human–structure interaction. In this study, the interaction between the structure and the pedestrian is not explicitly considered, yet few remarks will be presented in section “Results and discussion” as the field test results are discussed.

**Transfer functions**

The previous section discussed widely used pedestrian load models related to walk-induced vibrations. This section introduces how human biomechanical features are interpreted using transfer functions and how standing pedestrian data can be used for modal identification. In order to understand the vibration transmission from structural to pedestrian mechanical systems, a multiphase signal processing procedure can be pursued. According to the proposed scheme, determination of structural vibration is the key goal to identify structure’s dynamic characteristics. On the other hand, such vibration cannot be directly measured in case of a wearable or smartphone sensor scenario, since the sensor is completely decoupled from the structure. Instead, the measured pedestrian vibration response is a combination of structural vibration response and human body’s biomechanical features. For this reason, in order to obtain structural vibrations from indirect pedestrian data, pedestrian’s dynamic system properties should be determined. If the system properties are accurately selected, pedestrian vibration response can be converted back into structural response by transfer functions in the frequency domain. In this way, although the pedestrian data are indirect and masked with human biomechanical features, transfer functions can be used to convert pedestrian measurements into structural vibration response by isolating biomechanical effects from smartphone data. The generalized formulation for transfer functions, representing MDOF systems as single-input single-output processes, is given as follows:

$$H_{\text{system}}(w) = \sum_{r=1}^{N} \frac{A_r}{(w_r^2 - w^2 + 2 \cdot i \cdot w \cdot w_r \cdot \xi_r)}$$

**Figure 3.** Walk-induced pedestrian force models.
where \( r \) is the mode number, \( w_r \) is the modal frequency, \( \xi_r \) is the damping ratio, \( i \) is the complex number, \( w \) is the frequency variable, and \( A_r \) is the complex modal constant. For an SDOF system, this form can be interpreted in terms of the mechanical system parameters such as follows:

\[
H_{\text{system}}(w) = \frac{1}{\sqrt{(k - w^2 \cdot m)^2 + (w \cdot c)^2}} \tag{3}
\]

where \( m, c, \) and \( k \) are the mass, damping, and stiffness constants of the SDOF system.

Researchers have adopted different biomechanical models for different actions and postures.\(^{33-48}\) Besides, it is widely discussed that the biomechanical properties extensively vary among different test subjects.\(^{49}\) For instance, eight subjects are represented with SDOF models of the same stiffness and damping such as \( k \text{(N/m)} = 116,000, \) and \( c \text{(Ns/m)} = 2310 \) but different masses such as \( m \text{(kg)} = \{90, 84, 99, 70, 82, 91, 94, 72\}.\(^{55}\)

Using these parameters, Figure 4 presents exemplary transfer functions of subjects ranging between 50 and 95 kg. Similar to the force models existing in the literature, transfer functions of different subjects may not accurately represent others’ behavior, for example, resonant frequency of a 50 kg (7.6 Hz) subject can be significantly different from a 95 kg (5.5 Hz) subject. In other words, structural response vibrations, which are the eventual target parameters, act as the input to the pedestrian’s mechanical system. Then, the vibration continues to evolve through the pedestrian’s body and the additional mechanical components (e.g. accessories such as bag, pocket, or phone case) and ultimately is sensed by the smartphone sensor.

Figure 5 shows a conceptual signal transformation path from structural vibration source to sensor data through a multilayered mechanical system chain. Initially, the vibration source is dependent on surrounding media such as operational, environmental, or ambient nature. Then, the source vibration signal is processed through the structural system and transferred to the pedestrian body as an input motion. In other words, structural response vibrations, which are the eventual target parameters, act as the input to the pedestrian’s mechanical system. Then, the vibration continues to evolve through the pedestrian’s body and the additional mechanical components (e.g. accessories such as bag, pocket, or phone case) and ultimately is sensed by the smartphone sensor.

In summary, the evolution of a vibration signal through a citizen-centered smartphone-based SHM system is composed of two distinct mechanical systems which are the structure and the pedestrian, respectively, and shall be distinguished from each other through an inverse process. In order to consider structural and pedestrian mechanical system as separate components, pedestrian biomechanical properties need to be determined. And to set the framework for this separation, transfer functions can be utilized. That is to say, the transition from structural response to pedestrian’s sensor measurement is a function of the pedestrian biomechanical system and therefore can be interpreted in terms of this biomechanical system’s transfer function. Likewise, knowing the biomechanical system properties enables to switch from pedestrian sensor data to the structural response by isolating the biomechanical features with the help of the transfer function.

Linear signals and systems principles suggest that response vibration time histories can be considered as the convolution of the input and the structural motion time histories, and convolution of two vibration time histories refers to the multiplication of two frequency
spectra. In other words, processing vibration signals through systems in series can be interpreted in terms of spectral changes in the frequency domain. In this way, procession of a vibration signal can be formulated with three components such as follows

\[ F_{\text{output}}(w) = H_{\text{system}}(w) \cdot F_{\text{input}}(w) \]  \hspace{1cm} (4)

where \( F_{\text{input}} \) is the input, \( H_{\text{system}} \) is the system, and \( F_{\text{output}} \) is the output values in the frequency domain. In other words, these parameters represent the forcing function, the transfer function, and the response function of a mechanical system, respectively. Adding multiple mechanical systems on top of each other in series can be represented with convolution operands in the time domain or multiplication operands in the frequency domain. Following this approach, two in-contact mechanical systems such as a structure and a pedestrian body can be represented with individual systems connected to each other where the structural output is imposed as the pedestrian input. Accordingly, the multilayered mechanical system can be formulated with two transfer functions such as follows

\[ F_{\text{intermediary}}(w) = H_{\text{structure}}(w) \cdot F_{\text{source}}(w) \]  \hspace{1cm} (5)

and

\[ F_{\text{sensor}}(w) = H_{\text{pedestrian}}(w) \cdot F_{\text{intermediary}}(w) \]  \hspace{1cm} (6)

where \( F_{\text{intermediary}} \) is the structural response, \( H_{\text{structure}} \) is the structure’s transfer function, \( F_{\text{source}} \) is the structural input, and \( H_{\text{pedestrian}} \) is the human biomechanical transfer function, whereas \( F_{\text{sensor}} \) is the output obtained from the smartphone sensor signal. Eventually, provided that the source function and the biomechanical system are known, these two equations can be merged with the help of intermediary element, and the structural system can be identified from indirect pedestrian data such that

\[ H_{\text{structure}}(w) = \frac{F_{\text{sensor}}(w)}{H_{\text{pedestrian}}(w) \cdot F_{\text{source}}(w)} \]  \hspace{1cm} (7)

If the source vibration is idealized as white noise, the equation can then be reduced to the following

\[ H_{\text{structure}}(w) = \frac{F_{\text{sensor}}(w)}{H_{\text{pedestrian}}(w)} \]  \hspace{1cm} (8)

According to this framework, smartphone sensor signals are combinations of the structural and the pedestrian features. And eliminating pedestrian features from sensor data will result in structural features. The sensor data collected from a pedestrian standing on a bridge represent the nominator spectra, whereas the denominator spectra is constructed by collecting pedestrian data standing on a rigid zone, for example, basements, streets without extreme vehicle traffic, or building ground levels if the substructure is negligible. Dividing sensor spectra by pedestrian spectra will return structural system spectra, which can eventually be used as a measure of modal identification. In order to present the proposed approaches with a real example, the next section introduces field tests conducted on a single-span existing bridge and real pedestrian data.

**Field tests**

In the previous sections, biomechanical models, walk-induced vibrations, and transfer functions are discussed. In order to connect these concepts with mobile...
sensors carried by smartphone users, the methodology is demonstrated on an actual bridge example with real pedestrian data. Mudd–Schapiro Bridge, as shown in Figure 6(a), is a 10-m single-span pedestrian link bridge connecting two high-rise buildings in Columbia University Morningside Campus, New York. The structural system consists of steel members with rigid connections, transferring the bridge loads to the adjacent buildings through a lower arch. Using an iPhone 5 with the accelerometer model LIS331DLH (ST Microelectronics),26 structural vibration measurements are indirectly measured through pedestrians, as shown in Figure 6(b)–(f).

Previous studies discussed that device model, orientation, position with respect to the structure, and measurement duration play an important role in the vibration measurements as well as the type of loading and sensor–structure coupling.26,27,31,32 Potential pedestrian postures and activities on a civil infrastructure are unlimited; therefore, only few common scenarios are tested in this study which include the following: smartphone (1) directly attached to the bridge deck surface, (2) resting in a bag on the deck, (3) in a pedestrian’s pocket, and (4) in a backpack carried by a pedestrian. Table 1 summarizes the variation sources in structural vibration data extracted from pedestrians, sources of uncertainties, positive and negative extremes in sensing conditions. Vibration measurements can be more representative of structural characteristics, if they are conducted under ideal conditions. For example, broadband vibrations are capable of exciting multiple modes without signal corruption due to any nonstructural frequency content. Setting a stationary position for the device and maintaining coupling conditions and proper alignment of phone axes are other citizen-induced problems that might have influence on vibration signal quality.

Considering all these uncertainties together with pedestrian posture and activity, it is cumbersome to make a strict classification or adopt generalized modeling criteria. In order to simplify pedestrian posture, activity, and their effects on structural vibration measurements, the tests presented in this study are based on certain layout assumptions. For example, the phone,

| Source    | Optimistic case              | Pessimistic case           | Affected process |
|-----------|------------------------------|----------------------------|------------------|
| Vibration | Ambient (broadband)         | Operational (narrowband)  | Loading          |
| Activity  | Stationary                  | Moving                     | Sensing/loading  |
| Attachment| Direct (glued)              | Indirect (e.g. pocket)     | Sensing          |
| Orientation| Face up or down/portrait/landscape| Combined                  | Sensing          |

Table 1. Sources of uncertainties in pedestrian-extracted structural vibration data.
located in a bag or in a pocket, is adjusted to portrait position. In real life, phone layout can be different from these scenarios, yet it is possible to detect the layout with accelerometer and magnetic compass data and even to convert the vibration axis from local coordinates to structural coordinates. Similarly, the stationary or standing pedestrian tests are conducted at the bridge mid-span, which may not be the case as discussed in Ozer and Feng. Yet, as these factors are discussed in previous works, the posture and activity tests in this study present exemplary but fundamental cases rather than covering all possible combinations.

Table 2 presents the test descriptions followed throughout the field tests. A case is composed of four tests and each test includes 30-min vibration data. In total, there are eight cases presented in this study, which are based on 16 h of real pedestrian data. Test 1–4 (Case 1) and Test 9–12 (Case 3) sets are used to represent walk-induced forces, Test 5–8 (Case 2–7) and Test 25–28 (Case 7) sets are conducted under no human body involvement, and Test 13–16 (Case 4) and Test 29–32 (Case 8) sets are used to develop standing pedestrian transfer function on a rigid location. And finally, Test 13–16 and 29–32 sets are used to eliminate human-induced effects from Test 5–8 (Case 2) or Test 25–28 (Case 7) sets, respectively, which are products of structural system as well as human biomechanics.

In these tests, at first, the vibration is locally stored, then post-processed for force estimation and modal identification. Ideally, the CS4SHM system uses a web-based processor to conduct signal processing operations. Vibration data measured by smartphones are wirelessly sent to the central server via an iOS application, and then, these signals are processed and the analysis results are stored in a cloud platform. The communication relies on Internet access, and the application provides the smartphones with a web view to connect to the central server.

**Results and discussion**

In the previous section, the theoretical framework for biomechanical models, walk-induced forces, and transfer functions are presented to utilize mobile pedestrian data for SHM purposes. Moreover, a series of pedestrian tests, each addressing a particular mobility scenario, are conducted while smartphone accelerometers recorded pedestrian’s vibrations under various scenarios. In this section, the test measurements are presented, the proposed force and modal identification methods are implemented, and the analysis results are discussed.

In total, 8 cases and 32 tests are conducted by recruiting a smartphone user as a pedestrian subject for 16 h of vibration measurement. Each four repetitive tests refer to a case representing particular measurement location, vibration source, and mobility. Basically, Case 1 and Case 3 data are processed to comprehend forces imposed by a walking pedestrian on a rigid platform and on the bridge, respectively. Relying on the insignificant difference between these two cases, the pedestrian–structure interaction during these tests are ignored. In Cases 2–7 and Cases 4–8, the pedestrian is standing on the bridge (structure) and on the ground level (rigid platform), respectively. Dividing Case 2 (or Case 7) spectra by Case 4 (or Case 8) spectra over the frequency domain, the resultant spectra is expected to present sole structural modal parameters. Finally, Case 5 and Case 6 present smartphone data which are free of human-induced vibrations, such that the device is placed on the bridge deck either in direct contact or in a bag. Figure 7 shows the time histories and the Fourier spectra from Tests 1, 5, 9, 13, 17, 21, 25, and 29 in a respective order. In this study, two main pedestrian mobility phenomena are taken into consideration which are walking (Cases 1 and 3) and standing (Cases 2, 4, 7, and 8). Other than these, Cases 5 and 6 are considered as output-only identification cases and references which are not influenced by pedestrian’s biomechanical features.

### Estimating pedestrian forces

In Case 1 and Case 3, assuming that the entire pedestrian mass contributes to the walk-induced force, the accelerometer data are used to scale the pedestrian
mass (e.g. 71 kg) in time series. Using the vertical component (smartphone $y$-axis) which coincides with the gravitational direction, walk-induced time history can be converted from acceleration to force. Figure 8 shows the exemplary time histories and corresponding Fourier spectra obtained from Case 1 and Case 3. It is intriguing but not trivial to compare mobile sensing results (Figure 8) with the theoretical model illustrated in Figure 3, yet the qualitative similarity is still significant both in the time and the frequency domains. The common value for both cases is the known pedestrian weight (700 N) accompanied by the measured time history of the pedestrian motion. The theoretical approach utilizes Fourier series for this purpose, mobile sensing directly extracts acceleration time history from smartphone measurement.

Looking at the force time history estimated by the smartphone, unlike the theoretical model, it can be observed that the peaks in the positive and the negative directions are not of same pattern. It is observed that the positive peaks are smooth in contrast to the sharp negative peaks. Such difference is due to smartphone’s position in pedestrian’s bag, as shown in Figure 6. As the pedestrian walks, smartphone accelerometer in $y$-axis records vertical pedestrian motion indirectly through the bag. Smartphone’s bottom surface rests on the bag and is not perfectly attached to the bag’s pocket.

While the pedestrian and the bag move toward the gravitational direction, there is no external inertia to drag the smartphone downward except phone’s mass. In contrast, when the movement is upward, the phone
is pushed against gravity via bag’s pocket. For this reason, change in the positive direction is more gradual, while negative peaks are abrupt. Nevertheless, both the theory and the smartphone estimations are periodical time series, ranging around a peak-to-peak amplitude of 600 N. Another observation is that the Fourier spectra obtained from smartphone measurement not only includes the vertical motion harmonics but also the harmonics related to the lateral and the longitudinal motion. For example, as expected, the dominant walk-induced frequency ranges around 1.9 Hz, and smaller peaks such as 2.8, 3.8, 5.6, 7.3, and 9 Hz are observed as multiples of the dominant frequency. This can be due to the deviation of smartphone axis while traveling which would introduce additional components in the axes other than vertical.

Comparing the walk-induced pedestrian motions on rigid surface (Test 4) with the bridge (Test 12), the difference is insignificant both in the time and the frequency domains. According to these results, there is no clear indicator of the change in measurement environment and structural features. One possible reason for such indifference is the dominance of walk-induced vibration with respect to the structural vibrations, sensitivity and resolution of the smartphone sensor, and motion damped out by the human biomechanical system. In the future studies, if the bridge data can be distinguished from the street data, walking pedestrian data can be used for structural system identification as well as standing pedestrian data. Moreover, this would bring new frontiers in pedestrian–structure interaction research but is not addressed in this study. At this stage, it is difficult to draw a concise conclusion based on a single structure, and collecting data from a large number of structures might provide more information.

**Isolating biomechanical effects and modal identification**

In this section, the main goal is to identify modal parameters of the bridge structure through standing pedestrian data sensed by smartphones. Cases 2, 4, 7, and 8 refer to the standing pedestrian tests, which are used to isolate human body and accessory effects from the smartphone data. These cases aim at comparing the vibration differences between two different media such as the bridge (deformable) and the street (rigid). In addition, to understand how pedestrian state, posture, and smartphone configuration affect the vibration features, two different attachment cases are presented. The first attachment case refers to the pedestrian carrying the smartphone in a backpack, whereas the latter case describes phone positioned in pedestrian’s pocket. There might be a variety of other posture and accessory combinations, and these two cases only present a basic understanding of the phenomenon. The goal of demonstrating two different attachment cases such as pedestrian’s bag and pedestrian’s pocket is to show how the biomechanical features of the same pedestrian impact the indirect structural response data sensed by the smartphone.

In both of the attachment cases, the same transfer function procedure is utilized, but the baseline transfer function differs depending on the attachment type. As previously discussed, the sensor output, measured by the pedestrian standing on a bridge, is a function of the structural and biomechanical features. Therefore, Fourier transform of the pedestrian standing on a bridge includes frequency content from the pedestrian as well as the structure. And eliminating biomechanical features from this modulated signal leads to the sole structural signal which can eventually reflect bridge’s current state. For this reason, pedestrian’s biomechanical system features should be removed from the output data. In order to determine pedestrian system spectra, vibration data of a pedestrian standing on a rigid surface can be utilized, since it is only a function of the pedestrian’s biomechanical features. If pedestrian system features are determined, biomechanical contribution can be removed from the mixed smartphone sensor signal by dividing the output spectra by the pedestrian’s system spectra.

Finally, the spectra due to structural vibrations can be inferred as the input to the pedestrian’s biomechanical system, which at the same time is structural output. Afterward, pedestrian input, or in other words structural output, can be used to identify structural modal properties without any biomechanical intervention. To summarize, output spectra obtained from a pedestrian standing on a bridge contains mixed characteristics from the pedestrian biomechanical system and the structural system. System spectra are constructed measuring pedestrian’s vibration response standing on a rigid platform (e.g. street level). Finally, input spectra, which is the division of output by system spectra, reflect pure structural characteristics isolated from biomechanical features and can be used for modal identification. Figure 9 summarizes how the transfer functions are used to remove biomechanical effects for modal identification in Mudd–Schapiro Bridge example.

Based on these principles, pedestrian-induced vibrations can be utilized for structural modal identification if the following criteria are satisfied:

1. The bridge source vibration is of broadband frequency content.
2. The rigid zone measurements purely reflect pedestrian biomechanical features.
3. Pedestrian on rigid zone versus bridge measurements are compatibly paired in terms of posture and activity.
4. Structural integrity can be inferred if environmental effects on modal frequencies are ignorable.

Figures 10 and 11 show the output, system, and input spectra for two different attachment cases, which are phone placed in pedestrian bag and pocket, respectively. Looking at the system spectra of these two attachment cases, it can be observed that the mechanical features are subjected to change as the attachment media changes, implying that bag and pocket transfer functions are not exactly the same. On the other hand, for both cases, it can be seen that the system spectra has a direct impact on the output spectra, which significantly masks the input spectra, and accordingly, structural vibrations. Finally, using the transfer function procedure proposed previously, input spectra can be reconstructed from the output (pedestrian on the bridge) and the system (pedestrian on the street or rigid surface) spectra. Looking at the input spectra which are representative of the structural vibrations, structural peaks can be observed much more clearly than the indirect pedestrian signals (output spectra). For example, in both attachment cases, the second and the third modal frequencies around 20 and 30 Hz are the same as the ones obtained from output-only cases studied in Cases 5–6. The first mode peak, 8.5 Hz, is somewhat less significant since the biomechanical system frequencies are
dominant between 5 and 10 Hz frequency bands. Such difference can be seen looking at the Case 5–6 examples showing the spectra obtained from phone directly attached to the bridge deck surface without any biomechanical intervention.

Figure 12 shows the Fourier spectra obtained from output-only cases, Cases 5–6. The cases shown in Figure 12 represent smartphone measurements with relatively less citizen-induced uncertainties, since there is no biomechanical intervention throughout the measurement process. On the other hand, the ground vibration transferred to the smartphone is still expected to vary for the bag case because it still introduces a mechanical interlayer between the input and output signals. The latter case is a better coupling scenario where the phone is directly in contact with the ground and therefore provides a reliable reference spectra for the rest of the measurements. Nevertheless, the modal identification results even under extreme sensor mobility match the reference operational modal analysis studies of the bridge conducted repetitively in the past.27,31,32

The basic principle in the proposed platform is that modal parameters are sensitive to structural damage. For example, changes in the structural system such as stiffness will be reflected on the identification results. For this reason, monitoring of modal parameters helps the authorities to assess the structural integrity and take action accordingly. Studies have shown that the modal identification results gathered at different damage states return different structural reliability values, which is a strong measure of the structural health.3,4 As these monitoring results are collected frequently, in the long run, environmental effects can also be eliminated from the identification results, and the remaining outcomes will purely depend on structural deterioration.71 To summarize, if correct long-term monitoring strategies are adopted and modal identification results are observed accordingly, damage characteristics can be captured from the mobile pedestrian data.

Conclusion
This study explores the potential of using vibration data measured by mobile pedestrians’ smartphones and identifying the bridge structures’ modal parameters. Pedestrians as smartphone users serve as mobile sensors
with a crowdsourcing engagement. However, vibrations measured by the pedestrians’ smartphones are affected by their human body biomechanics. Thus, this study addresses this technical challenge by removing the biomechanical effects from crowdsourced smartphone data to extract the bridge structural vibrations and subsequently the structural modal parameters.

Two major realistic pedestrian mobility scenarios are taken into consideration such as walking and standing. For the walking case, sensor carried by the pedestrian is used for rough estimation of walk-induced forces on the structure. After a thorough theoretical review, some of these models are taken as references, and the smartphone-based force identification results are qualitatively compared to demonstrate the validity of mobile pedestrian data. In contrast to the theoretical pedestrian force models, smartphone time histories are not perfectly sinusoidal, but still periodical, and is of similar peak-to-peak order in the time domain. In the frequency domain, it is seen that the smartphone measurements resemble a resultant force of lateral, longitudinal, and vertical pedestrian forces rather than vertical component alone. This is expected since smartphone axes are subject to change throughout pedestrian motion, although it is aimed to align smartphone y-axis toward gravitational direction. Nevertheless, monitoring results show that the data acquired from walking pedestrians can be of great importance to identify dynamic loads due to pedestrians.

For the latter scenario, that is, standing pedestrians, first of all, pedestrian biomechanical features are determined in terms of Fourier spectra. These spectra are measures of an intermediary mechanical system between the sensor and the structure and is constructed from smartphone sensors carried by a pedestrian while standing on a rigid surface. Observing two different configurations such as smartphone in a bag and smartphone in a pocket, it is illustrated that the system spectra can change depending on the smartphone’s attachment on pedestrian body.

In order to cancel out biomechanical effects due to human body, following a transfer function development and conversion procedure, the system spectra can be used to eliminate citizen-induced vibration content and produce pure structural vibration spectra from pedestrians standing on a bridge. On the other hand, it is seen that pedestrian biomechanical features extensively affect 5–10 Hz frequency bands, and this reduces modal identification quality within this range. For higher modes, identification results are as accurate as output-only cases (cases with direct sensor–structure contact and no pedestrian influence).

The test results presented in this study are collected from a single pedestrian subject under controlled conditions (pedestrian standing still, walking with the same pace), and in real life, the pedestrian behavior can be more uncertain, complex, and time dependent. Besides, development of a pedestrian’s system transfer function autonomously can be very cumbersome and requires deeper understanding of human motion as well as effects of accessories. Gathering data from a large number of smartphone users systematically would help researchers to gain more insights regarding indirect structural vibration sensing and isolating nonstructural pedestrian effects. In addition, extension of this mobile sensing approach to other wearable sensors such as smartwatches or activity wrists might possess similar and even more practical potential.

Nevertheless, the two cases demonstrated throughout this article are keystones of a novel methodology shifting from conventional SHM systems to citizen-engaged, crowdsourced, and smartphone-based SHM systems. Pedestrians can operate smartphones as mobile SHM devices and provide the monitoring system with valuable data. As shown in this study, estimated forces and modal identification results can help to experimentally assess the structural demand and the bridge system properties, respectively. Further advancements in this field is prospective in terms of how they combine mobile and smart technologies with pedestrian contribution and eventually help evaluating structural features in a sustainable and self-governing way.

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Appendix I

Notation

\begin{align*}
A_r & \quad \text{complex modal constant} \\
c & \quad \text{damping constant} \\
f_p & \quad \text{activity rate} \\
F_p(t) & \quad \text{pedestrian-induced force} \\
G & \quad \text{pedestrian weight} \\
F_{\text{input}}(w) & \quad \text{input spectra} \\
F_{\text{intermediary}}(w) & \quad \text{redundant spectra connecting adjacent systems} \\
F_{\text{output}}(w) & \quad \text{output spectra} \\
F_{\text{sensor}}(w) & \quad \text{spectra obtained from the sensor} \\
F_{\text{source}}(w) & \quad \text{vibration source spectra} \\
H_{\text{pedestrian}}(w) & \quad \text{pedestrian transfer function due to the biomechanical system} \\
H_{\text{structure}}(w) & \quad \text{system's transfer function} \\
H_{\text{system}}(w) & \quad \text{stiffness constant} \\
m & \quad \text{mass constant} \\
w_r & \quad \text{modal frequency} \\
\alpha & \quad \text{Fourier coefficient} \\
\xi & \quad \text{damping ratio} \\
\phi & \quad \text{phase shift}
\end{align*}