INVITED PAPER

Crowdsensing Framework for Monitoring Bridge Vibrations Using Moving Smartphones

This paper discusses new services that can be delivered to urban environments through big data generated by the public's smartphones, enhancing the relationship between a city and its infrastructure.

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ABSTRACT | Cities are encountering extensive deficits in infrastructure service while they are experiencing rapid technological advancements and overhauls in transportation systems. Standard bridge evaluation methods rely on visual inspections, which are infrequent and subjective, ultimately affecting the structural assessments on which maintenance plans are based. The operational behavior of a bridge must be observed more regularly and over an extended period in order to sufficiently track its condition and avoid unexpected rehabilitation. Mobile sensor networks are conducive to monitoring bridges vibrations routinely, with benefits that have been demonstrated in recent structural health monitoring (SHM) research. Though smartphone accelerometers are imperfect sensors, they can contribute valuable information to SHM, especially when aggregated, e.g., via crowdsourcing. In an application on the Harvard Bridge (Boston, MA), it is shown that acceleration data collected using smartphones in moving vehicles contained consistent and significant indicators of the first three modal frequencies of the bridge. In particular, the results became more precise when informatics from several smartphone datasets were combined. This evidence is the first to support the hypothesis that smartphone data, collected within vehicles passing over a bridge, can be used to detect several modal frequencies of the bridge. The result defines an opportunity for local governments to make partnerships that encourage the collection of low-cost bridge vibration data, which can contribute to more effective management and informed decision-making.

KEYWORDS | Big Data; Bridge Management; Crowdsourcing; Damage Detection; Structural Health Monitoring; System Identification; Vehicular Networks; Wireless Sensor Networks; Intelligent Infrastructure

The state of U.S. infrastructure can be described as expiring: about 40% of bridges are over 50 years old; in each day of 2016, Americans took 188 million trips over structurally deficient bridges [1], [2]; and the backlog in bridge rehabilitation is estimated at $123 billion. For effective commerce and transit between U.S. states, federal laws require biennial bridge condition evaluations. Local governments and transportation authorities manage bridges and are responsible for a majority of the funding; they employ inspections, then form and prioritize plans based on engineering assessments and allocated budgets. Yet, modern inspection protocols are sparse in time, and often do not include sensors or other technological tools, and as a result, can miss damage indicators and/or lead to improper diagnoses.

A visual inspection is the primary condition evaluation method which, while often thorough, is subjective by nature and can be impaired by obstructive nonstructural elements or other physical restrictions [3]–[5]. Even if a compromised structural component is in clear sight of a professional bridge inspector, early signs of damage,

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e.g., local yielding or microcracking, can be simply undetectable to the human eye. More frequent monitoring guarantees higher confidence in structural assessments. Advanced notice of structural deficiencies can save hundreds of millions of dollars in bridge repairs [6] while maximizing its service and lifecycle. At last, bridge systems must be resilient, with a transparent and quantifiable reliability if they are expected to support potentially more annual trips than ever before through population growths [7], new waves of transportation modes [8], and mobility patterns [9], [10].

Ubiquitous smartphones currently include over a dozen sensors and can collectively generate massive amounts of data that enable insight at the resolution of an individual, defining new opportunities to study human activity. Digital traces [11], [12] capture human mobility [8], [13], [14], and can reveal patterns which help us better understand how people use and interact with the urban environment [15], [16]. Such realizations have highlighted inherent similarities and differences in human tendencies among cities around the world [17]. Finally, through Internet-of-Things (IoT) connectivity, smartphones have an ability to facilitate mass participation and information gathering, as illustrated by mobile applications, whose service is dependent on individual user contributions, e.g., Google Maps, Yelp, Waze.

Which services can be delivered to urban environments through big data generated by the public's smartphones? Can digital data, produced by ubiquitous smartphone sensing, supply bridge condition information cost-effectively, thereby creating a new relationship between a city and its infrastructure? These are some of the questions that are investigated in this paper.

I. INFERRING STRUCTURAL PROPERTIES FROM VIBRATION DATA

A. Motivation

Unknowns about the true state of any structural system begin as early as the design phase, in which assumptions and simplifications on structural behavior are common practices (albeit necessary and embedded in design codes). The construction process further contributes to unexpected differences between the design and built system. These two items alone provide adequate justification for establishing the original (baseline) conditions of a built structure through inspection and explicit measurements. When the structure is in service, engineers must accept uncertainties within operational (everyday) behavior, which are related to variations in usage, material properties, inherent defects, and environmental conditions among other factors.

Data collection and analysis are essential to bridge management systems [18]. Regardless of its age, up-to-date knowledge of a bridge's structural properties and behavior is highly valuable for condition forecasts and to effectively manage it as an asset [19]–[22]. Digital sensors and data acquisition systems can address the frequency and subjectivity challenges currently faced in visual inspection methods by facilitating continual information procurement and measuring physical phenomena with dedicated devices. Modern sensor network technology is capable of recording ambient vibrations of a civil structure, e.g., accelerations; such data captures the inherent, cyclic dynamic characteristics of the system, which are tied to its physical stiffness and mass, as well as material properties. An ability to monitor a structure's operational activity over an extended period is key to tracking its physical attributes and a cornerstone in preventative maintenance.

B. Condition Monitoring and Evaluation of Civil Structures

Structural health monitoring (SHM) [23] research is dedicated to better understanding structural performance and determining the true conditions of a structural system through the analysis of field measurements (sensor data). Modern data acquisition systems consist of a fixed sensor network, whose scale and configuration can vary vastly depending on the application and technology implemented (some notable deployments are listed in Table 1). While the

Table 1 Selected SHM Sensor Network Deployments on Large Civil Structures

Year	Structure (Location)	Network size	Application(s)	Ref.
1992	Second Bosphorus Bridge (Turkey)	28 sensors	Modal identification	[25]
2003	Vincent Thomas Bridge (USA)	26 sensors	Modal identification	[26]
2009	Golden Gate Bridge (USA)	320 sensors	Modal identification; operational monitoring	[27]
2009	Guangzhou New TV Tower (China)	600+ sensors	Construction monitoring; modal identification; damage detection; finite-element model updating; operational monitoring	[28]
2010	Jindo Bridges (South Korea)	70 sensors	Modal identification	[29]

SHM field is diverse and continually expanding, its major objectives contain three recurring themes: damage detection (and characterization), prognostics, and risk assessment [5], which in terms of asset management, correlate with long-term performance tracking, inspection optimization, and decision-making assistance. Structural deterioration is immeasurable in itself, although through comparisons over time, distress indicators are inferable [24]. To achieve explanatory insights from collected data sets, computational procedures have been designed to manifest special features and metrics, often utilizing statistical frameworks and mathematical models.

System identification (SID) [30], the determination of structural dynamic properties from vibration data, is one of the most matured and repeatable processes available for civil structures. Over the past two decades, a plethora of techniques have emerged, with varied algorithmic complexities. Many are founded on time series concepts, e.g., autoregressive [31], or state-space [32]–[34] models, and recently some have incorporated machine learning [35] or Bayesian [36] frameworks. Furthermore, studies on the mathematical precision [37], [38] of modal identification techniques as well as long-term applications have allowed for a better understanding of robustness, i.e., how the results may be influenced by deterministic and stochastic variables. A great deal of the sophistication in SID methods can be attributed to the relative ease in observing the resonances of a dynamic system from output-only vibration data. As an example, it is possible to reveal structural modal (resonant) frequencies from a single data set through simple frequency domain approaches, e.g., Fourier transforms. Structural damage, on the other hand, is often a highly localized spatiotemporal phenomenon that is not omnipresent in such sensor data.

The vibration characteristics of a structural system are permanently altered by damage, which can initiate after a particular event or develop gradually over time. At any rate, a local stiffness reduction, such as a crack, will affect structural parameters or modal properties to some degree, e.g., decrease in frequency, increase in damping, and modified mode shapes [39]. Damage identification (DID) strategies have a clear belonging within frameworks for risk assessment and bridge management. Accordingly, in SHM, there is considerable ongoing attention on the detection, localization, and quantification of structural damage (the DID trio) using sensor network data [38]–[43]. Because damage is a broad and complex entity that for all practical purposes is immeasurable, more effort is needed to expose its attributes. Many techniques aim to extract damage sensitive traits from the data via signal processing, feature extraction [45], [46], time-series methods [40], [47], or statistical classification/clustering [23]. Furthermore, damage tends to be highly localized (and potentially sparse) in space, and generally, its presence does not necessarily impact structural modal properties to an extent that is distinguishable from operational variation (although a counterexample is presented in [48]).

The first consequence is the realization that sensor networks with a larger spatial coverage have a greater ability to collect data near a damaged location, which permits identification. Second, DID methods require data from an undamaged reference structural state in order to properly characterize an unknown state (a statistically significant difference between damage sensitive features indicates damage). Regular and archival monitoring data enable condition evaluations to occur at a rate and detail that surpass modern visual inspection protocols, thereby increasing the likelihood that structural damage is properly identified while it is treatable.

C. Drawbacks of the Fixed Sensor Network Paradigm

Data collection for SHM has relied on fixed sensor networks, which must be designed, installed, and maintained by experienced personnel. These networks can be as simple or elaborate as the budget allows. For instance, long-term and cyber–physical monitoring systems [49], [50] empower regular monitoring and provide an ability to view structural performance metrics in real time; yet, while comprehensive, the high costs associated with equipment and maintenance mean that this highly technological approach is only practical for a select number of bridges (usually those newly constructed, or in critical condition). City departments of transportation do find importance in collecting response data from the bridges they manage; however, they operate under a limited budget, which cannot afford the procurement and maintenance of a measurement system for each bridge. It seems as though the adoption of high tech monitoring systems in SHM may unintentionally accelerate the disconnect between bridge inspection protocols and the data-driven tools available.

Whether the goal is SID or DID, the size and arrangement of the fixed sensor network plays a crucial role in the informatics that can be extracted. The need for optimal sensor placement and compressed sensing strategies in SHM have suggested that while a larger fixed sensor network is known to provide advantageous information in comparison to smaller ones, the costs associated with such systems can be prohibitive to research budgets. Fig. 1 illustrates how fixed sensor network parameters impact SID results. In particular, the number of sensors deployed restricts the structural mode shape information that may be determined; if only few sensors are available, higher order mode shapes cannot be estimated accurately—a problem that is analogous to aliasing in discrete signal processing. High fidelity spatial information is more valuable in DID, e.g., techniques based on mode shape curvature [51], [52], since damage-prone areas cannot be known *a priori* and higher order structural modes have shown to have a higher sensitivity to damage, even though dynamic properties are in general not good damage features.

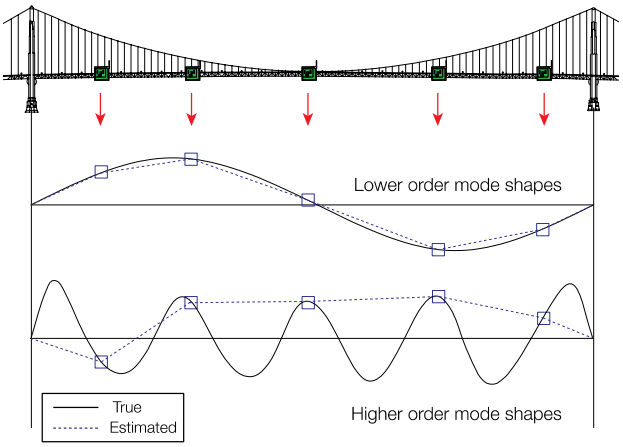

Fig. 1. ***Illustration depicting the limitations in spatial information provided by fixed sensor networks. In general, N sensors distributed along a dimension can successfully reconstruct mode shapes having no more than N – 1 points of inflection. For example, five sensors provide sufficient resolution for a lower order mode shape, but are inadequate for higher order mode shapes, i.e., those with five or more points of inflection.***

D. Mobile Sensor Networks as a Scalable Monitoring Solution

Over the past decade, there has been interest in the problem of identifying structural properties, i.e., SID, from mobile sensor network data. Mobile sensor networks are attractive because they address the shortcomings of fixed sensor networks by achieving a dense spatial coverage using fewer sensors [53], [54]. In fixed sensor networks, each sensor is dedicated to a particular point on the structure. Mobile sensors scan structural vibrations, making it possible to measure vibrations from multiple bridges, using the same equipment, within a short time frame. In essence, a single mobile sensor can provide information comparable to that provided by numerous fixed sensors. Studies have proven that mobile sensors can capture modal property information [55]–[57]. In particular, it has been shown that the fundamental frequency of a bridge can be detected from a vibration sensor mounted in a moving vehicle [58]–[61]. These results suggest that with the proper analytical tools, it may be possible to shift data dependence from a dense fixed sensor networks to mobile sensor networks, which are simpler to implement and have lower setup costs.

While innovative, these methods have not yet provided an ability to estimate bridge modal properties in the field with a performance comparable to the current standard, which is SID using fixed sensor data. Simultaneously, in the digital age, an identification technique for mobile sensor data with consistent and accurate estimates in practice can significantly impact the rate and scale at which vibration data are collected and analyzed. The current state of the art in modal identification methods for mobile sensors aims to 1) match the capabilities available with methods designed for fixed sensor data; and 2) illustrate the advantageous spatial information that is exclusive to sensors with mobility. Recently, the extended structural identification using expectation maximization (STRIDEX) method [62], [63] achieved these goals while proving that one mobile sensor could provide spatial information comparable to 120 fixed sensors.

In contrast to a network of fixed sensors, the quantity of mobile sensors does not inherently restrict the spatial information that is captured. This superior feature is demonstrated experimentally, using the testbed described in [62]. Fig. 2(top) shows two mobile sensor network setups, containing two and four sensors, respectively. The mobile sensor cars containing accelerometers traversed the span of the beam (3048 mm), then returned to their starting positions, at a speed of 114 mm/s, while sampling at 280 Hz. The structural modal properties (frequencies, damping ratios, and mode shapes) of the specimen were determined through SID using STRIDEX and are displayed at the bottom of Fig. 2. The high-resolution mode shapes illustrate how relatively few moving sensors can provide rich spatial information, which can support DID. With mobile sensing, dedicated devices are no longer needed; therefore, the deployment and maintenance needs of a sensor network are reduced substantially. The benefits are twofold: fewer sensors provide more spatial information, and can scan several structures more quickly. Mobile sensor networks are conducive to regular bridge monitoring, which is essential to a bridge management system.

II. SMARTPHONES AS MULTIPURPOSE INFRASTRUCTURE SCANNERS

A. Civic Data Collection Through Human Mobility

Mobile sensor data contain a denser spatial resolution when compared to that collected by an equivalent number of distributed fixed sensors. In the digital age, high smartphone ownership levels in urban hubs have reduced the need to procure dedicated devices in order to densely cover a city. Specifically, smartphones carried by humans create a large-scale mobile sensor network. Throughout hundreds of millions of daily trajectories, humans scan city infrastructure routinely and comprehensively. Numerous studies have illustrated the many ways in which the analyses of such big data streams can generate latent information that is useful to the public, the urban planning community, and local government entities [64], [65]. Even before mobile phones reached peak levels in technological capabilities and ubiquity, researchers have been involved in the development of data collection, processing, and management systems to compute real-time traffic metrics based on aggregated vehicle trips [54], [66], [67]. In

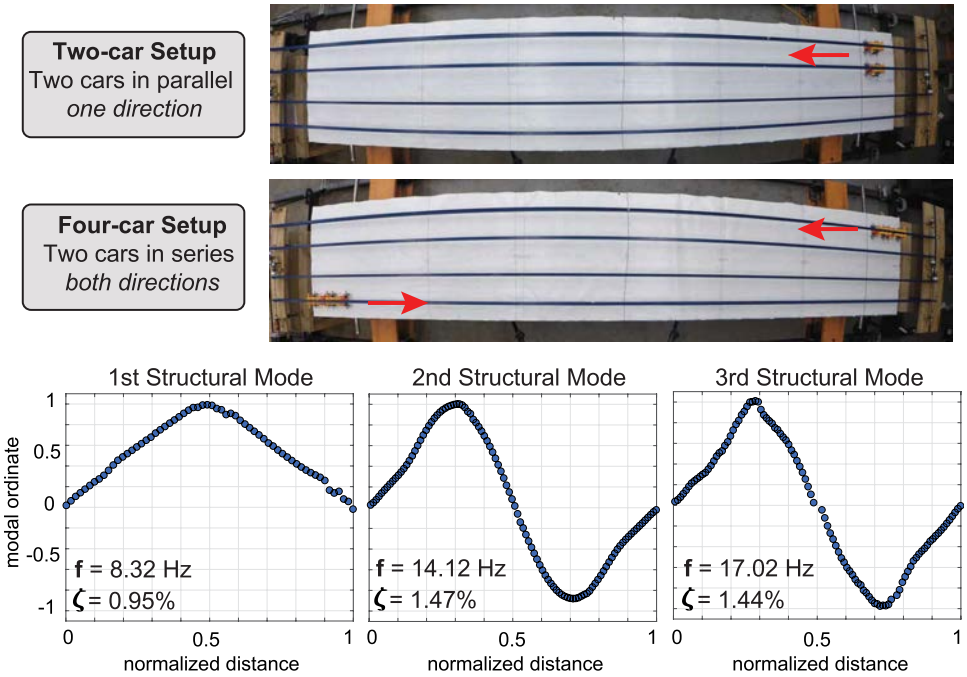

Fig. 2. ***Experimental mobile sensing platform at Lehigh University. Three structural modes, complete with frequency (f), damping (ζ), and mode shapes, are identified from wireless accelerometers in moving pulley-driven cars. High-resolution mode shapes are extracted using the STRIDEX SID method. Until recently, this has traditionally required a dense distributed fixed sensor network.***

Fig. 3, the pervasive sensing of smartphones in a city is illustrated for Boston using data from the users of a particular smartphone app. Detailed map inferences can be extracted from sparse and noisy GPS traces collected from within vehicles—as data accumulates over longer collection periods, the maps gain precision [68].

Currently, similar tools [69] are integrated into smartphone navigation applications, which provide advanced features to its users, e.g., route recommendations and real-time traffic updates. This example follows a basic principle of crowdsourcing: each user contributes unique, presumably useful data with the corollary that as user levels increase, the quality and value of the collective information also improve. The result is that crowdsourcing schemes may initially require a certain amount of regular user contributions to guarantee a service. In a commercial sense, this recursive relationship can potentially obstruct the growth of newly launched crowdsourcing initiatives: if the user is not provided a service, what is the incentive to participate? For local governments, crowdsourcing offers new insights on human activity and a channel for civic interaction. In a smart cities landscape, automatic diagnoses of complex urban problems could contribute to a better quality of life for residents.

Fig. 3. ***Representation of human mobility in Boston, produced from smartphone app user data. Residents habitually scan the city using smartphone sensors, at a high spatial resolution.***

B. Applications in the City of Boston

The Mayor's Office of New Urban Mechanics in the City of Boston (henceforth "The Office") embraced big data as an opportunity to better maintain urban infrastructure and enhance public safety. In 2012, with industrial and academic support, The Office launched their first crowdsourcing program called *Street Bump* in response to road surface problems, mainly potholes, which represent a longstanding quality-of-life issue experienced by city residents as well as a road maintenance costs [70]. The smartphone application transmits the accelerometer and GPS measurements into an anomaly detection and decision support system [71]. The objective was to locate actionable bumps in city streets, a classification which would help Boston manage repairs. While the identification of road surface features from sensors in vehicles is not a new concept [72]–[74], this was perhaps the first initiated by the local government to address an urban problem. Ultimately, the program did not succeed as a robust pothole finder in itself, as it was difficult to distinguish a pothole from other conditions, e.g., sunk casting, with high certainty. Yet,

this project demonstrated that big data can indeed provide a distinct service to the city. Rather than focusing on potholes, these data sets can be used to cost-effectively evaluate ride smoothness in a more generic sense, e.g., rideability. In the long term, such metrics could be linked with the pavement condition indicator that is currently included in MassDOT Highway Division asset management reports.

In 2015, The Office partnered with Boston's Vision Zero Task Force and Cambridge Mobile Telematics to introduce the *Boston's Safest Driver* smartphone application as part of an effort to eliminate fatal traffic crashes by 2030. Through Vision Zero, Boston has outlined a multifaceted action plan that includes education and enforcement programs to reduce distracted and impaired driving. The key offering of the app is a personalized evaluation of the user's driving behavior based on speed, acceleration, braking, cornering, and phone distraction [75]. The user receives an objective score based on his/her activity, which provides a unique opportunity for self-reflection and elicits social dialogues about safe driving habits. Since the program's commencement, several competition cycles have completed, throughout which prizes were awarded weekly to top drivers, the most improved scores, new users, as well as those who chose car-free trips. The app has recorded over 200 000 trips with user levels near 1800 on average and about 5000 during competitions. The data indicated reductions in higher risk actions for the top 25% of users. In addition, speeding decreased by 35% and phone distraction dropped 47%. These preliminary results suggest that users adopted safer driving habits when they knew their activity was being monitored. Aside from helping the public drive more safely, this program instills notable social benefits. Whether an individual uses this tool as a metric for self-improvement or to compete with friends, the social aspects of *Boston's Safest Driver* are highly valuable features that lead to conversations in communities about safe driving.

It remains challenging to attract a large user base and keep them engaged in certain apps. The user levels of other smartphone apps managed by Boston indicate that incentive and service are primary factors. For example, the *ParkBoston* app facilitates an everyday city activity by allowing its users to pay for metered parking directly from their mobile devices. Accordingly, the *ParkBoston* app was downloaded over 400 000 times within its first two years. Comparatively, the services provided by apps such as *Street Bump* or *Boston's Safest Driver* may be perceived as amenities with little immediate value, making it is difficult to quickly attain mass user levels. One way to mitigate this effect would be to merge existing apps that utilize human mobility and similar sensor readings into a centralized hub or multipurpose app.

A municipality that initiates crowdsourcing programs may be able to develop a reputation as a proactive problem solver. Through the *Street Bump* and *Boston's Safest Driver* programs, the City of Boston engaged its residents, demonstrated the capabilities of smartphones for crowdsourcing civic data, and explored how big data can be an asset to addressing complex urban issues. Big data can help streamline improvements to physical infrastructure; it can also ignite individual probes for positive social change throughout the community. Over a longer term, information from crowdsourced data can help shape innovative policies that are mindful of sociotechnical trends.

C. Measuring Vibrations in Civil Engineering Using Smartphones

Smartphones simplify the collection and distribution of sensory data but they measure imperfectly. The sensors that come standard in smartphone models were not designed for scientific applications; they were selected based on factors such as functionality, power consumption, size, and cost. Accelerometers in smartphones are subject to some basic signal processing problems, e.g., temporal jitter, high noise, clipping, missing data, etc. [76]–[78], which can limit overall reliability. Nonetheless, the resulting data have been shown to supply information that is useful to civil engineers, especially when part of a crowdsourcing campaign.

As previously mentioned, mobile sensor networks for SHM have shown promise, yet lack successful demonstrations on large-scale bridges in the urban environment. Recent studies have corroborated the performance of smartphone accelerometers (while stationary) in civil engineering applications on structures in a controlled setting and through comparisons with calibrated reference sensors. It has been shown that an individual smartphone can measure accelerations with an accuracy that captures fundamental signal properties, such as amplitude and frequency content [79], [80].

With a long-term goal of crowdsourcing structural vibration data, recent work has looked at stationary smartphones and participation from pedestrians. In an application on an indoor pedestrian bridge, spatiotemporally mixed data were collected by consecutively placing one smartphone at eight positions; then, the frequency domain decomposition (FDD) technique [81] was implemented to find three natural frequencies, whose corresponding mode shapes were constructed after combining phase information from reference results [82]. Additional studies have focused on reducing the influence of certain undesirable features of smartphone data so that they may be better suited for SHM methods available for fixed sensor data [83]. The biomechanical effects of a standing human were isolated to minimize pedestrian-induced vibrations [84]. Gyroscope and magnetometer sensors were utilized to correct misaligned signals from phones fixed to a structure [77].

In an average sense, signal features of crowdsourced smartphone data can more closely match estimates from a higher quality accelerometer. Recent applications using smartphones as seismometers have suggested that, in some applications, it is possible to overcome measurement fidelity problems by aggregating heterogeneous data sets [76], [85], [86].

III. BRIDGE FREQUENCY DETECTION USING SMARTPHONES IN PASSING VEHICLES: APPLICATION ON THE HARVARD BRIDGE

A. Objectives and Scope

This section investigates a real-world example of monitoring bridge vibrations using a smartphone in a moving vehicle, which is applicable to an individual's daily commute. The Harvard Bridge is a 25-span (five continuous sections), haunched steel girder bridge with a total length of about 660 m; it connects Boston and Cambridge over the Charles River in Massachusetts, USA and serves on the order of 30 000 daily trips. The study has three main objectives:

1) estimate modal frequencies of the Harvard Bridge using a traditional fixed sensor network and SID procedure;
2) demonstrate the capabilities of an individual smartphone accelerometer in the context of a passing vehicle;
3) evaluate the prominence of the bridge frequencies in aggregate mobile sensing data collected using smartphones in moving vehicles.

The mobile sensor data considered in the application are a limited representation of the variety presented by a smartphone-based crowdsensing platform. In a true widespread crowdsourced implementation, the vehicle system, vehicle speed and path, smartphone model, and its position within the vehicle are all influential variables. This application considers a fairly large data set which includes variety among vehicles and sensors. Yet, a limited range of vehicle speeds and only one sensor position (flat on dashboard) are considered.

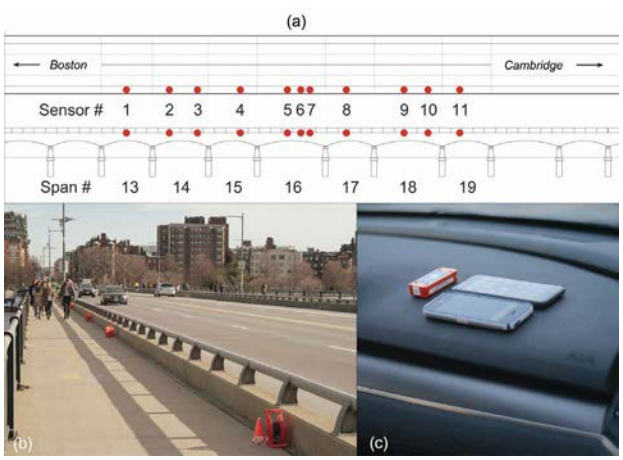

Fig. 4. ***(a) Plan and elevation views of a segment (spans 13–19) of the Harvard Bridge with fixed sensor network layout. (b) Photograph of the fixed sensors on the East side of the Harvard Bridge. (c) Photograph of the reference sensor and smartphones on a vehicle dashboard.***

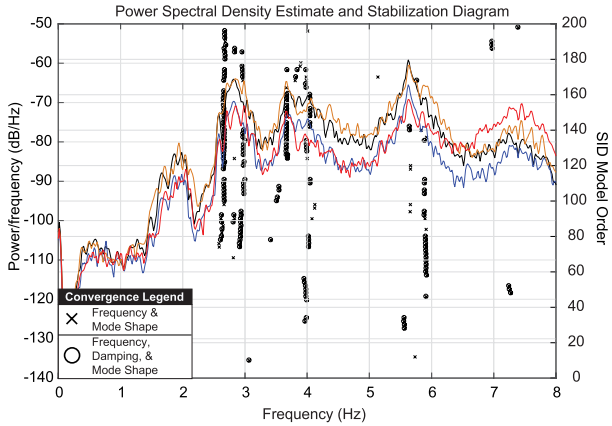

Fig. 5. ***Power spectral density (PSD) estimates and ERA-NExT stabilization diagram (determined using the SMIT program) based on fixed sensor data set #18. The solid lines are the PSD estimates for four sensors (6, 7, 9, and 11) with power levels indicated on the left ordinate. The black markers (circles and crosses) superposed on the plot indicate convergence at a particular model order (right ordinate) during the ERA-NExT process. Vertical trends of convergence markers confirm structural modal properties in the data. In other words, these frequency peaks can be explained by the bridge dynamic system. Note an absence of a convergence marker trend does not necessarily reject a peak as a structural modal frequency. It is instructive to process additional data sets to confirm further modes.***

B. Frequency Identification of the Harvard Bridge Using a Fixed Sensor Network

A network of 11 wired accelerometers (PCB 393B04) was distributed across seven spans (13–19) of the Harvard Bridge. The sensor network [pictured in Fig. 4(a) and (b)] recorded traffic-induced bridge vibrations on the east sidewalk at 2048 Hz during two consecutive high-traffic hours. The measured accelerations are expected to have captured the operational behavior of the bridge such that the dominant frequencies in the data are representative of the bridge's structural dynamical properties.

The Harvard Bridge is not a simple structure; it comprises five continuous sections. The deck joints introduce dynamics that are more complex than those of a fully continuous bridge, e.g., closely spaced modes. Yet, it is difficult to understand its behavior in full with an unknown excitation and a limited number of fixed sensors. The power spectral density (PSD) estimates (solid colored lines in Fig. 5) show several frequency regions with significant power levels, each suggesting the presence of a structural modal frequency. A few of these regions include smaller peaks that are consistent among the sensors, e.g., just below 3 Hz. At a first glance, it appears that the bridge has some closely spaced modal frequencies but overall this is inconclusive. A formal SID method must be implemented to determine which of the peaks in the PSD estimates correspond to structural modal frequencies.

The ERA-NExT method [87] was selected for SID using the SMIT computer program [88]. For each data set,

ERA-NExT produced a stabilization diagram, whose purpose is to highlight the peaks that are associated with structural modes. The standard method is to view the identification results for increasing SID model orders and measure the consistency among the estimates using convergence criteria. In Fig. 5, a stabilization diagram is superposed on the PSD estimate to illustrate this process for one data set (#18). The right ordinate of the plot indicates the model order (even numbers 2 through 200). The vertical trends of the black convergence markers confirm specific structural modal frequencies.

The participation (presence) of individual structural modes within the measurements is dependent on the dynamic loading conditions, e.g., traffic on a bridge. In most cases, the input excitation of the structure cannot be measured and as a result, multiple sets of structural response data are analyzed. In this study, the bridge's modal properties were evaluated by reviewing 18 stabilization diagrams, each corresponding to one 6-min data set. Afterwards, three dominant frequencies were identified as 2.05 Hz, 2.66 Hz, and 2.88 Hz; these are only a few of the modal frequencies of the Harvard Bridge.

C. Mobile Sensing Experiments on the Harvard Bridge

Regarding the mobile sensor data, acceleration measurements were collected using two smartphones (iPhone 5S and iPhone 6) and a reference sensor (Mide Slam Stick C). In each vehicle trip, the sensors were mounted on the dashboard of the vehicle [illustrated in Fig. 4(c)] and were triggered manually. The data includes 42 trips, mixed between two vehicles (Honda CRV and Honda Civic) over the bridge at slow speeds during rush hour (further details in Table 2). Smartphone sensor data were recorded at 100 Hz using the *Sensor Play* iOS app, which includes gyroscope and GPS measurements.

In general, high traffic conditions create special circumstances that can improve data quality: larger bridge vibration amplitudes, slower vehicle speeds, and longer data sets. Large bridge excitation levels can increase the presence of bridge vibration signatures, e.g., modal properties, within the mobile sensor data. Slower vehicle speeds provide more samples per location (higher spatial resolution) and reduce noise generated by poor pavement conditions. Finally, a larger number of observations of the involved dynamical systems will better support the solutions to the inverse problem.

D. Frequency Analyses of Aggregate Acceleration Data

The mobile sensor data were analyzed using simple frequency domain techniques to exemplify the content within raw, or minimally processed, smartphone acceleration measurements. The methods here are "model-free"; they do not require spatial information to function and are applicable to unsynchronized data sets. It is expected that the inclusion of additional sensor data, e.g., GPS, gyroscope, and/or the implementation of a more elaborate technique, designed specifically to process mobile sensor data for SID or DID, could extract further detailed information.

First, as a comparison between the frequency content recorded among the various sensors, a short-time Fourier transform (STFT) was implemented to display time-dependent frequency signatures. Fig. 6 displays three STFT plots for the longest data set (#11, 464 s), which was collected within vehicle 1. During heavy traffic, the vehicle traveled at a slower average speed (stop-and-go conditions), which

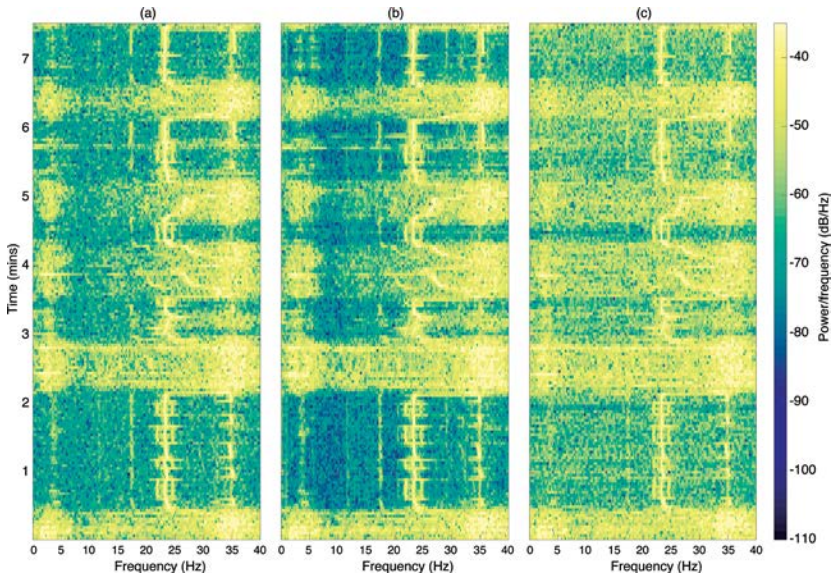

Fig. 6. ***Short-time Fourier transform (STFT) of mobile sensor data collected within vehicle 1, traveling southbound over the Harvard Bridge during heavy traffic (trip #11): (a) reference sensor (Mide Slam Stick C); (b) smartphone 1 (iPhone 5S); and (c) smartphone 2 (iPhone 6).***

Table 2 Summary of Vehicle Trips Over the Harvard Bridge

Vehicle	Speed (km/h)		Avg. Duration (sec)	Data Sets (Trip no.)
	Avg.	Std. Dev.		
1) 2005 Honda CRV	19.7	3.96	180	1 – 14
2) 2014 Honda Civic	16.5	3.95	225	15 – 42

resulted in a data set about three times longer than usual. Vertical trends in Fig. 6 indicate consistently dominant frequencies in the signal over time, which are expected to reveal characteristics of the dynamic vehicle-bridge system. Overall, Fig. 6 shows similar frequency trends among the different sensors. The smartphone sensors were able to capture temporal frequency patterns which matched those of the reference sensor, further supporting the performance of the smartphone accelerometers. This plot suggests that the information retrieved through individual vehicle scanning may not be significantly limited by the capabilities of accelerometers available in smartphones, i.e., qualitatively, smartphones can capture accurate frequency content.

To gain further insight on the prominence of particular frequencies in the mobile sensor data, power spectral density (PSD) estimates were computed for the vertical acceleration channels using Welch's method of averaged periodograms [89]. These plots describe the signal's power levels at each frequency over the entire trip rather than specific instants. The basic hypothesis here is that bridge resonant frequencies will have a persistent presence in the vehicle trips, despite data heterogeneity.

The method used to evaluate dominate frequencies and aggregate results is described graphically in Fig. 7. Local maxima of the PSD estimates were detected and evaluated using a generic peak-picking method. In this study, the prominence of a peak was evaluated as the power level at the peak of interest minus the lowest power level of the adjacent local minima. With this relative measure, contributions from nearby peaks can be removed. These values were aggregated and divided into 12 categories based on variable combinations (smartphone 1, smartphone 2, both smartphones, reference sensor, vehicle 1, vehicle 2, and both vehicles). Finally, the values in each category were normalized to have a maximum value of 100.

The normalized cumulative prominences (hereafter "peak scores" for simplicity) are shown versus frequency in Fig. 8. For each category, detection thresholds are defined based on the 95-percentile of the peak score distribution (Fig. 7, panel 4); the thresholds are indicated as red dashed horizontal lines in the plots. Simultaneously, the Harvard Bridge modal frequencies—determined using fixed sensor data—are included as colored vertical bars, each with a width of ±3%. The P and R values in the top-left corner display the *precision* and *recall* metrics for each data category [90]. *Precision* is the ratio of true positives to the total number of positives; it measures the relevancy of the significant peak scores (i.e., the positives). *Precision* values below 50 indicate a larger portion of false positives. *Recall* is the ratio of true positives to the sum of true positives and false negatives; it measures the completeness of the relevant peak scores (those at the bridge frequencies). For example, *recall*

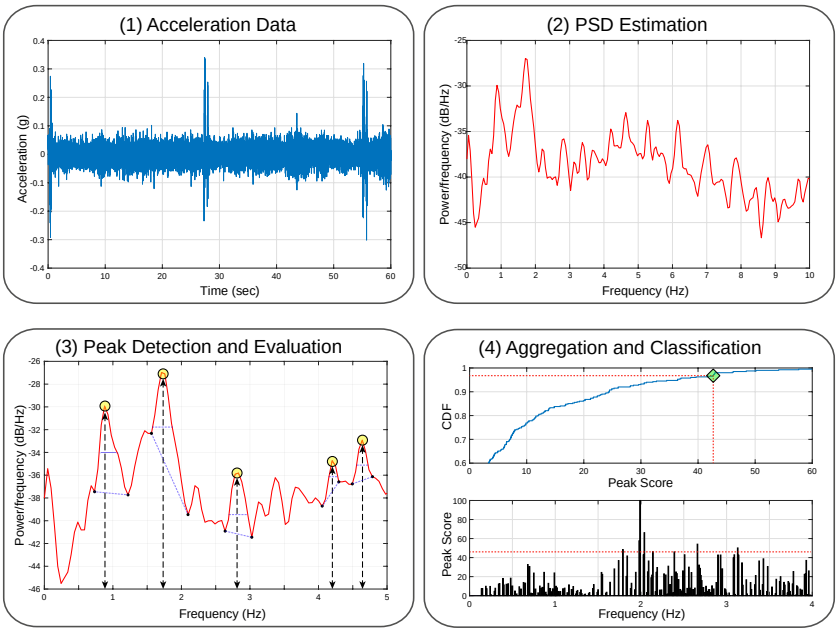

Fig. 7. ***Spectral peak evaluation process utilized for the mobile sensor data. Acceleration data (1) is processed to estimate the PSD (2). Peaks in the PSD estimates are detected (3) and evaluated using a "peak score" (a metric that can be defined per application). The peak scores are aggregated (4) and statistically significant values can be identified using empirical cumulative distribution functions.***

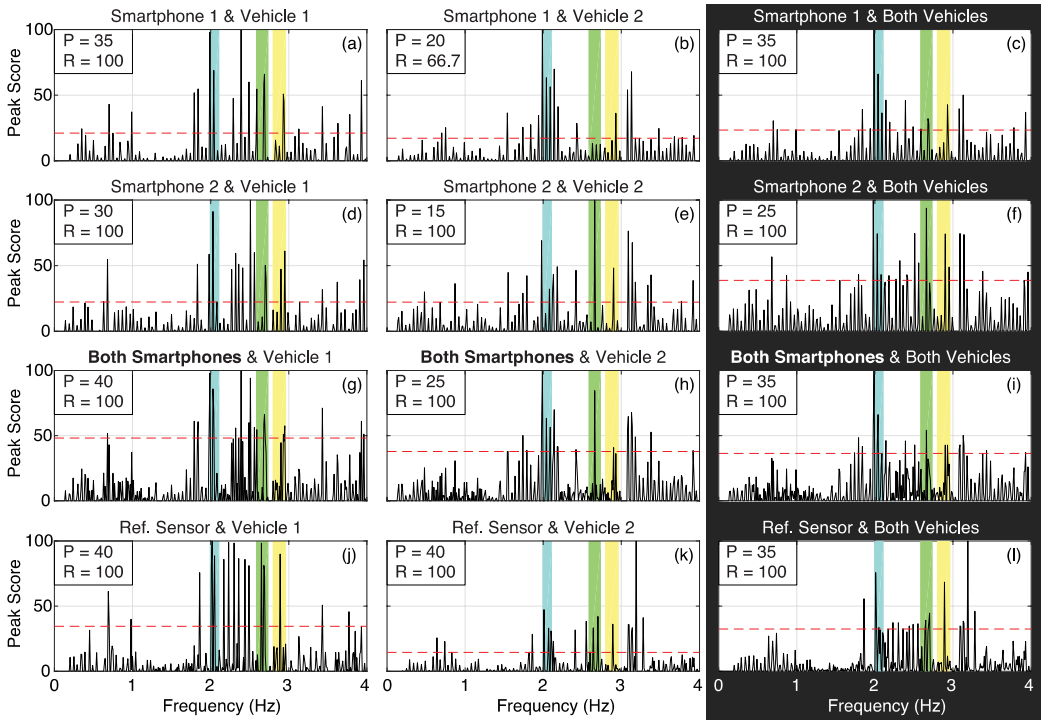

Fig. 8. ***Normalized cumulative peak prominences (referred to here as "peak scores") at each frequency for sensor data collected in a vehicle traveling over the Harvard Bridge. In each data subset, the peak scores above the horizontal dashed line are in the upper five percentiles. Three bridge frequencies identified from the fixed sensor data (2.05 Hz, 2.66 Hz, and 2,88 Hz) are highlighted as colored vertical bands, each enclosing ±3%. The data are divided into 12 subsets: (a) smartphone 1 and vehicle 1; (b) smartphone 1 and vehicle 2; (c) smartphone 1 and both vehicles; (d) smartphone 2 and vehicle 1; (e) smartphone 2 and vehicle 2; (f) smartphone 2 and both vehicles; (g) both smartphones and vehicle 1; (h) both smartphones and vehicle 2; (i) both smartphones and both vehicles; (j) reference sensor and vehicle 1; (k) reference sensor and vehicle 2; and (l) reference sensor and both vehicles.***

values of 100 correspond to the detection of three true positives (one at each bridge frequency).

Overall, the peak scores from the aggregated smartphone data are consistent with those from the reference sensor. Out of all the categories, those pertaining to the reference sensor had the highest precision values, i.e., fewest false positives, which is expected. In all 12 categories, there were significant peak scores at two out of three bridge frequencies (first and third), resulting in recall values greater than 66. For the exception of one case [Fig. 8(b)], all data categories contained significant peak scores for all three bridge frequencies (recall values equal to 100).

Most notably, when the smartphone categories were aggregated (third row of plots), the precision improved. For example, for vehicle 1, the combined results from smartphones 1 and 2 [Fig. 8(g)] were just as good as those from the reference sensor [Fig. 8(j)]. In addition, combining smartphones was observed to be effective in suppressing false positives. For instance, for vehicle 2, there is a false positive at 1.55 Hz for the individual smartphone cases [Fig. 8(b) and (e)] while the peak score at this frequency is insignificant for the reference sensor [Fig. 8(k)]. Yet, when the smartphone data are combined [Fig. 8(h)], the peak score falls just below the threshold, and thus becomes a true negative. Further suppression of this frequency is observed when both the smartphones and vehicles are combined [Fig. 8(i)]. These results show that the bridge's modal frequencies have a notable presence in the moving smartphone data.

There were some significant peak scores that only persisted in each vehicle category and could not be explained by the bridge's dynamic properties. These peaks occurred near 0.70 Hz, 1.84 Hz, and 3.43 Hz (and elsewhere) in vehicle 1 data (first column of plots) and around 2.42 Hz and 3.15 Hz in vehicle 2 data (second column of plots); it is possible these frequencies represent aspects of the moving vehicle dynamics. If the effects of different vehicles and smartphones are random and independent, these results suggest two points: 1) frequencies unrelated to the vehicle–bridge system may vanish, in an average sense, as the aggregated data sets become more diverse; and 2) collective smartphone accelerometer data can generate information comparable to a higher quality accelerometer (precision in this example).

E. Considerations for Future Work

The previous section demonstrated how an intrinsic structural feature can be extracted from a specific class of smartphone data that are readily available in urban

environments. Modal properties do not necessarily provide a measure of structural condition; yet, condition evaluations can benefit from incorporating modal property information. Furthermore, crowdsourcing such data presents an opportunity to estimate the modal properties of potentially thousands of bridges, cost-effectively, which would be useful to engineers, and over time, can support condition assessments. While these results are encouraging, it is important to reiterate that the limits of this simple data-driven approach have not yet been fully tested. In general, PSD estimates are affected by sensor noise, sampling rate, data length, and spectral smoothing. The key benefits here are the cost-effectiveness of smartphone data and the added value in aggregating the results from numerous trips.

Vehicle scanning data are influenced by dynamic vehicle–bridge interaction; variables encompassing the vehicle system, vehicle route, road profile, and bridge system define the complexity of the interaction effects as well as the presence of bridge vibrations within the recorded signal. Over the past two decades, studies related to the interaction problem have established the governing differential equations, constructed helpful simplified models, and conducted experiments (real and synthetic) [58]–[61]. For instance, studies on single-span bridges have concluded that vehicle scanning data include special signals at vehicle vibration frequencies and a driving frequency, which are independent of the bridge system. In addition, it is known that certain aspects of the interaction are subdued in the cases of slow vehicle speeds, stiff vehicle suspensions, and smooth road surfaces [91], [92]. These interaction effects were not considered explicitly in this approach, although based on the literature, it is expected that in the application, slow vehicle speeds during peak traffic hours contributed to the method's success.

It is suggested that data acquisition and preprocessing methods could include supplementary information (metadata) to preselect (or otherwise identify) scientifically preferable circumstances and mitigate experimental uncertainty. In future work, additional smartphone sensors such as GPS, magnetometer, or gyroscope can be incorporated to enhance the results, e.g., reconfigure the smartphone coordinate system [77], compile measurements at particular locations [93], estimate structural mode shapes [62], etc. There is also a need to study the synchronization problem posed by multiple moving sensors with independent and potentially irregular sampling properties [78], [94], [95]. Finally, as vehicular networks emerge for urban sensing, the design of intercommunication systems should consider costs related to data processing and transmission [96]–[99].

IV. CROWDSOURCING BRIDGE VIBRATION DATA

A. Long-Term Goals and Data Stream Characteristics

An overarching goal behind collecting mass smartphone data is to reform the nature of the challenges faced throughout infrastructure management. Structural evaluations and decision making are based solely on subjective and infrequently collected information, sets of visual inspections of bridges, which are constrained by municipality budgets, can miss early signs of damage, and can lead to inaccurate prognoses. If local municipalities could access enormous data sets from smartphone vehicle scans and the bridge information potential concealed within, infrastructure maintenance problems could be reshaped into those rooted in engineering and computer science, for which there is preexisting motivation for engineers, researchers, and businesses to solve.

Aggregating results from lower quality sensors can collectively deliver rich content [85], [86], [100], and in this case, the public has already purchased the sensors (their smartphones), and will deploy them sufficiently during their daily routines. Municipalities may need to vest the responsibilities and initial costs for data management, such as initiating data procurement programs via smartphone apps and configuring data repositories. Yet, this presents an opportunity for a local government to collaborate with academic institutions and/or industry partners who have mutual interests and complementing strengths. Furthermore, a mobile smartphone bridge monitoring program could be supported by acceleration and GPS data that are being collected as part of an existing civic engagement program, e.g., *Street Bump* or *Boston's Safest Driver*. Regardless, the effort is an investment: the potential volume and spatiotemporal resolution of subsequent structural health informatics could help engineers and government entities make more informed decisions on bridge management, which are intended to reduce maintenance costs and increase a bridge's service by extending its lifespan.

There are two key advantageous characteristics of crowdsourced bridge vibration data streams: 1) high volume; and 2) high velocity. Details of these attributes are dependent on individual participation, which can be difficult to predict with high accuracy; generally speaking, they govern the size of the big data. Yet, given the high annual average daily traffic levels for urban bridges, even low penetration rates can generate thousands of data sets daily.

Another important characteristic of the crowdsourced data is heterogeneity [101]. Vehicle scanning measurements of the same bridge will differ substantially among users, thereby adding a layer of complexity on the interaction effects. Vehicle properties, smartphone model, location within the vehicle, and other variables, are all contributing factors. User metadata can help explain or account for the influences of some of these variables. Some information such as vehicle make and model, number of passengers, tire pressure, etc., could potentially be entered into an interface by the user. These metadata could generate direct feedback to the user, e.g., suggest a tailored smartphone setup for optimal data quality, and/or be stored for analytical context. Alternatively, certain properties may be estimated to an extent using data recorded in normal driving conditions (nonbridge trips). Overall, data diversity becomes a useful feature as the number of data sets available becomes very

large. If these variables are random and independent, it is expected that the most persistent frequencies in the collected data would be those representative of bridge dynamics.

B. Toward an Automated Bridge Management System

A bridge management system receiving daily streams of vehicle scanning data has four functions, which may be automated:

1) extraction of bridge condition information from incoming mobile sensing data;
2) organization of data archives and prior statistics;
3) condition evaluations based on vehicle-scanning informatics, structural plans, and visual inspection records;
4) dissemination of reports to authorities and coordination of corresponding actions.

Analyses of data from an initial gathering period, e.g., a few months, up to one year, are needed to establish the baseline (reference) conditions of a bridge. Subsequently, bridge informatics computed from incoming data can be compared with those observed in the past, under similar circumstances. One goal is to determine whether the most recent analytics indicate a structural state that is different from the reference condition. Statistical methods for classification, clustering, or control processes [46], [102], etc., can be applied to identify substantial changes or abnormal trends in structural features while accounting for uncertainty [103], [104]. As historical information on structural condition accumulates in the database, a confidence is earned in data-driven evaluations, and artificial intelligence [105] or deep learning techniques may be implemented to extract further latent insights. That is, the bridge management system can develop an ability to learn, similar to capabilities of speech recognition algorithms [106], [107] or self-driving vehicles.

These tools are most effective when they supplement existing maintenance protocols; their added value is that they empower more frequent and data-substantiated structural evaluations at a relatively low cost. While there are bound to be highly technical aspects embedded in such an automated bridge management system, visual inspections by professional engineers are irreplaceable. Furthermore, structural condition results must be conveyed in a manner that is clearly interpretable by those who have the authority and expertise needed to make judgements, such as public works offices, city officials, stakeholders, etc. An automated bridge management system is an interactive platform that acts as an interface between the digital and physical worlds by integrating visual inspection data, e.g., photos, and presenting analytics visually. Previous research has shown that state departments of transportation have interest in incorporating interactive digital platforms into existing bridge management systems [108].

The design and deliverables of a prospective automated bridge management system are illustrated in Fig. 9. On the right of the dashboard screen, high-level information related to overall bridge health, upcoming maintenance actions, and recent data streams are provided. On the left, the analytics are mapped to an interactive bridge model, which facilitates the understanding of structural behavior at a component level for nonexperts as well as highly localized information for inspectors. Fig. 9 demonstrates one instance, out of all

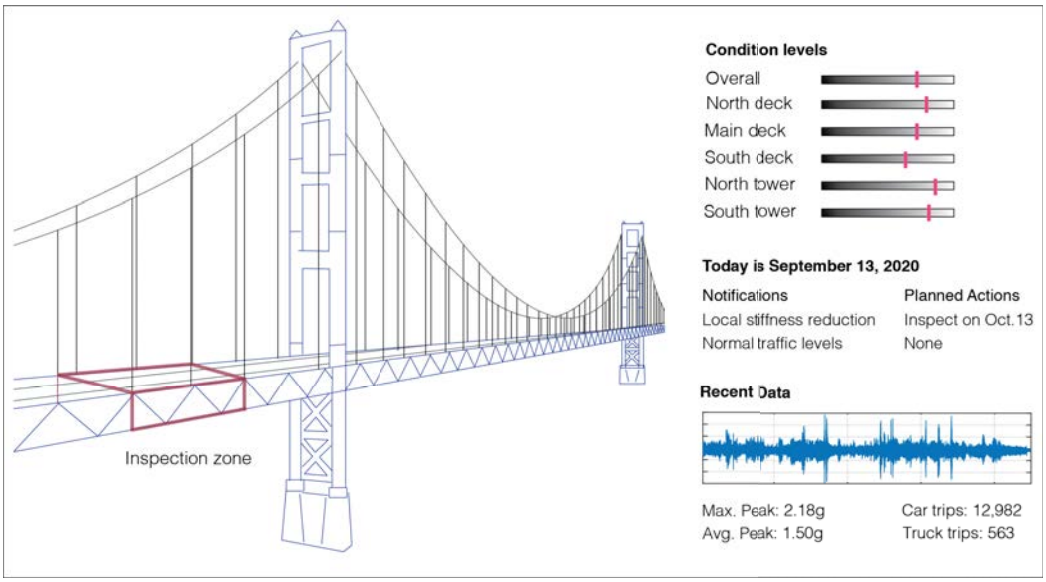

Fig. 9. ***Depiction of a digital dashboard of a bridge management system, which is fueled by streams of mobile sensor data. Current structural conditions can be displayed in a manner that is informative to professional engineers and city officials. Baseline structural performance metrics are established over an initial data gathering period–their precision improves as data accumulates. Statistically significant changes in informatics can serve as early indicators of structural damage, at which point a detailed inspection may be warranted.***

the possible forms and functions, of such bridge management systems, which are to be customized according to the specific needs of the appropriate public works offices, engineers, and officials in the city.

V. SUMMARY AND CONCLUSION

A coincidence of circumstances in consumer technology, ageing infrastructure, government innovation, and structural health monitoring (SHM) research has established an opportunity to monitor bridge vibrations using crowdsourced smartphone data. Cities worldwide are enduring widespread infrastructure epidemics at a time when they are experiencing rapid technological developments and paradigm shifts in human mobility. Standard bridge evaluation methods rely on visual inspections, which face limitations in frequency and subjectivity that ultimately affect the structural assessments on which maintenance plans are based. The operational (everyday) behavior of a bridge must be observed over an extended period, e.g., years, to sufficiently track its health and avoid unexpected rehabilitation. SHM sensor networks utilize dedicated devices to record field measurements, which are analyzed using mathematical tools to determine the true conditions of a structural system. Mobile sensor networks are conducive to monitoring urban bridges vibrations regularly, with benefits that have been demonstrated in recent SHM research.

The Mayor's Office of New Urban Mechanics in the City of Boston initiated two smartphone-based civic engagement programs which demonstrated smartphone capabilities for crowdsourcing sensory data, and explored how big data can be an asset to addressing complex urban issues. Prior research with smartphone accelerometers suggested that resulting information may not be significantly limited by the capabilities of cheaper sensors. In an application on the Harvard Bridge, it was shown that smartphone data, collected within a moving vehicle, contained consistent and significant indicators of the first three modal frequencies of the bridge. This result confirmed that bridge modal frequencies can be detected from this class of mobile smartphone data. In particular, when aggregated, the smartphone results improved in precision and, in one case, rivaled those of the reference sensor. The outcome is an opportunity for local governments to collaborate with entities having complementing strengths, to encourage mass collection of data containing bridge vibrations, which can contribute to more effective management and informed decision making. Over a longer period of time, continued programs can keep these urban assets in circulation throughout their design lives, reduce their maintenance costs, and potentially increase their service by extending their lifespans. ■

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