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Smartphone data streams for bridge health monitoring

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Abstract

Knowledge on the dynamic properties of bridges in a city can improve condition assessments, maintenance scheduling, and emergency planning to better serve the public. Currently, bridge vibration data is obtained primarily by researchers through the use of a sophisticated sensor network that is composed of fixed sensor nodes. Recent studies have supported the alternative of mobile sensor networks, which are capable of delivering important structural information, e.g., modal properties, requiring less setup efforts and using fewer sensors. Simultaneously, digital technology has spawned data initiatives such as crowdsensing, in which individuals can collectively sense the urban environment. The prevalence of smartphones, which contain various advanced sensors, is rapidly restructuring researchers' perceptions of data collection. This paper discusses the confluence of these emerging technologies, which can provide regular infrastructure data streams, within structural health monitoring (SHM) procedures for the immediate goal of system identification (SID) and towards automated maintenance of bridges. Will researchers continue to install sensor networks and collect their own data or will they start to source resident smartphone data? One of the objectives of this ongoing work is to quantify expected smartphone data stream volumes that would be applicable to SHM processes. As an example, the number of smartphones that traverse the Harvard bridge in a month is quantified.

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Keywords: Smartphones; Mobile Sensors; Urban sensing; System Identification; Bridge Monitoring; Smart Cities; Crowdsensing

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1. Introduction

Civil infrastructure systems inherit uncertainty from stochastic processes in the physical world, which influence structural behavior and service life. Digital data collected using sensor networks fuel the observation-based methods of structural health monitoring (SHM). These SHM techniques aim to build knowledge on existing conditions, which contribute to the management, maintenance, and repair of the infrastructure systems on which the public relies. Data collection technologies and methods have evolved substantially over the past two decades. Today, researchers have many options when it comes designing a sensor network. SHM applications with wireless sensor networks have facilitated large-scale sensor deployments [1–3]. With embedded microprocessing units, smart sensors bring computation closer to the site of the sensor network, which can enable real-time results [4–6]. Long-term monitoring projects have demonstrated sensor network resilience and quantified changes in structural features with respect to environmental conditions [7–9], e.g., excitation amplitude, temperature, etc. Accordingly, the procedures to analyze SHM data for system identification (SID) [10–12], damage detection [13–15], or finite-element model updating [16], have also developed into reliable and robust frameworks, often embedding statistical methodologies.

There remains a need to further reduce the cost and labor associated with sensor deployments and data acquisition. Fixed sensor networks have served as the staple for data collection in SHM since its inception; however, it is important to acknowledge their limitations. With fixed sensors, the majority of structural vibration measurement projects is initiated by SHM researchers. It is these same researchers who have the equipment and experience necessary to retrieve advanced insights on infrastructure condition. It is important to note that local governments and transportation authorities do participate in funding many of these research projects. However, given the current scale of structurally deficient bridges in the US (and elsewhere) and the maturity of the SHM field, it seems the public could be better served by these technologies. If SHM researchers could find a way to tap into another data source, or more widespread and cheaper data collection methods, SHM techniques may have a larger impact on infrastructure. By expanding the existing knowledge of infrastructure condition, local authorities can detect structural deficiencies more quickly, thereby saving millions of dollars on unexpected repair bills, maximizing public service, and reducing unnecessary risks.

2. Extracting bridge information from mobile sensor data

2.1. Benefits of mobile sensor networks

The ultimate drawback of a fixed sensor network is that each sensor provides singular spatial information. If more spatial information is solicited by an SHM objective, e.g., determining high-resolution mode shapes, one must either purchase sufficient sensor devices, or aggregate results from various network configurations. These proposed solutions are associated with a higher cost in dollars and time, respectively. Mobile sensor networks, on the other hand, are capable of a higher spatial coverage using fewer sensors; in short, a single mobile sensor delivers spatial information comparable to what would be provided by numerous fixed sensors [17–19]. With reduced setup costs, mobile sensor networks can facilitate SHM data collection and make it more accessible for new parties to participate, e.g., local authorities or the general public.

2.2. Processing mobile sensor data

While there have been a few studies on detecting modal properties using mobile sensing data in the field [20,21], this is a new area of research which has been mostly unsupported from SHM analysis techniques. As a result, there has been little motivation to implement large-scale mobile sensor networks in practice. For fixed sensor networks, state-space approaches have been applied extensively to analyze measurements of dynamic systems and extract important structural features [12,22,23]. The first-order matrix form condenses the model coefficients, which represent the system, into a matrix parameters and facilitates additive stochastic variables, which often approximate unmeasured phenomena, e.g., signal noise. Recently, a framework was proposed to consider mobile sensor network data. When classified as dynamic sensor network (DSN) data, mobile sensor data can be modeled exactly with the truncated physical state-space model (TPM) [24].

The TPM is comprised of the state and observation equations, Eqs. (1) and (2), respectively. The states $\boldsymbol{x}_k$ represent the structural responses at a time-step k for a fixed set of points in space. The observations $\boldsymbol{y}_k$ are the DSN data, e.g., mobile sensor data, at time-step k, whose locations vary over time. The state matrix A defines how the states behave over time and the product $\Omega_k C$ relates the observations to the states (note this product is time-variant, in accordance with the positions of the mobile sensors). The input of the system is $\boldsymbol{\eta}_k$, which, if unmeasured can be assumed to be random. The sensor measurement noise $\boldsymbol{\nu}_k$ is often assumed random Gaussian.

$$\boldsymbol{x}_k = A\boldsymbol{x}_{k-1} + \boldsymbol{\eta}_k \tag{1}$$
$$\boldsymbol{y}_k = \Omega_k C\boldsymbol{x}_k + \boldsymbol{\nu}_k \tag{2}$$

The TPM is capable of processing DSN measurements from a structural system. Time-series models are commonly embedded in SHM methods for SID, damage diagnostics, or finite-element model updating. As an example, the STRIDEX algorithm was recently proposed as a scalable output-only SID method for DSN data. Using simulated data and a mobile sensor platform in a laboratory [17], it was demonstrated that the identification performance standards established by fixed sensor SID methods, are also achievable using mobile sensors and STRIDEX [25]. By adapting familiar models and analytical tools, it is anticipated that applications of mobile sensors in SHM will grow.

3. Smartphones as urban sensors

3.1. New fields of study driven by smartphone data

There are over two billion smartphone users in the world [26]. Over the course of five years, the percentage of U.S. adults who own a smartphone has jumped from 35% to 68% [27]. These smartphone devices commonly contain over a dozen sensors, consequently merging digital data into everyday human life. Many of the sensor types included in smartphones, e.g., accelerometers, cameras, microphones, and others, are those which can also be found in a controlled laboratory setting. Furthermore, given the competitive nature of the market, the variety and accuracy of these sensors tend to improve considerably with each new smartphone model, e.g., recently, the number of devices with near-field-connection technology and fingerprint sensors has grown sharply. From the perspective of a researcher, the prospect of mass smartphone data presents a variety of novel opportunities to study human behavior and their interaction with the urban environment.

Cellular data provided by Telecom Italia was analyzed by Calabrese at al. [28] to expose urban dynamics and activities in Rome in real-time. As another example, using mobile phones with detailed Geographic Information System (GIS) data, urban road usage patterns were quantified by Wang et al. [29] in the San Francisco Bay Area, which highlighted road segments with consistently high congestion. Daily origin-destination patterns, which included commuting flows, were estimated by Alexander et al. [30] using Call Detail Record (CDR) data from mobile phones. Furthermore, a variety of methods have been developed to detect road surface condition problems, e.g., potholes, using smartphone vibration data collected while in a moving vehicle [31–33]. These studies unveil a hidden digital layer that exists within modern cities. By studying digital traces of city residents generated by smartphones, researchers can better understand how people move and live in cities. Ultimately, these insights can help configure the function and layout of tomorrow's urban systems for an optimal human experience.

3.2. Crowdsensing bridge vibrations

Motivated by the current infrastructure deficit in the US and the success of aforementioned crowdsensing applications, the concept of utilizing crowdsourcing bridge vibration data is suggested. City residents collectively provide a stream of vibration data. This data is expected to be collected from within a vehicle during daily commutes over urban bridges and includes the vibrations of both the vehicle, the bridge, and interaction effects [34]. The data is then processed with appropriate SHM tools to extract bridge information including, but not limited to, structural modal properties. As mentioned earlier, many of these analytical tools are still in development –

nonetheless, once available they can be applied to archived data sets. The primary goal is to establish baseline conditions for a particular structure, which represent undamaged or “healthy” structural states. Then statistical tests can be conducted to compare current and past structural features. All information would be stored in a health database for future analyses. Abnormal or statistically significant values identified during the diagnosis may correspond to a change in structural condition, e.g., damage, which could automatically trigger a notification to the local bridge authority.

4. Quantification of mobile smartphone data streams

4.1. Harvard Bridge example

With a framework to process crowdsourced data streams for bridge health monitoring, it is instructive to estimate the number of data streams that might be available. In this section, a lower bound for the number of daily smartphone trips over the Harvard bridge, which connects Boston and Cambridge, MA, is computed using Call Detail Record (CDR) data. This study analyzes Air Sage CDR data, which included activity from four months in 2009 from one million phone users in the Boston Metro area (this was about 26% of the 2009 cellphone user population). Statistics from 2009 establish the device ownership levels of a US resident [35–37]: (i) 26% smartphone penetration rate and (ii) 85% of adults own a cellphone. Within the CDRs, given a US resident owns a cellphone, the probability that the phone is a smartphone is 0.30. Accordingly, assuming the available CDR data were random samples of Boston Metro phone users, the counts were scaled by 15% to estimate smartphone activity for the entire Boston Metro population. It is worth noting that national smartphone ownership levels have risen substantially since 2009 and that Massachusetts owns significantly more smartphones in comparison to the national average [38]. The following is intended as a preliminary evaluation of the number of smartphone trips over the Harvard Bridge. Furthermore, this study only considered Boston-Cambridge trips between the hours of 6AM and 10AM. Therefore, it is understood that these values underestimate current daily activity.

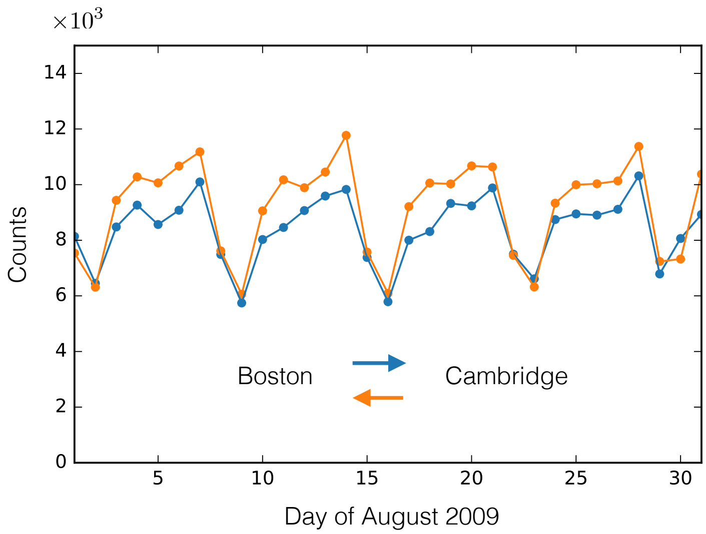

Fig. 1. Number of smartphone crossings over the Harvard Bridge in August 2009 between 6AM and 10AM. The blue points indicate outbound trips and the orange points are inbound trips. August 1, 2009 was a Saturday.

Locations and their timestamps were extracted from the CDR data using existing techniques [39–41]. Fig. 1 shows the number of inbound and outbound smartphone trips over the Harvard Bridge for every day in August 2009. The plot reveals higher activity during the morning commute on weekdays. The highest number of smartphone trips was observed on Thursdays and Fridays, while the fewest trips occurred on Sundays. Overall, there were roughly

18,000 smartphone trips over the bridge each weekday and about 14,000 smartphone trips on Saturday or Sunday. These values are consistent with MassDOT traffic volume counts.

5. Conclusions

This paper explored the concept of using ubiquitous smartphones to crowdsense bridge vibration data. The truncated physical model (TPM), which is capable of processing mobile sensor data for structural health monitoring (SHM) purposes, was reviewed. Recent applications of analyzing smartphone data in urban settings to better understand human behavior and activity were discussed. A framework for integrating crowdsourced bridge vibration data streams into a bridge condition database was discussed, in which, incoming data are compared with structural features that represent "healthy" or undamaged states. With this concept, smartphone data contributes to the daily maintenance of infrastructure systems, thereby taking preventative measures against unforeseen deteriorations that may ultimately restrict public service. Finally, using Call Detail Record (CDR) data, the number of smartphone trips that cross the Harvard Bridge was computed to evaluate expected crowdsourced data stream volumes.

Nomenclature

$\boldsymbol{x}_k$	discrete-time state variable at time step k
A	discrete-time state matrix
$\boldsymbol{\eta}_k$	stochastic state input at time step k
$\boldsymbol{y}_k$	observations at time step k
Ω_k	mode shape regression term at time step k
C	discrete-time observation matrix
$\boldsymbol{v}_k$	stochastic measurement error at time step k

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References

[1] S.N. Pakzad, Development and deployment of large scale wireless sensor network on a long-span bridge, Smart Structures and Systems. 6 (2010) 525–543. doi:10.12989/sss.2010.6.5_6.525.

[2] J.P. Lynch, Y. Wang, K.J. Loh, J.-H. Yi, C.-B. Yun, Performance monitoring of the Geumdang Bridge using a dense network of high-resolution wireless sensors, Smart Materials and Structures. 15 (2006) 1561–1575. doi:10.1088/0964-1726/15/6/008.

[3] J.M. Ko, Y.Q. Ni, Technology developments in structural health monitoring of large-scale bridges, Engineering Structures. 27 (2005) 1715–1725. doi:10.1016/j.engstruct.2005.02.021.

[4] Y. Gao, B.F. Spencer, M. Ruiz-Sandoval, Distributed computing strategy for structural health monitoring, Structural Control and Health Monitoring. 13 (2006) 488–507. doi:10.1002/stc.117.

[5] J.P. Lynch, Decentralization of Wireless Monitoring and Control Technologies for Smart Civil Structures, Stanford University, 2002.

[6] T. Kijewski-Correa, D.K. Kwon, A. Kareem, A. Bentz, Y. Guo, S. Bobby, et al., Smartsync: An integrated real-time structural health monitoring and structural identification system for tall buildings, Journal of Structural Engineering. 139 (2013) 1675–1687. doi:10.1061/(ASCE)ST.1943-541X.0000560.

[7] I. Behmanesh, B. Moaveni, Accounting for environmental variability, modeling errors, and parameter estimation uncertainties in structural identification, Journal of Sound and Vibration. (2015) 1–19. doi:10.1016/j.jsv.2016.03.022.

[8] M.D. Spiridonakos, E.N. Chatzi, B. Sudret, Polynomial chaos expansion models for SHM under environmental variability, ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering. B4016003-1 (2016).

doi:10.1061/AJRUA6.0000872.
[9] M. Kurata, J. Kim, Y. Zhang, J.P. Lynch, G.W. Van Der Linden, V. Jacob, et al., Long-term assessment of an autonomous wireless structural health monitoring system at the new Carquinez Suspension Bridge, Security. 7983 (2011) 798312-798312–9. doi:10.1117/12.880145.
[10] T.J. Matarazzo, S.N. Pakzad, STRIDE for Structural Identification using Expectation Maximization: Iterative Output-Only Method for Modal Identification, Journal of Engineering Mechanics. 142 (2016) 4015109. doi:10.1061/(ASCE)EM.1943-7889.0000951.
[11] G.H. James, T.G. Carne, J.P. Lauffer, The Natural Excitation Technique (NExT) for Modal Parameter Extraction From Operating Wind Turbines, Albuquerque, NM, 1993.
[12] J.-N. Juang, E. Cooper, J.R. Wright, An eigensystem realization algorithm using data correlations (ERA DC) for modal parameter identification.pdf, (1988) 10.
[13] R. Yao, S.N. Pakzad, Autoregressive statistical pattern recognition algorithms for damage detection in civil structures, Mechanical Systems and Signal Processing. 31 (2012) 355–368. doi:10.1016/j.ymssp.2012.02.014.
[14] Y. Lei, A.S. Kiremidjian, K.K. Nair, J.P. Lynch, K.H. Law, T.W. Kenny, et al., Statistical Damage Detection Using Time Series Analysis on a Structural Health Monitoring Benchmark Problem, (2003).
[15] M.B. Nigro, S.N. Pakzad, S. Dorvash, Localized Structural Damage Detection: A Change Point Analysis, Computer-Aided Civil and Infrastructure Engineering. 29 (2014) 416–432. doi:10.1111/mice.12059.
[16] M.I. Friswell, J.E. Mottershead, Finite Element Model Updating in Structural Dynamics, 1995.
[17] M. Horner, K. Kosner, K. Korneva, T.J. Matarazzo, S.N. Pakzad, A Wireless Mobile Sensor Platform for Structural Health Monitoring, in: Proceedings of the Joint 6th International Conference on Advances in Experimental Structural Engineering (6AESE) and 11th International Workshop on Advanced Smart Materials and Smart Structures Technology (11ANCRiSST), Urbana-Champaign, IL, 2015: pp. 1–7.
[18] T.J. Matarazzo, S.N. Pakzad, Structural Modal Identification for Mobile Sensing with Missing Observations, Journal of Engineering Mechanics. 142 (2016) 4016021. doi:10.1061/(ASCE)EM.1943-7889.0001046.
[19] B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, et al., CarTel : A Distributed Mobile Sensor Computing System, in: Proceedings of the 4th ACM Conference on Embedded Networked Sensor Systems, 2006: pp. 125–138. doi:10.1145/1182807.1182821.
[20] C.W. Lin, Y.B. Yang, Use of a passing vehicle to scan the fundamental bridge frequencies: An experimental verification, Engineering Structures. 27 (2005) 1865–1878. doi:10.1016/j.engstruct.2005.06.016.
[21] Y.-B. Yang, C.W. Lin, J.D. Yau, Extracting bridge frequencies from the dynamic response of a passing vehicle, Journal of Sound and Vibration. 272 (2004) 471–493. doi:10.1016/S0022-460X(03)00378-X.
[22] M. Chang, S.N. Pakzad, Observer Kalman Filter Identification for Output-Only Systems Using Interactive Structural Modal Identification Toolsuite (SMIT), Journal of Bridge Engineering. 19 (2013) 4014002. doi:10.1061/(ASCE)BE.1943-5592.0000530.
[23] J.-N. Juang, M.Q. Phan, Identification and Control of Mechanical Systems, Cambridge University Press, Cambridge, 2001.
[24] T.J. Matarazzo, S.N. Pakzad, Truncated Physical Model for Dynamic Sensor Networks with Applications in High-Resolution Mobile Sensing and BIGDATA, Journal of Engineering Mechanics. 142 (2016) 4016019. doi:10.1061/(ASCE)EM.1943-7889.0001022.
[25] T.J. Matarazzo, S.N. Pakzad, Scalable Structural Modal Identification using Dynamic Sensor Network Data with STRIDEX, Submitted to Computer-Aided Civil and Infrastructure Engineering. (2017).
[26] EMarketer, Number of Smartphone Users Worldwide from 2014 to 2020 (in Billions), Statista - The Statistics Portal. (2016).
[27] M. Anderson, Technology Device Ownership: 2015, Technology Device Ownership: 2015. (2015) 1–4.
[28] F. Calabrese, M. Colonna, P. Lovisolo, D. Parata, C. Ratti, Real-Time Urban Monitoring Using Cell Phones: A Case Study in Rome, IEEE Transactions on Intelligent Transportation Systems. 12 (2011) 141–151.
[29] P. Wang, T. Hunter, A.M. Bayen, K. Schechtner, M.C. González, Understanding road usage patterns in urban areas., Scientific Reports. 2 (2012) 1001. doi:10.1038/srep01001.
[30] L. Alexander, S. Jiang, M. Murga, M.C. González, Origin-destination trips by purpose and time of day inferred from mobile phone data, Transportation Research Part C: Emerging Technologies. 58 (2015) 240–250. doi:10.1016/j.trc.2015.02.018.
[31] T.S. Brisimi, C.G. Cassandras, C. Osgood, I.C. Paschalidis, Y. Zhang, Sensing and Classifying Roadway Obstacles in Smart Cities: The Street Bump System, IEEE Access. 4 (2016) 1301–1312. doi:10.1109/ACCESS.2016.2529562.
[32] A. Mednis, G. Strazdins, R. Zviedris, Real Time Pothole Detection using Android Smartphones with Accelerometers Research domain • Road infrastructure as blood vessels, (2011).
[33] R. Kumar, A. Mukherjee, V.P. Singh, Community Sensor Network for Monitoring Road Roughness Using Smartphones, Journal of Computing in Civil Engineering. 4016059 (2016) 1–11. doi:10.1061/(ASCE)CP.1943-5487.0000624.
[34] R. Cantieni, Dynamic Behavior of Highway Bridges, Düubendorf, 1992.
[35] MediaPost, Number of smartphone users in the United States from 2010 to 2019 (in millions)*, Statista. (2015).
[36] GSMA, Smartphone penetration in the United States from 2008 to 2014 (in percent of new handset sales), Statista - The Statistics Portal. (n.d.).
[37] L. Rainie, Cell phone ownership hits 91% of adults, Pew Research Center Fact Tank. (2013).
[38] T. File, Computer and Internet Use in the United States, 2013.
[39] F. Calabrese, M. Diao, G. Di Lorenzo, J. Ferreira Jr., C. Ratti, Understanding individual mobility patterns from urban sensing data: A mobile phone trace example, Transportation Research Part C: Emerging Technologies. 26 (2013) 301–313. doi:10.1016/j.trc.2012.09.009.
[40] S. Phithakkitnukoon, T. Horanont, G. Di Lorenzo, R. Shibasaki, C. Ratti, Human Behavior Understanding, in: International Workshop on Human Behavior Understanding, Springer Berlin Heidelberg, 2010: pp. 14–25. doi:10.1007/978-3-319-02714-2.
[41] H. Wang, F. Calabrese, G. Di Lorenzo, C. Ratti, Transportation Mode Inference from Anonymized and Aggregated Mobile Phone Call Detail Records, in: Wang, H., Calabrese, F., Di Lorenzo, G., & Ratti, C. (2010, September). Transportation Mode Inference from Anonymized and Aggregated Mobile Phone Call Detail Records. In Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference, IEEE, 2010: pp. 318–323.